An Edge Processing Solution Development for Vessel Condition Monitoring

Anna Lito Michala

Submitted for the Degree of Doctor of Philosophy

Department of Naval Architecture Ocean & Marine Engineering
University of Strathclyde
Glasgow, Scotland, UK

2018

Signed: Date:

Στον Γιάννη.

Acknowledgements

This brief section could not ever be enough for me to express my gratitude to all the people that have helped me in making this body of work a reality. However, I have tried to include at least all those that have helped shape the journey in chronological order.

Firstly, I would like to take this opportunity to thank one of the most inspirational people in my academic life Prof. M. Katevenis. He has been my idol as a lecturer throughout my undergraduate studies and a light push towards the right direction for much of what came later. Unknowingly, he has fuelled my passion for computing, hardware, architectures and all that came with it.

I would never have embarked on this adventure without I. Vourganas and his persistent nagging. So, I must say this was not easy on him either; convincing me to do anything I mean. I must thank him for being there, for giving me the hope and courage to start this journey and providing the support it took to complete it.

I would like to thank the NAOME department for giving me the opportunity and background knowledge in the world of ship condition monitoring. Also, along the same lines I would like to acknowledge the support and assistance provided by Dr. G. Theotokatos on several levels both directly related and unrelated to this thesis. Mostly though I would like to thank my supervisor Dr A. Coraddu for without his keen interest and support the thesis submission would never have been possible. And of course, my examiners Prof. L. Oneto and Prof. I. Andonovic. Finally, I would like to express my gratitude for the support received from EU MR and Inspection Capabilities for Enhanced Ship Safety projects in making ends meet.

An important thank you must be devoted to Dr. C. Tachtatzis and team for their feedback which gave me hope. I would have given up if it was not for their critical evaluation of this work at a time of dire need. Moreover, a major thanks to Dr. J. Singer and Dr. C. Perkins for evaluating my work, providing me with a wealth of knowledge and supporting me in the last leg of the journey.

Last but not least, I would like to thank my family and a few but important friends that have listened to me, my trouble and my thoughts and contributed in their unique ways in my long, difficult but ultimately fulfilling task.

Contents

Acknowledgements i

Contents ii

Nomenclature xii

Publications xvi

Abstract xix

Chapter 1: Introduction 1

1.1 Context & Motivation 2

1.1.1 Condition Monitoring in Non-Maritime Industries 5

1.1.2 Condition Monitoring in Shipping 7

1.1.3 Research Impact & Benefits to Stakeholders 14

1.2 Research Question, Aims and Objectives 16

1.3 Literature Review 17

1.4 Contributions 31

1.5 Disertation Layout 34

Chapter 2: Methodology 36

2.1 Overview 37

2.2 Requirements 39

2.3 System Component Analysis 45

2.3.1 Data Acquisition 45

2.3.2 Data Transmission & Management 48

2.3.3 Data presentation 52

2.4 Component Development 53

2.5 Algorithm Development 58

2.6 Decision Support System 65

2.7 System Integration 69

Chapter 3: Evaluation 72

3.1 Hardware Development 73

3.2 Software Development 77

3.3 Technical Evaluation 87

3.3.1 Experiment Setup 87
3.3.2 System Verification and Validation Strategy 90
3.3.3 First Case Study: Pressure Measurements 92
3.3.4 Second Case Study: High Load Performance 98
3.3.5 Third Case Study: Temperature, Vibration Measurements 108
3.4 Business Case Evaluation 119
3.4.1 Cost/Benefit Analysis 123

Chapter 4: Discussion 126
4.1 System Performance 127
4.2 System Impact 132
4.3 Comparison to Commercial Systems 134
4.4 Transferability, Limitations & Threats to Validity 136

Chapter 5: Conclusions 139
5.1 Conclusions 140
5.2 Future Work 141

References 144

Appendix A – Development Standards 181

Appendix B – Ship Noise Profile and Wireless Application in Hazardous Conditions 186

Appendix C – User Manual 189

Appendix D – Technical Datasheets 191
Engine datasheet 191
Sensor datasheets – Pressure sensor 195
Sensor datasheets – Vibration sensor 199
ZigBee datasheet 201
BBB hardware spec 206

Appendix E – DSS UML diagram 209

Appendix F – Third Case Study Correlation Analysis Results for All Instances 212

Appendix G – WMN suitability validation methodology 232

Appendix H – Power 235

Table of Figures

Figure 1:1 – Growth of economy in the EU and relation to Merchandise trade source UNCTAD (2015), (2016), (2017) 2017 values forecasted. 2
Figure 1:2 – Trends in Global Merchandise and Seaborne Trade source UNCTAD (2015), (2017). 2
Figure 1:3 – European Marine Casualty Information Platform reported accidents/incidents 2011-2016 source EMSA (2015), (2017). 3
Figure 1:4 – Lives lost compared to passengers carried by air transport in the past six decades (DNV GL, 2014). 7
Figure 1:5 – Percentage of global fleet using PMS and CBM according to data from Shorten (2012)... 8
Figure 1:6 – Typical marine engines adapted from MS (2016). 22
Figure 1:7 – Stages of information processing and processing paradigms. 24
Figure 1:8 - Dissertation layout diagram. 34
Figure 2:1 – Methodology. 38
Figure 2:2 – System Requirements Categorisation. Key Performance Indicators (KPI) sourced from MARINTEK, (2010). 40
Figure 2:3 – Strategy for novel maintenance system development. 41
Figure 2:4 – Data management system needs based on literature review identified considerations. 42
Figure 2:5 – Ship selected critical systems and resulting subsystems. 44
Figure 2:6 – Data management sequence. 51
Figure 2:7 – Proposed methodology implementation overview. 53
Figure 2:8 – Integrated DAQ component for signal harnessing. 54
Figure 2:9 – Pre – processing and filtering raw data to reduce wireless network traffic. 55
Figure 2:10 – Embedded and Wireless system state machine. 56
Figure 2:11 – Format of communication protocol. 58
Figure 2:12 – Data flow through Post-processing and into analysis tool and DSS. The tool data flow internal sequence was adapted from Lazakis et al. (2017). 63
Figure 2:13 – Post processing received data method to provide open-ended output for compatibility. 63

Figure 2:14 –Data transmission decision algorithm to minimise bandwidth use when at sea. 64
Figure 2:15 – Algorithm used to incorporate basic Machine Learning in DSS......... 68
Figure 2:16 – Integrated system overview illustrating the DAQ and the collection point along with the data flow block diagram (*mng stands for management). 70
Figure 2:17 –System Overview........ 71
Figure 3:1 – Selected sensors for installation on the engine (a) pressure sensor (b) vibration sensor. 73
Figure 3:2 – (a) BNC connector to embedded system wiring diagram redesigned based on Measurement Computing (2012) and (b) typical BNC connector for PCB layout with bayonet lock to secure the cable (photograph of purchased part used for system implementation). 74
Figure 3:3 – Electronic configuration of the sensor with an internal amplifier connected to signal conditioning circuit. 75
Figure 3:4 – Analogue and digital electronics for the connection of the sensors to BBB. 76
Figure 3:5 – Main hardware blocks and connections used for the benchtop model device........ 77
Figure 3:6 – Initial break-out model with battery support for the connected pressure sensor and micro-USB connection to power-bank for BBB (left) and USB connection to Wireless breakout board in cardboard housing (right)........ 77
Figure 3:7 – Layout of the system and wireless data transmission node proposed ship installation........ 77
Figure 3:8 – Linux system architecture using sysfs, systemd and system kernel utilities. 79
Figure 3:9 – UML diagram of the wireless chip driving library with the added functionality for network and error management both from the local and the remote processors........ 81
Figure 3:10– Process to setup PRUs for ADC sampling of any desired sampling rate up to 100Ksps based on BBB specification and guidance from (Molloy, 2015a)..... 82
Figure 3:11 – Flow of central collection point DAQ software implementation........ 83
Figure 3:12 – DSS Java program represented as a standard UML diagram............. 85

Figure 3:13 – Updated prediction analysis tab of the GUI presenting the statistical degradation analysis used for the DSS on a camshaft bearing which is found to be in a warning condition. 87
Figure 3:14 – Updated actions tab of the GUI presenting the additional functionality for completing an action which is suggested for a warning raised by the DSS for a camshaft bearing. 87
Figure 3:15 – Benchtop model of the DAQ measurement unit powered by a battery set for the sensor and a battery bank for the BBB board (Left). BBB to Li-Po battery photograph (centre) and connection diagram (right). 88
Figure 3:16 - The Engine Room in the Laboratory, image captured from control area through the glass window. 89
Figure 3:17 - Board connected to signal conditioning circuit and sensor (left) and receiver board connected to local PC (right). 90
Figure 3:18 - Four DAQs with virtual sensors: (a) and (b) housing and antennas, (c) and (d) wireless transmitter development boards and embedded BBB Linux boards, battery powered. 90
Figure 3:19 – Methodology and direct path produce two different outputs from the reliability analysis tool. 91
Figure 3:20 – Experimental setup with controllable changes to pressure over time: (a) the pump was connected to one end of a hose while the sensor inserted at the other; gaps were sealed, (b) a picture of the sensor inserted into the tube with the far end of the tube sealed on the floor of the engine room. 93
Figure 3:21 - Raw data collected from the sensor without pre-processing. 94
Figure 3:22 – Pre-processed mean pressure data received. 95
Figure 3:23 – Post processed data generated at the main collection point based on received pre-processed information. 95
Figure 3:24 – Data set correlation between post-processed values and raw values is at the highest possible value (primary and tertiary datasets). 96
Figure 3:25 – Data set correlation between mean pre-processed values and raw values is low (primary and secondary datasets). 96
Figure 3:26 – Predicted condition based on first set of data (raw data). 97

Figure 3:27 – Predicted condition based on second set of data (post-processed data). 97
Figure 3:28 – Correlation of the two predicted reliability result sets........................ 97
Figure 3:29 – Example of data that has been allowed for processing through the MRA even though they were indicative of a sensor providing erroneous readings (In this case values lower than expected kg/cm^2). 98
Figure 3:30 – All 7 virtual sensors connected from the Analogue I/O (ports 33 to 40 – refer to Appendix D for additional information on port mapping and connection allocations). 100
Figure 3:31 – Pressure sensor installed on the machine and connected to the DAQ system. 101
Figure 3:32 - Deployment in Engine Laboratory, image captured from control area through the glass window. 102
Figure 3:33 – Number of bytes transmitted after pre-processing against raw data bytes throughout the month. 104
Figure 3:34 - Packets successfully received for each sensor on 1st, 2nd or later transmission attempt. 105
Figure 3:35 - Example of correlation analysis between initial data and post-process generated data for two cases (a) the virtual sensor (No. 11) (b) the physical sensor (No. 39). 107
Figure 3:36 – Worst case result of correlation analysis between initial data and post-process generated data (a) the two sets presented against the time for the duration of the case study (b) correlation analysis. 108
Figure 3:37 – Reliability analysis result for the recorded temperature sensor on the laboratory diesel engine. 111
Figure 3:38 – Statistical properties results of pre-processing of bearings 1(a, b) and 2 (c, d) mapped to the reliability results of post-processing. Series marked with * in the legend are plotted on the secondary vertical axis (right side) while the remaining are plotted against the primary vertical axis (left side). 113
Figure 3:39 – Statistical properties results of pre-processing of bearings 3 (a, b) and 4 (c, d) mapped to the reliability results of post-processing. Series marked with * in the legend are plotted on the secondary vertical axis (right side) while the remaining are

plotted against the primary vertical axis (left side). DSS warnings are vertical orange lines and DSS failures are vertical red lines. 114
Figure 3:40 – Statistical properties results of pre-processing in experiment 2 mapped to the reliability results of post-processing. Series marked with * in the legend are plotted on the secondary vertical axis (right side) while the remaining are plotted against the primary vertical axis (left side). DSS warnings are vertical orange lines and DSS failures are vertical red lines. 116
Figure 3:41 – Statistical properties results of pre-processing in experiment 3 mapped to the reliability results of post-processing. Series marked with * in the legend are plotted on the secondary vertical axis (right side) while the remaining are plotted against the primary vertical axis (left side). DSS warnings are vertical orange lines and DSS failures are vertical red lines. Vertical green lines signify lifted warning/failure state. 117
Figure 3:42 – Cost of loss of productivity against machinery/equipment criticality, adapted from SKF (2016). 119

Table of Tables

Table 1:1 – Comparative analysis of CM data acquisition methods applicable to shipping.......... 9
Table 1:2 – Ship machinery/equipment grouped by set of applicable monitoring methods.......... 10
Table 1:3 - Recorded parameters, source (BV, 2014, LR, 2013, RINA, 2012b)....... 18
Table 1:4 – Sensors, installation and processing methods, sources (Li et al., 2012, eGreenShip, 2012a, 2012b, 2013, Jardine et al., 2006, Jiang and Yan, 2008). 28
Table 2:1 – Comparison of Linux quick start development boards (values marked with * indicate that the option is not readily available and would require significant software development overhead).......... 47
Table 2:2 – Comparison of Industrial Wireless Protocols.......... 50
Table 2:3 – Configuration settings.......... 54
Table 2:4 – Additional configuration settings (continues from Table 2:3).......... 56
Table 2:5 – Default operation modes timing and indicative data requirements. 56
Table 2:6 – Commands for network management, diagnosis and configuration setup. 57
Table 2:7 – Data-specific system configuration settings for any sensorial input. 59
Table 3:1 – Characteristics of the diesel engine in the marine engine laboratory at the University of Strathclyde.......... 89
Table 3:2 – Configuration settings for the first case study. Values -1 were used to indicate that there was no limit or threshold for this case study.......... 93
Table 3:3 – Configuration settings for the second case study. 100
Table 3:4 - Measured parameters from ship's main engine.......... 103
Table 3:5 – Results of correlation analysis in terms of R^2 values for each sensor instance for Temperature (T) and Pressure (P) measurements. 106
Table 3:6 – IMS dataset experiments and recorded failures.......... 109
Table 3:7 - Measured parameters from IMS dataset on bearing vibration measurements.......... 109
Table 3:8 – Configuration settings for the second case study. 110
Table 3:9 – Correlation between raw and processed IMS dataset on bearing vibration measurements for experiment 1. 115

Table 3:10 – Correlation between raw and processed IMS dataset on bearing vibration measurements for experiment 2. 118
Table 3:11 – Correlation between raw and processed IMS dataset on bearing vibration measurements for experiment 3. 119
Table 3:12 – Summary of wireless network benefits. 122
Table 3:13 – Costs associated with adoption of proposed CM method. 123
Table 3:14 – Benefits of adopting the proposed CM method over non-CM methods. 124
Table 3:15 – Benefits of adopting the proposed CM method over other CM methods. 124

Table of Pseudo code

Pseudo code 2:a – Signal type data pre-processing algorithm. 60

Pseudo code 2:b – Value type data pre-processing algorithm. 62

Pseudo code 3:a – Example of entries in the configuration file. 78

Pseudo code 3:b – Wireless transmission routine. 79

Pseudo code 3:c – State Machine. 80

Nomenclature

Acronym	Definition
3G	3rd Generation (wireless mobile telecommunications technology)
6LoWPAN	IPv6 over Low-Power Wireless Personal Area Networks
ABS	American Bureau of Shipping
AC	Alternating current
ACK	Acknowledgement
ADC	Analogue to Digital Converter
Aft Camshaft Bearing T	Aft Camshaft Bearing Temperature
AM	Amplitude Modulation
ANN	Artificial Neural Network
BBB	BeagleBone Black
BCM	Business Cantered Maintenance
BMT	British Maritime Technology Group
BNC	Bayonet-Neil Concelman
BSI	British Standards Institution
BV	Bureau Veritas
CAD	Computer Aided Design
CapEx	Capital Investment Expenses
CBM	Condition Based Maintenance
CCS	Continues Current Source
CCTV	closed-circuit television
CE	Conformité Européenne
CG	Conflict Graph
Class	Classification Society
ClassNK	Class Society Nippon Kaiji Kyokai
CM	Condition Monitoring
CO2	Carbon Dioxide
CRC	Cyclic Redundancy Code
CSMA-CA	Carrier-Sense Multiple Access with Collision Avoidance
CSV	Comma Separated Values
Cylinder Input JCFW P	Cylinder Input JCFW Pressure
Cylinder x Output Exh Gas T	Cylinder x Output Exhaust Gas Temperature
DAQ	Data Acquisition
DC	Direct Current
DNT-SMD	Dust Networks' Time Synchronized Mesh Protocol
DNV-GL	Det Norske Veritas and Germanischer Lloyd Class
DoD	Department of Defence (USA)
DoT	Department of Transport (USA)
DSP	Digital Signal Processing
DSS	Decision Support System

DTO	Device Tree Overlay
ECSA	European Community Ship-owners' Association
ECSA	European Commission
EEA	European Economic Area
EEDI	Energy Efficiency Design Index
EGS	Enhanced Group Call
EMC	Electromagnetic Compatibility
EMI	Electromagnetic Interference
EMSA	European Maritime Safety Agency
EP	European Parliament
EU	European Union
Ex.Gas Out After Turbo Chargx T	Exhaust Gas Output After Turbo Charger x Temper-ature
FDMA	Frequency Division Multiple Access
FFT	Fast Fourier Transform
FM	Frequency Modulation
Fore Cam Bearing T	Fore Camshaft Bearing Temperature
GE	General Electric
GMDS	Global Maritime Distress and Safety System
GPIO	General Purpose I/O
GPRS	General Packet Radio Service
GSM	Global System for Mobile communication
GUI	Graphical User Interface
HCM	Hull Condition Monitoring
HDMI	High-Definition Multimedia Interface
I/O	Input/Output
IACS	International Association of Classification Societies
ICS	International Chamber of Shipping
IEEE	Institute of Electrical and Electronic Engineers
IMO	International Maritime Organisation
INCOSE	International Council of Systems Engineering
INMARSAT	International Marine/Maritime Satellite
IntShaft x Bearing T	Int Shaft x Bearing Temperature
iOS	iPhone Operating System
IoT	Internet of Things
IPMS	Integrated PMS
ISA	International Society of Automation
ISM Band	Industrial, Scientific and Medical Radio Band
ISM Code	International Safety Management Code
JCFW x Output T	Jacket-Cooling-Fresh-Water x Output Temperature
KPI	Key Performance Indicator
LAN	Local Area Network
LR	Lloyd's Register
MAC	Media Access Control
Main Eng Start Air P	Main Engine Start Air Pressure
Main Engine Control Air Input P	Main Engine Control Air Input Pressure
Main Lube Oil Input P	Main Lube Oil Input Pressure

Main Lube Oil Input T	Main Lube Oil Input Temperature
MARINTEC	Norwegian Marine Technology Research Institute
MARPOL	International Convention for the Prevention of Pollution from Ships
MCM	Machinery Condition Monitoring
MEMs	Micro-Electro-Mechanical System
MEPC	Marine Environment Protection Committee
MIP	Maxim Integrated Products Inc.
MoD	Ministry of Defence
MRA	Machinery Reliability Analysis
MRV	Monitoring, Reporting and Verification
MSG	Maintenance Steering Group
MSP	Maritime Service Portfolios
MTBF	Mean-Time Between Failures
NAVTEX	Navigational Telex
OEM	Original equipment manufacturer
OpEx	Operational Expenses
OS	Operating System
PAS	Publicly Available Specification
PC	Personal Computer
PCB	Printed Circuit Board
PCMS	Propulsion Condition Monitoring Service
PHY	Physical Layer
Piston CO Input P	Piston CO Input Pressure
PMS	Planned Maintenance System
PoF	Probability of Failure
PRU	Programmable Real-time Unit
PWC	PricewaterhouseCoopers
QoS	Quality of Service
RBM	Risk Based Maintenance
RCM	Reliability Centred Maintenance
RF	Radio Frequency
RINA	Registro Italiano Navale
SBC	Single Board Computers
Scav Air Manifold P	Scaveng Air Manifold Pressure
Scav Air Rec 1 T	Scaveng Air Rec 1 Temperature
SCU	Signal Condition Unit
SD-Card	Secure Digital Card
SEEMP	Ship Energy Efficiency Management Plan
SKF	Svenska Kullagerfabriken
SME	Small and medium-sized enterprise
SoC	System on a Chip
SOLAS	International Convention for the Safety of Life at Sea
SPI	serial peripheral interface
SSE	Ship Systems and Equipment
SSH	Secure Shell
SUBMEP	(Submarine Maintenance Engineering, Planning and Procurement

TCLO 1 Input P	TCLO 1 Input Pressure
TCLO 1 Input T	TCLO 1 Input Temperature
TCLO 1 Output T	TCLO 1 Output Temperature
TDMA	Time Division Multiple Access
Thrust B. LO Out T	Thrust Bearing Lube Oil Outlet Temp
TPM	Total Productive Maintenance
UART	universal asynchronous receiver-transmitter
UK	United Kingdom
UNCTAD	United Nations Conference on Trade and Development
US (USA)	United Sates (of America)
VBM	Vibration Based Maintenance
Wi-Fi	Brand name for IEEE 802.11b Direct Sequence Wireless communication standard (often mistakenly referred as Wireless Fidelity)
WirelessHART	Wireless Highway Addressable Remote Transducer Protocol
WLAN	Wireless LAN
WMN	Wireless Multihop Network

Publications

The author has contributed to the following conference and journal articles in order to disseminate the performed research and validate it through feedback. The publications in this list also appear as a footnote in the section of this thesis, where the content of the section has been published.

Journal papers

LAZAKIS, I., DIKIS, K., MICHALA, A.L. & THEOTOKATOS, G. 2017. Advanced Ship Systems Condition Monitoring for Enhanced Inspection, Maintenance and Decision Making in Ship Operations. *Transportation Research Procedia*, 14, 1679–1688.

Relevance: Presentation of a case study utilising an earlier version of the decision support user interface presented in this thesis in conjunction with the machinery reliability analysis tool.

Quality: Second most-cited in the maritime stream (1/3 of 486 total articles) and within the top 3% of most-cited publications of volume with 7 citations within 13 months.

Conference papers

MICHALA, A. L. & VOURGANAS, I. 2017. A Smart Modular Wireless System for Condition Monitoring Data Acquisition. *In: Proceedings of the 16th International Conference on Computer and IT Applications in the Maritime Industries, Cardiff, 15-17 May*, Technische Universität Hamburg, Harburg, ISBN 978-3-89220-701-6, 212-225.

Relevance: Presentation of PhD methodology, Integrated system/implementation, software development of DAQ system and DSS system, mathematical models used for the DSS system, the second case study of this thesis along with results, discussion and related conclusions.

Quality: Conference of high esteem in this domain. Reviews of the conference with references to my contribution were published by the Royal Society of Naval Architects website, The Naval Architect journal, SSI corporate, DELL maritime division and HANSA International Maritime Journal.

MICHALA, A. L. & LAZAKIS, I. 2016. Ship machinery and equipment wireless condition monitoring system. *In: Proceedings of the International Conference of Maritime Safety and Operations, 13-14 October, University of Strathclyde, Glasgow*, ISBN No 978-1-909522-16-9, 63-69.

Relevance: Concept presentation of the DAQ system, description of the initial operation of the system and it's collaboration with the INCASS MRA tool. Presentation of part of the first case study and the identified short-comings of the MRA tool.

Quality: Top 6 most-cited of venue.

DIKIS, K., LAZAKIS, I., MICHALA, A.L., RAPTODIMOS, Y. & THEOTOKATOS, G. 2016. Dynamic risk and reliability assessment for ship machinery decision making. *In: European Safety and Reliability Conference, 25-29 September,* Glasgow

Relevance: Presentation of DSS tool interface as developed for the INCASS project used in case study with the MRA tool.

LAZAKIS, I., DIKIS K. & MICHALA, A. L. 2016. Condition Monitoring for Enhanced Inspection, Maintenance and Decision Making in Ship Operations. *In: Proceedings of the 13th International Symposium on Practical Design of Ships and Other Floating Structures, 4-8 September*, Copenhagen.

Relevance: Presentation of DSS tool interface as developed for the INCASS project used in case study with the MRA tool.

Quality: DTU statistics: 420 downloads in 14 month of conference proceedings.

MICHALA, A. L., LAZAKIS, I., THEOTOKATOS, G. & VARELAS, T. 2016. Wireless condition monitoring for ship applications. *In: The Royal Institution of Naval Architects Smart Ship Technology proceedings, 26-27 January*, London.

Relevance: Presentation of findings of literature review and gap, concept of proposed solution, and description of the DSS user interface.

Quality: Conference attended by researchers and industry from UK, EU, Japan and Korea establishing a new domain of smart ships, autonomous vessels and combed Computing Science and Marine Engineering.

MICHALA, A. L., LAZAKIS I. & THEOTOKATOS, G. 2015. Predictive maintenance decision support system for enhanced energy efficiency of ship machinery. *In: International Conference of Shipping in Changing Climates 2015 Conference proceedings, 24-26 November*, Glasgow.

Relevance: Presentation of the mathematical formulations for the incorporation of INCASS MRA results as input for the earliest version of the DSS tool.

Reports

DIKIS, K., LAZAKIS I. & MICHALA, A. L. 2015. D4.5 (WP4): Architecture, framework and development of Decision Support System. *Inspection Capabilities for Enhanced Ship Safety Consortium*, EC FP 7 (FP7/2007-2013). Grant Agreement No 605200.

Relevance: User manual for the DSS tool when used in conjunction with the INCASS MRA tool.

Abstract

In shipping, condition monitoring (CM) has the capacity for big data but also very high communications costs. Thus, the use of continuous condition monitoring in the shipping industry is not as prevalent as in others. It is found that trust in technology, data security/ownership, the capital cost of investment, cost of training, operational cost and direct benefit association are some of the most important inhibitors. To reduce the volume of data, edge processing is a new paradigm of computing. Its goal is to address the issues generated through the increasing flow of recorded data to central locations for big data analytics.

The existing solutions are adopted by 12% of the global fleet corresponding to the newbuilt ships, while sensors and monitoring infrastructure exists in the majority. Solutions targeting newbuilt ships have a requirement of extensive refitting and training overheads. Solutions for existing vessels are mostly hand-held equipment, do not support continuous monitoring and do not display the information in business relevant terms. A wireless ship CM reduces capital investment costs but has high operational costs due to the centralised data processing software.

The proposed novel system is edge processing wireless ship CM data under constrains. The system's traffic reduction is achieved through feature and event extraction on the data acquisition devices. Also a data management strategy is implemented along with decision support which provides direct benefit association with maintenance actions. The multi-constrain multi-parameter approach identifies the best maintenance action to be taken onboard the ship. Finally, minimal satellite data transmission provides visibility of condition to shore.

The system was successfully applied in case studies. According to the evaluation results, the system is reliable and suitable for the application, is able to identify and suggest appropriate maintenance actions and offers several benefits against other currently available maintenance and condition monitoring approaches.

Keywords: Data acquisition, wireless data transfer, industrial wireless application, condition monitoring, ship machinery and equipment.

Chapter 1: Introduction

This chapter presents an introduction to the thesis. Initially, the context is presented starting with the marine sector and followed by condition monitoring systems. The motivation is demonstrated through the identified business needs, constrains and technology adoption inhibitors. Also, the impact and benefits to stakeholders are discussed. The research question as well as the aims and objectives of the thesis are outlined in Section 1.2. Section 1.3 presents a literature review of existing technologies and their suitability in addressing the identified needs, constrains and inhibitors. Section 1.4 summaries the key findings and highlights the contributions of the proposed research. Finally, Section 1.5 presents the dissertation layout.

1.1 Context & Motivation

The marine and maritime sector is one of the pillars of the modern economy, employing 1.5 million people globally (ICS, 2017, IMO, 2013). In 2013 90% of the world trade (Fang et al., 2013) and in 2015 80% of merchandise trade (United Nations, 2016) was seaborne. In gross tonnage 40% of the world fleet is register in countries of EEA (ECSA, 2013, Oxford Economics, 2015, ECSA, 2016). The 90% of external merchandise is transported in the EU/EEA by ships (ECSA, 2010, EC, 2015). With EU recovering from the 2008 economic crisis the merchandise trade is also growing (Figure 1:1) with seaborn trade closely following this growth (Figure 1:2); demonstrating the economic impact of the marine sector.

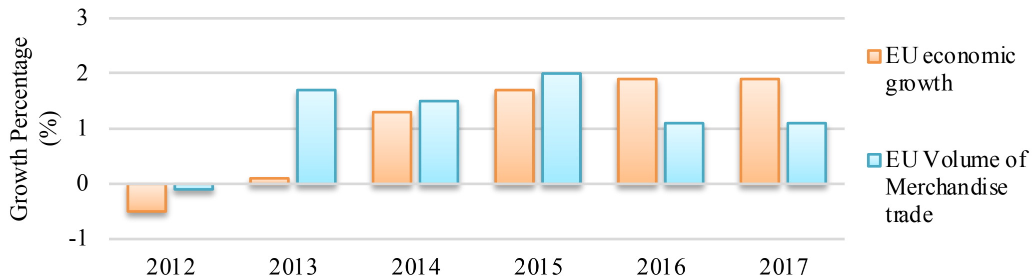


Figure 1:1 – Growth of economy in the EU and relation to Merchandise trade source UNCTAD (2015), (2016), (2017) 2017 values forecasted.

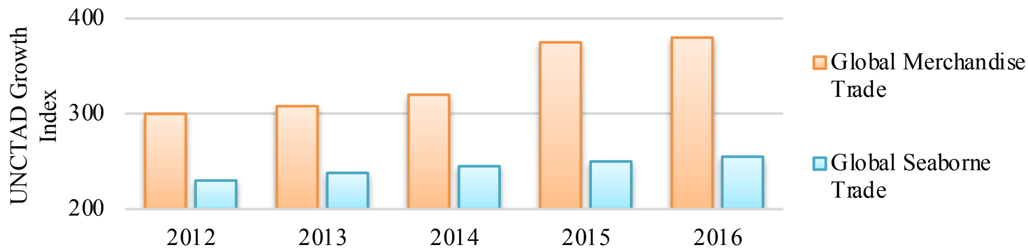


Figure 1:2 – Trends in Global Merchandise and Seaborne Trade source UNCTAD (2015), (2017).

An important factor for the operation of the sector is the availability and reliability of ships (Anderson, 2007, Moubray, 1996, 1997), which makes correct maintenance paramount (Lazakis, 2011). Maintenance actions cost 10% – 15% of the operating budget of a vessel (EC, 2015, Rofle, 2015, Stopford, 2009) while maintenance departments have the largest demand in staff and business expenses (Lazakis et al., 2016b). Correct maintenance is also necessary for compliance with safety and environmental regulations which are becoming more stringent (EP and EC, 2015, ECSA, 2013, MEPC, 2011, Pitblado, 2001, Mobley 2001d). For example, Ship Energy Efficiency Management Plan (SEEMP) regulation mandates 50% reduction of naval industry emissions by 2025 (ECSA, 2012). Also correct maintenance reduces unexpected failures that can lead to: safety, loss of ship, detrimental effects on the local environment, and casualties (Hassler, 2016, Li et al., 2012, Mei and Yin, 2009, DoD, 2005).

According to Nowlan and Heap (1978), a direct connection exists between maintenance, reliability and safety of a system. In terms of safety, within EU, the trend of accidents/incidents reported is increasing (Figure 1:3). From the reported number of accidents that lead to casualty, the fifth most important reason at 12% was damage to ship equipment (2011-2014) rising over 30% in 2016 (EMSA, 2015, 2017). Maintenance is the most important contributing factor related to accidental events and equipment failure by a large margin (EMSA, 2015). Such accidental events can cause disruption to ship operations or even render it unavailable (DoD, 2005).

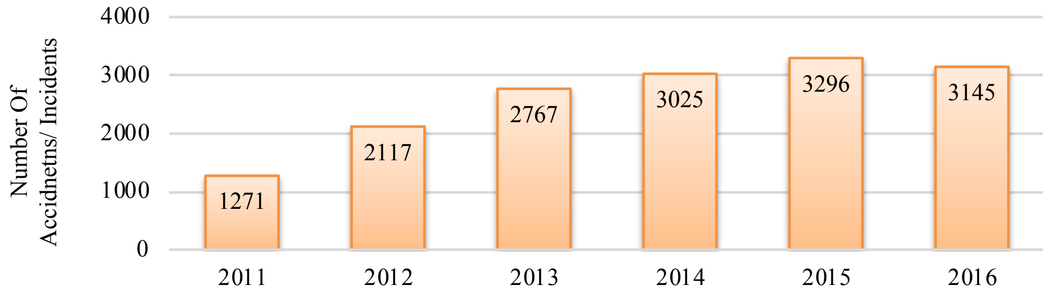


Figure 1:3 – European Marine Casualty Information Platform reported accidents/incidents 2011-2016 source EMSA (2015), (2017).

Hence, maintenance is not only mandatory (SOLAS, 1914, 1929, 1948, 1960, 1974, Furuseth, 1914, SSE, 2016, IMO, 1993b) but necessary. Traditional approaches such as surveys/inspections (IACS, 2004) introduce failures due to human error (Dhillon and Liu, 2006, Stephens et al., 2000, Reason, 1997, Smith, 1992, Dhillon, 1986) which can result in casualty (Dunn, 2006) and have not been effectively addressed through training guidelines (Pitblado, 2001). Several standards (Shin and Jun, 2015, BSI, 2014, BSI, 2008, MoD, 2006a), regulation (IMO, 2015), certification processes (Lazakis et al., 2015) and Classification Society (Class) requirements (Lazakis et al., 2016c) govern the implementation of ship surveys and inspections. According to these requirements surveys are scheduled based on age and manufacturer guidelines. However, 77% of ship equipment/machinery failures are not related to age (Allen, 2001, Conachey, 2004).

Thus, several management strategies have been developed to address maintenance scheduling (Nenni, 2013), operational life-cycle management (DNV GL, 2014) and asset management (van Dongen, 2016, Takata et al., 2004). These strategies aim to:

- *identify and diagnose failures ahead of time (Mechefske, 2005)*
- *support better spare part inventory management (Schwabacher, 2005, Kelly, 1997)*
- *schedule maintenance efficiently (Schwabacher, 2005)*
- *reduce overhaul cycles (Nemarich et al., 1990)*
- *increase availability of ship (Maggard et al., 1989)*
- *avoid unnecessary maintenance actions (Schwabacher, 2005)*
- *maintain operating performance of the system at optimum or within desired limits (Prajapati et al., 2012).*
- *support optimal utilisation of ship and personnel (van Dongen, 2016)*
- *Support business needs and goals (Iung et al., 2009) such as:*
    - *productivity (Belak, 2004)*
    - *profit (Waeyenbergh and Pintelon, 2002, Kelly, 1997),*
    - *maintenance effectiveness (Ahuja, 2009),*
    - *product quality, reduction of waste, and safety (Maggard et al., 1989)*

To achieve the goals of these maintenance strategies, continuous Condition Monitoring (CM) is needed (Laird, 1989) combined with predictive maintenance and remote visibility (Iung et al., 2009, DoD, 2008). CM can be viewed as a set of steps starting from the acquisition of data through appropriate sensors or other methods, progressing to feature extraction and finally leading to analysis, diagnosis and decision making assistance (Delvecchio, 2012). CM requires a higher initial investment (SKF, 2012b) and an increased demand for training (Shorten, 2012, SKF, 2012b, Griffin, 2011). However, the failure rates are drastically reduced (Dod, 2008), safety increased (Peters, 2015), risk minimised (Peters, 2015, Griffin, 2011, Sutton, 2010) and cost of maintenance optimised (Shin and Jun, 2015, Shorten, 2012, Griffin, 2011, Smith, 2001) while human error is reduced enhancing the quality of maintenance (Moghaddam and Usher, 2011, DNV GL, 2014, Jardine et al., 1997, DoD, 2008, IMO, 1993a).

This approach demonstrates increased life-time of equipment (Carretero et al., 2003) in aviation (Guo et al., 2016), oil and gas (Calixto, 2016), and railway sectors (Al-Douri et al., 2016). The following subsection reviews the application and benefits of CM in the sectors of power generation, industrial and aviation in association with ship applications.

1.1.1 Condition Monitoring in Non-Maritime Industries

CM and fault-finding methods have been established and are integral to the power system generation and distribution infrastructure (Rahman et al., 2012, Sujatha and Vijay Kumar, 2014, Sujatha and Vijay Kumar, 2013, Rigatos and Siano, 2016) as power generation is of utmost importance (El-Hawary, 2008) and power outages have significant practical and economic impacts (Verayiah et al., 2014). Examples of advanced CM for nuclear power generation exist in abundance (Hashemian and Bean, 2011, Liu et al., 2013, Wang et al., 2016). Similarly, CM is important in the distribution and generation systems and is installed in sub-stations (Baker, 2010), generators (Chang et al., 2016), and other critical equipment (Rigatos and Siano, 2016). With renewable energy sources, power systems have increased in complexity (Jatzeck and Robinson, 1996), are continuously more remotely located, difficult to access, and increasingly more vulnerable (Mozina, 2007). Hence, CM is central to the design of machinery/equipment such as wind turbines (Yang et al., 2016) and inverters (Kamel et al., 2015). In most cases the CM system is also remotely accessible (Igba et al., 2016). In this sector, CM is deployed extensively, can be installed in locations and areas difficult to access or impossible to access without disturbing the system, ensures uninterrupted operation, and is necessary to avoid the catastrophic effects that power cuts cause.

In close resemblance to the power generation industry, general industrial applications have also encapsulated CM over the years. As presented by Byrne et al. (1995), the use of CM in industrial processes can be directly linked to an increase in productivity. Humphreys et al. (2014) prove that CM, used appropriately and effectively, can provide sustained quality of produced work. The applications include cutting tools (Nouri et al., 2015), complex grinding processes (Humphreys et al., 2014) and pumps (Myhre et al., 2014) among several others. Methods vary depending on the application and may be from as simple as trending averages to coefficient analysis and neural networks etc. (Nouri et al., 2015). Most often, a large amount of collected data is required for the appropriate application of CM, especially in applications that are relatively novel (Humphreys et al., 2014). Improved asset management and information gathering from difficult to access areas (Myhre et al., 2014) are of significance and can be related to the shipping industry.

The aerospace industry is perhaps the one of closest resemblance to the marine and maritime industry. That is due to several facts such as the mechanical parts utilised, the size of the structures involved and the operational conditions. In both cases, vessels operate away from land, are exposed to the effects of weather conditions, utilise a limited crew, inaccessible support and have limited or no access to spare parts.

However, there are some significant differences, mostly accounted for in the way aircrafts are produced in contrasts with building ships. Globally dry cargo newbuilt ship orders reduced by 32% from 2012 to 2013, containers by 8%, tankers by 3%, bulkers by 30%, ferries by 12% and passenger ships reduced by 4% (ECSA, 2013, ECSA, 2012). It is estimated that the global ship and boat building market in 2016 had a negative growth factor of -5.6% (IBISWorld, 2016). Aircrafts are produced identically in large numbers with incorporated CM. On the other hand, ships are uniquely and not often built, making the application of aircraft CM approaches a high cost, leading to vessel dependent implementations (SKF, 2011). As such, a CM system that is applicable to several ships would need to be highly versatile and easily adjustable. Thus, shipping lacks integration of automated CM systems which can be linked to the increasing accidents trend (Section 1.1).

Foremost, the aerospace industry is one of the first to assume CM, (DeMott, 1978a, DeMott, 1978b), and indeed the one that drove the migration to predictive and proactive maintenance management (DNV GL, 2014), still today advancing machinery/equipment (Tourvalis, 2007) and structure (García et al., 2014) CM. The impact is clear in that through the application of these approaches air transport has become increasingly safer since 1980's and continues to move in the direction of decreased risk (DNV GL, 2014, DoD, 2008) (Figure 1:4). The importance of CM was recognised and as a result enforced over survey/inspection maintenance (MSG, 1980). The decade that elapsed, between the implementation of CM and benefit demonstration, was needed for CM to provide sufficient data for statistical analysis to become accurate in the prediction of faults.

Risk reduction was not the only demonstrated benefit. Associated reduction in cost and an increase in reliability was also recorded over the same period (Smith, 1992, US

DOT, 2015, DNV GL, 2014). The economic benefits of the application of CM are not only directly linked to maintenance but also extend to several other aspects of the aircraft's operation and life cycle as in ship operations.

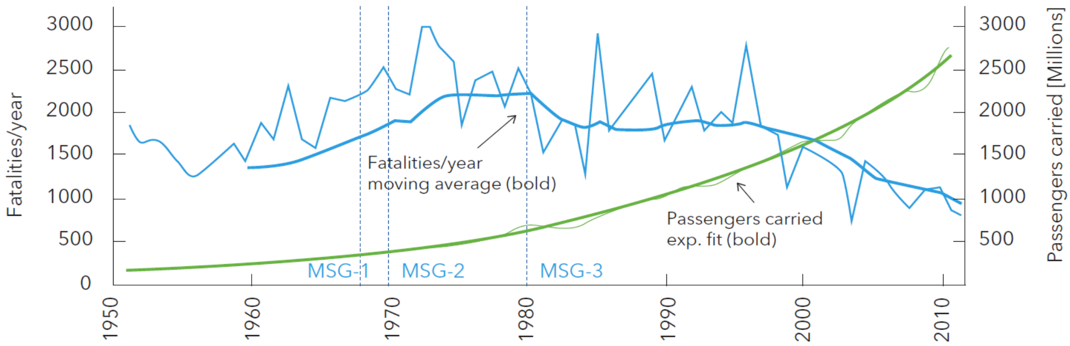


Figure 1:4 – Lives lost compared to passengers carried by air transport in the past six decades (DNV GL, 2014).

1.1.2 Condition Monitoring in Shipping

In contrast with the extended application of automated continuous CM in power generation, industrial and aviation domains, most maintenance of ships is preventive (Shorten, 2012); resulting in unexpected failures. The shipping industry is at a disadvantage when faced with unplanned maintenance events compared to other onshore industries, due to[1]:

- *limited spares available onboard the vessels. Usually well managed, through experience and regulation (Kendall, 1986),*
- *being difficult to deliver spares or even impossible, especially for ships travelling long distances (Kendall, 1986),*
- *the necessity for inspections and other maintenance tasks to be carried out while the ship is at sea by the crew (Lyridis et al., 2005); e.g. adhere to safety regulation, keep the seagoing capability, critical equipment (Ford et al., 2014). Other actions are planned for harbour or refitting periods (Verma et al., 2016) while vessels under-perform due to non-optimal condition (Hiekata and Moser, 2014). This leads to increased fuel consumption and other associated costs,*

[1] Constrains were verified through all of the publications in page xvi.

- *crew numbers are decreasing (Verma et al., 2016, Caesar et al., 2015, Mitroussi and Notteboom, 2015), crew may frequently change and as a result the experience gained on a particular vessel, the expertise and resources required for maintenance may not be available onboard (Verma et al., 2016).*
- *reduced maintenance budget (Michala et al., 2015) and increased maintenance costs (Moore Stephens LLP, 2015),*
- *inefficient operation; performance based maintenance management can increase the operational efficiency of ships (Hiekata and Moser, 2014), safety and protect the environment (EC, 2009).*

All these factors can be mitigated through the appropriate exploitation of technological advances in the area of CM. Also this area is expected to influence future developments in the sector and it is recognised as one of the important sectoral trends (LR et al., 2015). Currently, regulation (IACS, 2014) and Class (DNV GL, LR, RINA, BV, ABS) mandate only a Planned Maintenance System (PMS) (e.g. Rolls-Royce, 2015). The method of implementation can vary from manual to automated. Often companies rely on minimum requirements for compliance (Shorten, 2012). As a consequence, PMS is not *"appropriately implemented"* to assist in other areas of the business as well as in improving maintenance (Figure 1:5). Only 12% of the global fleet use CM and 2% use the results for automated Continuous Based Maintenance (CBM) management.

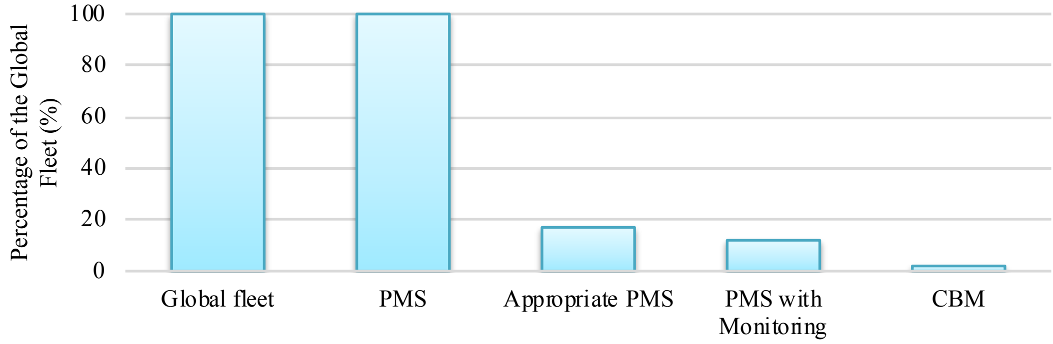


Figure 1:5 – Percentage of global fleet using PMS and CBM according to data from Shorten (2012).

This demonstrates a missed opportunity for the sector, as pressure and temperature sensors are pre-installed in the majority of machinery/equipment (Nemarich et al., 1990). Often leasing critical equipment/machinery is provided on a 'power-by-the-hour' basis with unplanned downtime expenses covered by manufacturers (Payne et al., 2002). Hence, manufacturers install CM on machinery/equipment for their personal competitive advantage. However, these independent CM systems are not interconnected (Carretero et al., 2003) and data collected are not often utilised by the operator or shipowner. CM in shipping is in its infancy with room for development (DNV GL, 2014); 60% of CM applications have failed to mature to successful implementation (Peters, 2015) and there are still limitations in the accuracy of the technology (Shin and Jun, 2015).

To start understanding the reasons, a comparative analysis of CM data acquisition methods applicable in shipping is presented Table 1:1. These methods are well supported by Class and Insurers of vessels (RINA, 2012a).

Table 1:1 – Comparative analysis of CM data acquisition methods applicable to shipping.

CM Data Acquisition Method	Advantages	Disadvantages
Visual Inspection (Moghaddam and Usher, 2011, DoD, 2008, SKF, 2008, Jardine et al., 1997, Tsang, 1995, White, 2014, Mobley, 2001c)	• *Low cost* • *Intermittent*	• *Not predictive* • *Introducing fault/failure* • *Human error* • *Unnecessary action* • *Disturbs operation*
Parameter Monitoring (MARINTEK, 2010, Tsang, 1995, McMenamin, 2015, Info Marine Sp, 2015, TWI, 2016, MICRO-EPSILON, 2016)	• *Low cost*	• *Can disturb operation*
Vibration Monitoring (Bab et al., 2017, Qiao et al., 2016, Lazakis et al., 2016b, Yang et al., 2016, Ono Sokki Co Ltd, 2016, Shin and Jun, 2015, Jee et al., 2014, Monition Ltd, 2014, Wärtsilä, 2014, Jauregui, 2014, Fan et al., 2011, SIKA, 2010, Mobley, 2001a, Mobley, 2001b, Mobley, 2001c, API 670, 2000, Al-Najjar, 1996, API 678, 1981)	• *Can be continuous* • *Early identification of failures*	• *Cost* • *Intrusive installation* • *Failure profiling using historical data* • *High frequency*
Thermography with Cameras (Glowacz and Glowacz, 2016, Tsanakas et al., 2016, Ibrahim, 2016, Absolute Electrics, 2016, Bagavathiappan et al., 2013, SIKA, 2010, Tsang, 1995)	• *Non-intrusive*	• *Cannot predict all the faults* • *Failure profiling using historical data* • *Cost* • *Adversely affected by ambient conditions*
Thermography with Sensors (Touret et al., 2018, Davis, 2015, Gupta and Peroulis, 2013)	• *Low cos* • *Can non-intrusive* • *Simpler technology* • *Used for performance monitoring*	• *Used in a subset of systems*
Tribology (Wan et al., 2016, MAI, 2016, Spectro Scientific, 2016, Cao et al., 2015, MRO, 2015, Rosenkranz et al., 2015, Coronado and Fischer, 2015, Wärtsilä, 2014, Li et al., 2012, Jiang and Yan, 2008, Mobley, 2001c)	• *Can verify faults identified by other methods*	• *Cost of investment & operation* • *Late identification* • *Usually intermittent* • *Cannot identify location of fault*

Table 1:1 cont. – Comparative analysis of CM data acquisition methods applicable to shipping.

CM Data Acquisition Method	Advantages	Disadvantages
Pressure Monitoring (SFK, 2016, The Motorship, 2015, Lees, 2015, Binsfeld Engineering Inc, 2015, eGreenShip, 2012b, SKF, 2008)	• *Used for performance monitoring* • *Combustion Engine monitoring* • *Usually installed by manufacturer* • *Sensors could be interfaced*	• *Highly intrusive* • *Potentially installation affects insurance and certification* • *Difficult to install retrospectively*
Strain Gauges (Binsfeld Engineering Inc, 2015)	• *Non-intrusive* • *Engine performance*	• *Low reliability* • *Historical data*
Sonic & Ultrasonic Methods (Caesarendra et al., 2016, Bhuiyan et al., 2016, SDT International - Bd., 2016, Wu et al., 2015, Jize, 2015, Mirhadizadeh and Mba, 2009, Kim and Lee, 2009, Mobley, 2001c)	• *Easier implementation*	• *Specific application areas*
Eddy current/Voltage (Li et al., 2016a, NTRC, 2016, Bonaldi et al., 2012, Greene, 2006)	• *Low cost*	• *Not applicable to some critical systems of ships* • *Intrusive*

However, these methods are not universally applicable. Further, 30% of equipment/machinery does not improve condition through continuous monitoring (Hashemian and Bean, 2011). Thus, monitoring methods need to be targeted and combined for a better assessment of the operating condition (Lees, 2015, The Motorship, 2015). The type of machinery or equipment and then, the nature of failures, dictate the monitoring method (Table 1:2).

Table 1:2 – Ship machinery/equipment grouped by set of applicable monitoring methods.

Ship machinery/equipment	Vibration monitoring	Ultrasounds	Tribology	Pressure	Temperature	Current & Voltage
ENGINES **(Main & auxiliary combustion engine)**	x		x	x	x	
PROPULSION, **gearbox, propeller & stern tube, thrust bearing, equipment bearings**	x	x	x		x	
GENERATOR, FIREFIGHTING **system, electrical motors,** ALARM **system**	x	x			x	x
Exchangers, switchboards, filters, boilers, Incinerator, pressure vessels/bottles, dampers		x			x	x
STEERING GEAR, **Windlass, stabilizer, compressors, Hydraulic pumps - cylinders**	x		x		x	x
Pumps, thrusters, fans, extractors, oil purifiers, bilge separators	x	x	x		x	x
Shaft seal, flexible connections, equipment seals	x				x	
Pipes, valves		x		x		

The table summarises the list of machinery and equipment on board a ship that would require CM. Critical systems highlighted using capitalised words were identified according to Class and regulation (IACS, 2014, IMO, 1993b) monitoring requirements, and critical systems analysis by Seastema Spa, (2016), Lazakis et al. (2016c), Babicz (2015), EGS (2015), INCASS (2014a, 2014b), Logimatic (2009), Andreson (2007), McGregor (1999), and Taylor (1996). Visual inspection, intermittent monitoring, thermal imaging, tribology, sonic/ultrasonic and eddy current methods cannot be generalised to cover all the required ship critical systems as they have limited applicability. Collectively Vibration, Temperature and Pressure monitoring address the monitoring requirements of all ship critical machinery and equipment. It must be noted though, that the operational profile and criticality of onboard equipment may differ between types of vessel. A successful CM system should be able to accommodate all these different monitoring methods and allow for interfacing to other data sources which are already being recorded in vessels. A modular method may be more appropriate, providing flexibility for the number of machinery and/or equipment monitored and the ability to adjust to the differences between ships.

As demonstrated in Table 1:2, to support total CM, systems, subsystems and components must be monitored (Seaworthy Engine Systems et al., 1982) adding complexity to the CM system (Hountalas and Kouremenos, 1999). For CM to be able to address all the business goals multiple criteria in the shipping environment must be additionally monitored (Emovon et al., 2015). This further increases complexity as demonstrated in Danaos (2009), where through monitoring several aspects of the business, the overall performance is assessed. Due to the complexity, a succesfull solution requires computerised systems and sophisticated software to perform complex data analysis (Jones and Collis, 1996). Thus, to implement CM effectively, application driven continuous monitoring equipment and advanced software need to be developed.

Further to address the reduced adoption (Figure 1:5), understanding of the needs of the industry is fundamental for the correct and useful application of CM (SKF, 2012b). Firstly, cost of capital investment is one of the main inhibitos[2] (SKF, 2012b). Wireless solutions may be the answer for reduced installation costs on ships, proven to be of

[2] Adoption inhibitors were verified through all of the publications in page xvi.

value as LAROS, (2015) has already commercialised such a system. However, there is no publicly available reference on the method used or effectiveness and suitability of this method for ship CM even though the benefits of using wireless networks have been validated for a multitude of applications; from laptops and mobile phones, to Internet of Things (IoT) and smart sensors (Xia et al., 2016). As wireless communication hardware becomes progressively less expensive, emerging applications are stimulated. The advances in mesh and multihop networks have also started finding applications into port ship-to-shore communication (Ming-Tuo et al., 2013). Today, with the rise of IoT, the development of embedded solutions is on the rise. Sensors and embedded applications are introduced to every aspect of human activity (Morgan, 2014). CM can significantly benefit from IoT advances and wireless smart sensor applications (Xia et al., 2016).

Secondly, increased training overheads are obstructing wider adoption of CM (Shorten, 2012, SKF, 2012b, Griffin, 2011). An appropriate system can address this aspect through automated CM data collection, analytics and simplified maintenance action decision support. Systems that translate data into useful information are often referred as Decision Support Systems (DSSs). Data can be presented as recorded, or it can be processed into values that will provide useful information to users and support their decision-making. Another inhibitor for the adoption of existing DSSs is that the direct benefit was not clearly identifiable by as much as 43% of shipping companies surveyed (EC, 2015, Shin and Jun, 2015). The best way of applying CM for the particular needs of the marine and maritime applications is not as yet identified. To achieve this, there is a need for tools that enhance the understanding of direct impact, making the benefits clear in business terms.

Additionally, other issues also need to be addressed. Inhibitors include lack of confidence or trust in new technology (DNV GL, 2014), confidentiality being of prime concern (Latarche, 2015), and the lack of trust in data security (Clarke et al., 2006). The latter is starting to change (Lloyd's List, 2014). Privacy and security are of paramount importance to the shipping industry (Adamson, 2016b). By following standards and guidance for the development and integration of cyber technology, the risk introduced through system considerations, human-system interaction, software, network communications, data assurance and cyber security can be managed as has been done in other industries (LR, 2016). Such an approach can increase trust and maintain confidentiality and security of data.

At the same time though, large amount of data is generated which have an impact on Internet usage and communications costs; a barrier in the adoption of CM (DNV GL, 2014). With systems such as GMDS, NAVTEX, and SafetyNET INMARSAT EGS commonly used, this amount of constant data flow is not sustainable or possible (eGreenShip, 2012a). Bandwidth is utilised not only for technical data but also crew recreational and communication activities (Adamson, 2015b). Developments in recent years, such as Inmarsat-5 have increased the available bandwidth to ships and coverage in areas were ships would previously be cut-off from access to communication links (Inmarsat plc, 2013), with wider availability and better speeds expected in the future (Adamson, 2016a, Satbeams, 2015). However, this is not yet the case. The traditional model of central data collection puts a burden to the business. Such centralised approaches are increasingly more difficult to implement especially when large amounts of data are generated even in wired applications.

In the recent decades, the ability to record data from multiple sensors has created a significant challenge as an enormous amount of data has resulted from the fixation on installing sensors to monitor "*everything*". More than 90% of the worlds data have been recorded between 2012 and 2014 (Lee, 2014). This quickly adopted trend has been referred to as *"Big Data"*, which describes both the amount and resulting issues. It has also opened up an exciting opportunity for businesses. Data analysis, gathering, and measurement of any aspect of business operation, equals in importance to stock exchange valuations (BU, 2016, Rosenbush and Totty, 2013). Big Data, if utilised appropriately, can accelerate business growth; viewing it as just technical data is a missed opportunity.

This trend of increased data generation created issues in the way data are managed and stored. Traditional databases become unusable when large amounts of read and write queries need to be executed (Bjeladinovic, 2018). Moreover, when complex queries are needed to cross-reference data from multiple sources, traditional database models are not able to perform in user-acceptable time frames. For these reasons, databases such as Hadoop have been developed, based on new database architectures such as object oriented and graph-based (Grover et al., 2015).

Further, incomplete datasets are another challenge for big data processing techniques (Ai et al., 2017). This refers to the correctness and continuity of the data set being processes to infer a high-level information set, such as reviewing the full vibration dataset of one engine over a period of 6 months with data points covering every millisecond of operation to infer its condition. Often due to issues with hardware or software components of the monitoring system, datasets are prone to noise, or gaps, referred to as *"dirty"* in literature. Techniques exist to address this shortcoming but are expensive in computational requirements. Examples of such techniques are the *"Byzantine algorithm"* (Klempous et al., 2006), the *"Brooks-Iyengar algorithm"* (Brooks and Iyengar, 1996) etc.

Finally, in the era of Big Data network resources are consumed by contextual data flowing towards central locations, predicted to create severe strain on cloud-based architectures and other similar central analytics models in the near future (Harth et al., 2017). Thus, new approaches such as edge processing have emerged to reduce network traffic which distribute the analytics or processing components. The application of these approaches on ship CM has not been studied thus far.

1.1.3 Research Impact & Benefits to Stakeholders

Monitoring and inspection requirements, for structures and machinery, from regulatory bodies and Class have been constantly increasing in complexity over the years (Michala et al., 2016b, LR, 2013). Hence, sophisticated software is more appropriate than human intervention to deduce useful information to help follow these requirements for data-driven timely, risk-based maintenance planning (DNV GL, 2014).

At the same time, for CM to be able to accurately predict faults and failures, a number of years of data collection and analysis may be needed. Exhaustive monitoring provides no additional benefit. However, critical machinery and equipment must be monitored. Even though this process looks like a daunting challenge, when the versatility of ships is considered, one has to admit that identical components are used in large numbers of vessels. Moreover, the process of collection of statistical data has already been under way for some years through developments within Class and databases such as OREDA (OREDA, 2016).

Unfortunately, there is a large gap between the technological advantages available in other domains and the actual implementation in the shipping domain which infers that the shipping industry has not quite adapted to the evolution (Adamson, 2015a). There are several reasons why the industry should incorporate new technologies in various areas including maintenance (LR, 2016):

- *increased business performance,*
- *compliance with environmental and safety regulation (SKF, 2012a),*
- *better availability and access to newly deployed satellite communications,*
- *to reduce the need for competent crew,*
- *to better support operations owing to low crew retention rates,*
- *to utilise knowledge gained from better data collection and analysis (Dikis et al., 2015),*
- *to benefit from preventive maintenance (Nemarich et al., 1990),*
- *to support better design,*
- *to allow integration of better flexibility and control,*
- *to optimise systems used and to enhance robustness (SKF, 2012a).*

Several benefits to the shipping industry stakeholders can be identified. Firstly, for owners and operators of ships, a solution must apply to a variety of vessels and machinery/equipment through a modular design. Secondly, the solution should require minimal investment in both cost and ease of deployment. Thirdly, the solution must require minimal training for the engineers onboard vessels. All this leads to better operating conditions of ships which result in a beneficial impact on safety of the personnel onboard as well as the general public (e.g. ferries).

Moreover, for Regulators and Class such a system can be beneficial in several areas. For example, through the minimisation of data transfer and installation cost, a broader adoption in many ships is possible. As such general statistical information can be collected from many ships and thus promote not only better maintenance and operating condition but also better understanding of overall ship systems. This could inform more fine-turned regulation and certification requirements. Moreover, data collected could be used in conjuction with the classification requirements of inspection; hence, make the inspector's work easier.

Additional benefits also exist for the manufacturers (OEMs and SMEs). CM can provide a better understanding of the performance of their equipment and the associated failures, used to improve designs. Furthermore, shipyards can benefit from such a system through more accurate record keeping. In this respect, identification of work to be performed or identification of weaknesses in designs is possible. Hence, a complete CM system applied on board can be exploited in a commercial system ready for the market demonstrating the additional benefits to currently available condition monitoring systems for all stakeholders.

1.2 Research Question, Aims and Objectives

A clear determination of the target of the research achieved is provided in this section, used as the main foundation for the development. According to the critical review of the literature the following two research questions were identified:

"Is it suitable to edge process and transmit equipment and machinery condition monitoring data wirelessly onboard a ship?"

"What is the minimum data transmitting quantity required to support condition monitoring without compromising the decision making process?"

This thesis proposes a novel system to become the pillar for future improved CM developed with domain specific constrains as a means to mitigate the reduction in crew numbers, optimise operating conditions, reduce the risk and increase performance while compiling with regulation. Through edge computing, wireless based data transfer and advanced decision support software, the inhibiting factors will be limited. Supporting edge computing at the Data Acquisition (DAQ) device level, the modular system can flexibly provide CM as well as other benefits, presented in Section 1.4.

The thesis aims to provide answers to the two research questions presented and thus address the identified gaps. The aim is to demonstrate that a system can be developed, and its performance validated. The system edge-processes and transmits data wirelessly to address the need for low installation cost. It also transmits the minimum amount of data to address the need for low operational cost. Finally, the system must be suitable for deployment near or at vessel machinery and equipment for condition monitoring. Another key aim is to successfully demonstrate the applicability, utility and benefits of the system.

The first objective is to propose a methodology to address both research questions.

The methodology includes hardware/software co-design development, deployment as well as proposed algorithms for data processing at the various stages within the topology. Moreover, the user interface for the presentation of the decision support will be developed.

The second objective is to identify the minimum data transmission required for decision support application onboard the vessel and transfer to shore, addressing the need for reduced operational cost.

Through the methodology proposed, the third objective is to prove edge processed wireless data transmission onboard and its application for condition monitoring purposes. This objective is: to demonstrate the validity of the methods and proposed system, and to demonstrate suitability for the application.

Finally, the last objective is to perform a cost benefit analysis, to provide evidence of cost reduction through use of the system and to demonstrate a clear reduction in the initial training overhead.

1.3 Literature Review

A clear view of challenges in ship CM applications emerged from the review of the context. The research questions were formed to enhance wider adoption of predictive maintenance in shipping via addressing the identified inhibitors and constrains. A literature review of existing ship CM systems, wireless applications, decentralised data processing and DSSs is presented in this section to identify the reasons behind the current adoption levels, the gap in proposed solutions and the potential of integrating them to a complete system.

To comply with regulatory and safety requirements several parameters are recorded by the ship crew at specific intervals. Table 1:3 presents a list of the data regularly recorded, as required by three classification societies for the main engine indicatively. Such measurements can be made digitally through sensors, either continuously or on interval. Additionally, some of these measurements are manually recorded by the crew on hand-written forms during interval inspection, based on manual gauges available on the equipment in question. In those cases, the sensor is analogue and not connected to any recording or data acquisition hardware. Thus, there is room for human error as well as room for missing important changes to the data. For example, transient changes due to minor errors or early signs of failure. However, in terms of statutory and regulatory obligations the necessary actions are taken and thus the operator meets the requirements. The extended monitoring requirements are presented in BV, (2014), LR, (2013) and RINA, (2012b) for a variety of machinery and equipment available onboard ships.

Table 1:3 - Recorded parameters, source (BV, 2014, LR, 2013, RINA, 2012b).

Source	Parameters for Main Engine
BV, RINA	power output
BV, LR, RINA	rotational speed (MICRO-EPSILON, 2016)
BV, RINA	indicator diagram (where possible)
BV, LR, RINA	fuel oil temperature and/or viscosity
BV, LR, RINA	charge air pressure
BV, LR, RINA	exhaust gas temperature for each cylinder
BV, LR, RINA	exhaust gas temperature before and after the turbochargers
BV, LR, RINA	temperatures and pressure of engine cooling systems
BV, LR, RINA	temperatures and pressure of engine lubricating oil system
BV, LR, RINA	rotational speed of turbochargers
BV, LR, RINA	vibrations of turbochargers
BV, LR, RINA	results of lubricating oil analysis
BV, LR, RINA	crankshaft deflection readings
BV, LR, RINA	temperature of main bearings

For new builds, integrated control and monitoring systems are available commercially. For example, the Acon (Rolls-Royce, 2011) system can provide full CM of machinery as well as control which includes propulsion plant, electrical power generation and distribution systems as well as auxiliary systems. The available software automates online documentation, trending, maintenance check lists and training through simulation videos. Other similar systems include the SFK Integrated condition monitoring system (SKF, 2016) and BMT SMART system (BMT, 2015). Weather and sea conditions as well as voyage data are required to extract useful performance information (BMT, 2015). These factors affect the operation of the ship and need to be incorporated for CM to be effectively implemented (Tsujimoto and Orihara, 2018). However, such systems come at a cost and new vessels are not frequently built. The percentage of newbuilt vessels in the global fleet is approximately the percentage of ships with existing full CM systems (Shorten ,2012); i.e. 12%.

Another approach is isolated CM targeting specific ship systems. These can be installed when a major refitting of the specific system is performed. For example, Wärtsilä (2012) supports real-time advice and periodic reports, based on continuous data collection. It monitors the propulsion system and requires oil, pressure and vibration analysis. In this case sensor intrusion is not avoidable. However, online oil analysis sensors are more prone to failure as they are exposed to the internal harsh environment of the machinery (Li et al., 2012). For older vessels, the control system exists but the CM attachment is not usually available.

Installing such systems to an older vessel requires a large refitting operation. It makes the capital cost of installation prohibitive, especially when the return of investment has not been validated (Shorten, 2012). Furthermore, some sensor schemes can only be applied at design stage such as the one proposed by Payne et al. (2002). Such systems are usually installed in a minority of vessels viz the newbuilt vessels.

Installation without extensive refitting is more appropriate for existing ships. Several such application examples of CM exist. Most commonly used are hand held equipment for thermal and vibration monitoring or performance monitoring (SIKA, 2010). They are portable and applicable to more than one ship; e.g. Pythia system by Hountalas and Kouremenos (1999). Moreover, in the event where acquisition of CM equipment is of no interest to the operator, there are companies that can provide the equipment and trained engineers on demand in order to further reduce the cost (TWI, 2016). However, these systems cannot be used continuously through the vessel's lifetime while sensors might be pre-installed and readily available (Lees, 2015).

Existing sensors could be interfaced and their data used for other applications directly or indirectly. In a reviewed case, a set of pressure, input and output temperature sensors pre-installed on a high-pressure air compressor available on a ship were utilised for CM purposes (Nemarich et al., 1990). The new CM interfaced the sensors, at the level of the old manual gages. However, an interface was developed and setup to be able to collect the corresponding signals. The intrusion of the sensors is an issue for hand held monitoring equipment as well (SKF, 2016, Greene, 2006). Several approaches, such as vibration, thermal imaging and ultrasonic measurements, do not require the sensors to be intrusively installed. However, the sensors necessary, such as ultrasonic microphones and thermal cameras, are prone to ambient noise and not suitable for continuous CM.

Another approach presented by Gupta and Peroulis (2013) is using a sensor that does not need to be installed on the bearing but externally to the machinery. A wireless sensor is presented in this work that can record temperature for bearing condition monitoring through metal thicker than 18-mm. Such a sensor could potentially be used to reduce intrusive installation. This approach is more favourable as it requires fewer disturbances to the machinery in question and is also wirelessly implemented.

As discussed in section 1.1.2. a wireless system could provide ease of installation for existing ships to allow a complete CM system implementation. Hashemian and Bean (2011) present a set of different wireless sensor technologies utilised for CM in reactors, nuclear power plants, critical equipment and general industrial applications. Technologies for networking can accommodate up to 30,000 nodes in industrial applications (Yang et al., 2013). It is not only possible for wireless networks to perform with high reliability under high electromagnetic interference, but also to transport substantial amounts of data. Through careful design, the software creates a significant system advantage under such traffic conditions. Specifically selecting the correct RF technology for the application, can provision high data rates (Ralston, 2007). Improved protocols and standards further enhance wireless network reliability, to the point that industrial control signals can be transmitted in real time to machinery and equipment (Shelby and Bormann, 2009a).

Wireless sensors offer very low-power-consumption systems that reliably send data through a network, while reducing calibration maintenance costs after installation (JaeHyuk et al., 2013). Moreover, pre-processing of data to reduce the amount of wirelessly transmitted information is a well-established strategy to improve network reliability and QoS (Feng et al., 2015, Yang et al., 2012). As processors with increased processing capabilities become available, more embedded systems are being designed for wireless industrial CM (Cheng et al., 2013). However, such applications have been restricted in scope, used mainly in embedded single sensor devices that do not provide access to the raw data. The edge-processing approach could be further expanded to address these shortcomings, strengthening system robustness when operating within the highly demanding environment of the ship engine room. With this excess of processing power, sophisticated algorithms can be used to perform pre-processing, pattern identification and network maintenance such as fault finding and healing of the wireless network at the edge. This is particularly important as monitoring data are more accurate and network or sensor faults do not introduce ‘dirty’ data (Nandi et al., 2014).

A ship CM wireless system that is commercially available and enables remote monitoring is LAROS (LAROS, 2015). This application claims to reduce the installation costs through the use of wireless data collection; without the need of extensive cabling over the vessel, reducing the cost of materials as well as cost and time of installation. The system is available with decision support software used on shore to analyse data and support maintenance action planning. Although the system is modular, the data is still processed centrally leading to high operational cost and satellite connectivity dependency. A decentralised approach would be more appropriate to address the need for reduced satellite communication costs and real-time decision support onboard.

The state-of-the-art in CM data processing is (i) embedded systems for data collection and transmission or (ii) embedded systems for immediate processing and actuation without transmission (Humphreys et al., 2014, Cheng et al. 2013). Particularly, Lilas (2009) presents the development of a data acquisition system, using an embedded system that collects data from several sensors and transmits them wirelessly to shore. A microcontroller is used to collect temperature, current and voltage information. A wireless link from ship-to-shore is used, to transfer the information and an application on shore is developed to process the information collected. Similarly, an embedded system approach was adopted in the academic project eGreenShip (2013). A variety of measurements including temperature, pressure and vibration were collected through the acquisition system for combustion engine monitoring. Finally, Nemarich et al. (1990) describe the developed CM model for a high-pressure compressor, for machinery and equipment monitoring. However, none of these cases implement significant computation on the edge of the network.

Reviewing the characteristics of the datasets and the frequency of collection is necessary to identify the applicable technologies for decentralised data processing. Several recorded parameters in ship CM are predominantly affected by the operating characteristics of the engine (eGreenShip, 2012a, 2012b, 2013). In general, typical engines for ships can be either 2-stroke or 4-stroke diesel engines (Figure 1:6), often subdivided by speed into three categories: slow, medium or high (Leduc, 2001). Heavy fuel, slow, 2-stroke diesel engines are common in larger vessels, and they usually operate at a speed close to 100 rpm for financial reasons (Wankhede, 2016). Measurements for pressure and vibration are typically collected at least once per revolution.

Temperature measurements are collected more sparsely in some cases. However, most measurements are needed per degree of revolution, 360 samples in a 100 rpm case.

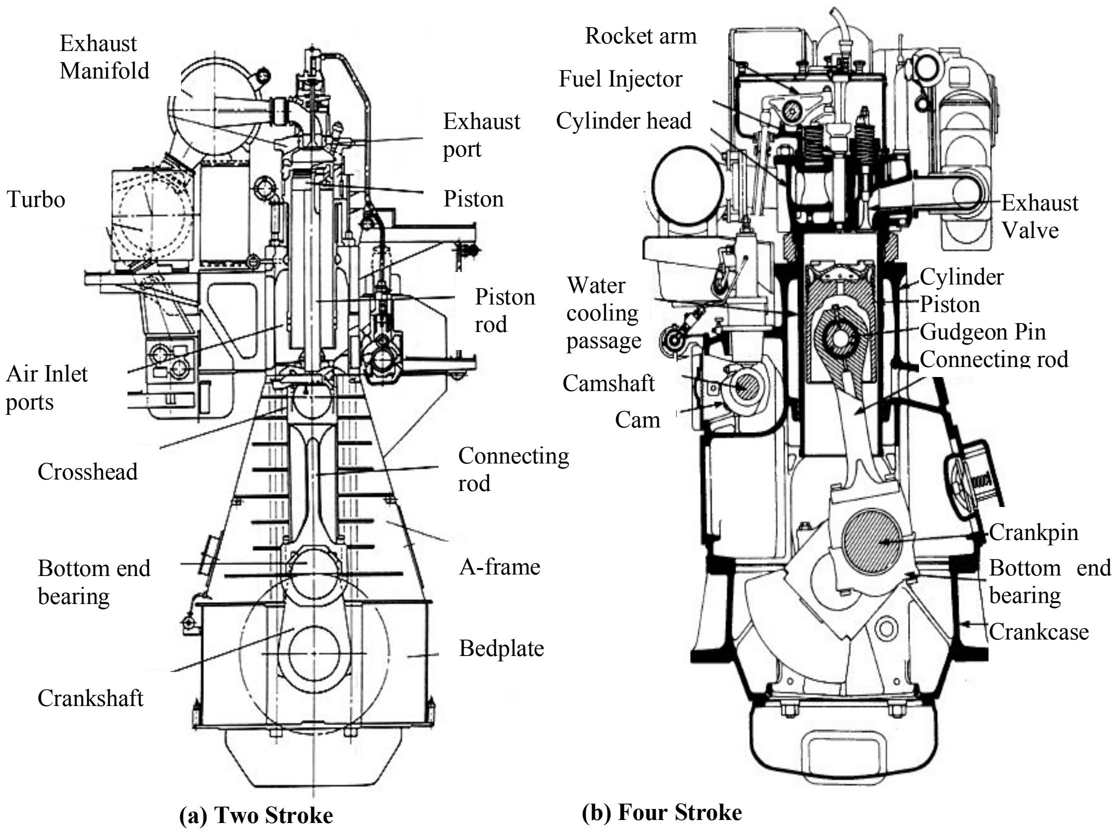


Figure 1:6 – Typical marine engines adapted from MS (2016).

An engine performing at 1000 rpm would require at least 1000 samples per minute (16.67 samples/second), with a maximum of 360,000 samples per minute (6000 samples/sec). Thus, the latter would require a 6kHz sampling rate, to capture the condition of the engine. If each of these samples corresponds to a 32 bit floating point record (4 bytes), it automatically translates to 24kB/second; thus, the capacity of the network that transmits these records from a single sensor needs to exceed 24kB/sec. Considering that 10 or 20 sensors may be installed in one single engine to capture all the required parameters, the network capacity needs to increase linearly with the number of sensors. A general function for calculating the capacity of the transmission medium and data rate requirements is presented in Equation 1:1.

$$C_{transm} = RPM * R_{deg} * B_{data} * n_{sensors} \qquad (1:1)$$

where C_{transm} *is the required capacity for storage and transmission of an* *engine that is performing in RPM revolutions per minute and data is collected in R_{deg}. – equal to the number of samples per revolution. Each data record occupies B_{data} bytes, in both storage and data transmission, and $n_{sensors}$ is the number of sensors installed on the engine.*

Based on Equation 1:1 the system covering the full ship for a significant period would collect and transmit a vast amount of data; using the above example 86.4 MB/hour/sensor, or 2.07GB/day/sensor. The wireless network capacity would be unable to transmit the amount of data required for more than a few sensors.

According to the ZigBee standard, the maximum possible capacity of each node is 62.5kB/s (250kbit/s) (ZigBee Alliance, 2016), supporting a maximum of 2 sensors at each node. If noise is considered together with the requirement for sending network operation data and time-stamps, it would become impossible to operate the network at this capacity. Under such operating conditions conflicts quickly hinder network performance, and data backlogs form at each node. As a result, delays in delivering data to the central hub would quickly render the information outdated and unusable. Moreover, a larger memory would be required on each node to store the backlog; making pre-processing is a fundamental requirement.

Pre-processing is used in a variety of applications, such as CM in aviation, where it is found that raw data do not provide any additional information to the end user (McFadyen and Adamson, 2016). Further, pre-processing allows the network bandwidth to be utilised to its full potential for prognosis and diagnosis of condition (Uhlmann et al., 2015, Feng et al., 2015, Yang et al., 2012, Vasilescu et al., 2005, Krenzel, 1992). New programming paradigms and systems architectures are starting to emerge in the domain of decentralised/distributed computing (Figure 1:7), to reduce network traffic which distribute the analytics or processing components; such as the one proposed by Harth et al. (2017).

The *"edge computing"* paradigm, or otherwise referred as *"edge processing",* is a recent development in computing systems, executing data processing near the location of data collection. In principle, information extraction or processing of data is conducted on intermediate servers or processing units of sufficient compute capability residing one step away from the device collecting the data (Varghese et al., 2017), known as the "edge of the network". The network is anything connecting the device to the Internet, inclusive of the Internet and the central data storing server. As this paradigm is still in early days of implementation there is debate around its definition. For example, *"fog computing"* is another closely related paradigm which is often mistakenly rerefered as edge computing in literature. However, in this approach processing is further distributed and dynamically shifting between the data collecting device and the cloud depending on several parameters such as network availability etc. (Ai et al., 2017).

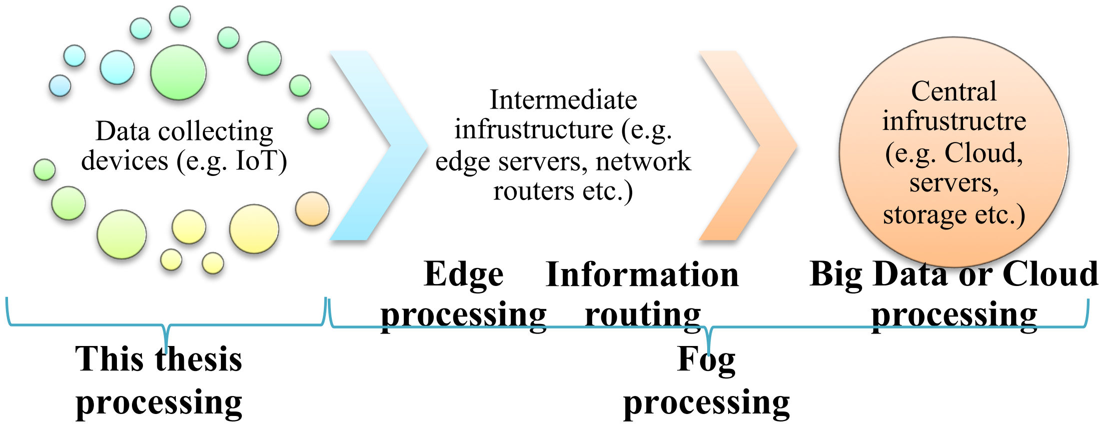


Figure 1:7 – Stages of information processing and processing paradigms.

Edge processing can reduce data traffic by 95% and application latency by between 40% to 60% (Varghese et al., 2017). However, this approach still transfers the data to local processing capable intermediate infrastructure and studies the reduction of data traffic from that point onward. This is the case for all the edge processing approaches reported in literature. A thorough review of those approaches can be found in (Harth et al., 2017). Significant research in this domain has been conducted for mobile phone applications. However, here the focus is on offloading computation away from the mobile device to preserve battery power but not offloading as far as the cloud to sustain low latency and high application response rates (Fernando et al., 2013). Examples of offloaded computation include map/reduce, per-node queries, 3D graphic maps of global environments. In that respect, this body of research solves a different practical need to the one investigated in this thesis.

Most recently, other architectures have started emerging in computing. For example, the one proposed by Hentschel et al. (2016) presents frameworks for moving the initial stage of analytics to the device that collects the data. This is a further extension of the edge processing paradigm. Moreover, the data analytics are decoupled from the data recording components. In this work the system architecture is not designed to sustain industrial applications, requires wired internet connection and considers only applications in smart campus scenarios. Additionally, the analytics component needs to be re-trained for every installation location, making the solution non-portable. This being the only example of its kind, such architectures need to be investigated further as they will need to address several challenges, such as performance within power budget, independence of the device, portability, reliability and suitability for individual application scenarios.

In shipping, these developments have not as yet had a large-scale impact, but it has become a more prominent topic for discussion, as more systems emerge to produce or manage data in the sector. As discussed previously, CM is one of these applications that have the capacity of producing Big Data. According to DNV GL, in 2015 Big Data trend exceeded predictions for growth and importance to the shipping industry (Adamson, 2015a). Big Data management techniques are usually focused on highly specific data feature extraction to assist informed decisions. Additionally, Big Data is used to cross-correlate different type of collected information in a business and deliver optimised solutions to business-wide problems. In that respect, the industry is still far from embracing these emerging technologies. Even though companies may already record and have full ownership of the necessary data for CM, they often do not have the resource or expertise to use them to their full potential (DNV GL, 2014).

To address the need of reduced traffic over the wireless network and utilise the increased processing capabilities of modern architectures, edge processing can be used to reduce the volume of recorded sensor data. Sensor data volume reduction is necessary in many applications for storage or transmission (Kwan and Luk, 2018). Volume can be reduced through compression or information extraction at the edge of the network.

Data Compression is a vast research domain and several approaches have been reported in literature (Oswald & Sivaselvan, 2018). According to Sayood (2017), these can be classified as:

- *Lossless; including Image compression, Context-based compression, Dictionary techniques, Arithmetic coding, Huffman coding, and*
- *Lossy; including Video compression, Audio coding, Wavelets and wavelet-*

based image compression, Sabband coding, Transform coding, Differential encoding, Vector quantisation, Scalar quantisation.

Commercial lossless compression tools include 7z and Winzip (Kwan and Luk, 2018) GZip and RAR (Oswald and Sivaselvan, 2018). Zhang at al. (2018) present a neural network approach for image and video data compression. Khan et al. (2017) present a lossless image compression method which claims faster processing and 25% higher compression rates that state-of-the-art. Oswald and Sivaselvan (2018) present a hybrid Haffman Encoding and Frequent Pattern Counting approach for text data; highest compression of two orders of magnitude in dense and large datasets. Si et al. (2017) propose a vector quantisation method to compress mobile device data traffic on 4G networks (video, images and text); highest compression rate (CR) of 4.5:1 with 2% error vector magnitude distortion. Image, video and text compression techniques however are not relevant to CM as the characteristics of the recorded information are fundamentally different.

Signal processing approaches are more relevant to CM. Ziran et al. (2017) demonstrate a compression of one order of magnitude (highest CR=27:1) through the proposed wavelet transform method (lossy). Similarly, de Souza et al. (2017) utilise lossy Singular Value Decomposition method for data compression to address bottlenecks due to the increasing volume of smart meter and grid data; highest CR=92:1 without affecting the decision-making process. Lossless (highest CR=3:1 using commercially available tools) and lossy approaches have also been applied to CM data (Kwan and Luk, 2018). According to Kwan and Luk (2018), CM data contain measurement noise which does not need to be preserved. Thus, lossy approaches are more appropriate as they can achieve higher compression rates; leading to lower consumption of transmission channel bandwidth. Their proposed lossy compression algorithm achieves 10:1 compression for CM sensor data.

Compression algorithms can be an efficient approach to reducing transmitted data in a CM application. However, they do not address the issues of ‘dirty’ data. A complete solution for CM needs to be able to identify when gaps in the data are due to a change in operational condition of the machinery/equipment (e.g. switched off), or due to a failure of the monitoring equipment (e.g. data acquisition equipment failure, software update). Such events could impact the maintenance action decision support process by introducing false negatives/positives (Ai et al., 2017). A solution that can effectively identify events and remove 'dirty' data would also reduce data volume through selectively removing unwanted data points.

Thus, information extraction can be utilised to achieve CM data compression and event identification through a single computation. A variety of methods for processing the collected data are applicable. According to Marwala (2012) the four different types of data recorded for CM in industrial environments are:

- *Time Domain: recorded raw data over a period of time*
- *Modal Domain: system natural frequency, damping ratio and mode shapes*
- *Frequency Domain: extracted from the data, through Fourier Transform*
- *Time-Frequency: the frequency domain changes with time (non-linear)*

The type of information recorded is a determinant for the processing method (Jiang and Yan, 2008). Depending on whether the measured parameter is sinusoidal or not, the method changes significantly (Jardine et al., 2006). Sensors often record in the time domain and the remaining data types must be extracted (Marwala ,2012). For the proposed methodology, temperatures are time domain signals, while and vibrations are analysed in both time and frequency domains; pressures can be either, depending on installation location. Thus, two different approaches for information extraction are necessary in ship CM.

Table 1:4 presents the corresponding data processing methods applicable to the sensors available for CM (eGreenShip, 2013, 2012a, 2012b, Li et al., 2012, Jiang and Yan, 2008, Jardine et al., 2006). The list is not exhaustive, as there has been an abundance of developed techniques for processing of waveforms and signals in CM applications. One example, uses autoregressive coefficients in order to extract useful information from the vibration signal in pre-processing (Al-Bugharbee and Trendafilova, 2015, Lynch, 2007). However, this approach requires higher pre-processing power and would be better suited to post-transmission feature extraction.

Table 1:4 – Sensors, installation and processing methods, sources (Li et al., 2012, eGreenShip, 2012a, 2012b, 2013, Jardine et al., 2006, Jiang and Yan, 2008).

Input data (data type)	Installation location	Data processing method
Velocity/speed sensor (sin)	Motors, Gears, Shaft	Mean Average, Time domain analysis, Fast Fourier Transformation (FFT), Instantaneous angular speed analysis, Polar presentation, short-FFT, Fuzzy logic, Artificial Neural Networks (ANN), Genetic Algorithm, Independent Component Analysis
Torque sensor, strain gauge (sin)	Shaft	As velocity
Temperature sensor, thermocouple (time)	Exhaust gas, Water Cooling system, Air supply system (before and after), Engine room, Fuel Oil system	Mean Average, Trend Analysis, Time series monitoring
Flow sensor (sin)	Fuel Oil system, Pumps, Pipes	As temperature
Air-mass sensor, anemometer (sin)	Air supply system	As velocity
Pressure sensor, Piezo-electric (time)	Water Cooling system, Exhaust system, Cylinders	As temperature and/or as velocity
Eddy current sensor (time)	Compressor system	As temperature
Emission combustion sensors (time)	Exhaust gas system	Comparison to baseline, As temperature
Laser velocity sensor (sin)	Cylinders, Motors	As velocity
Accelerometers used for vibration sensing (sin)	Main Engine, Bearings, Gears, Fans, Shafts, Machine Base (x and y axis measurements)	As velocity plus: Envelope analysis, Time domain analysis, Phase analysis, Orbit analysis
Displacement sensor (time/sin)	Existing gauges	Correlation of displacement, depending on measured value
Ultrasound sensors (sin)	Pipes, Variety of machinery, Fuel Oil system	As velocity plus: Comparison to baseline measurements
Camera (image)	Any of the above	Image processing

*Measured continuously or on interval according to regulation (measurement units in Appendix D). Extended monitoring requirements according to BV, RINA and LR classification societies in Appendix C

A promising approach is envelop analysis as presented by Feng et al. (2015). Several points raised in this work are of relevance to the proposed system. These are: pre-processing requires less power than transmitting the raw data, and the output of the analysis is suitable for further processing after transmission. This approach minimises the data required in order to identify faults in applications such as bearings (Chen et al., 2012). Most of these methods require extensive processing capabilities which are not readily available in typical embedded system implementations (García et al., 2014). Hence, the data need to be collected and then transmitted for processing.

Other methods are less demanding and could be performed directly before data transmission. For temperature and pressure, trend analysis and similarly, for vibration, FFT and Time Domain Analysis are well documented as appropriate pre-processing algorithms. This thesis proposes the implementation of these methods at the edge of the network, consuming minimal data processing and transmission resources.

Machine learning approaches are not applicable at the edge as they reduce portability and require high computational capabilities. However, for further processing of the recorded information at a central location, machine learning approaches are required to identify the condition of the machinery/equipment through multiple data stream feature extraction. In this space, several methods have been used; generally classified as correlation-based methods, finite element updating techniques (Michala et al., 2016a) and computational intelligence (machine learning) methods. A review of these methods is presented by Coronado and Fischer, (2015).

According to Coronado and Fischer, (2015), time domain analysis, time series monitoring, orbit analysis, instantaneous angular speed analysis, envelope analysis, phase analysis and trend analysis, as well as any method based on comparison to a baseline profile, is a correlation based method. Examples of machine learning methods, which are well established include Fuzzy Logic, Artificial Neural Networks (ANN) such as Markov Chain Monte Carlo and Bayesian Networks, Support Vector Machines, Genetic Algorithm and Independent Component Analysis. Additionally, several methods for ship condition prediction have been investigated from statistical approaches to Markov chains and Bayesian networks (Pintelon and Gelders, 1992, Valdez-Flores and Feldman, 1989, Cho and Parlar, 1991). Most often, quantitate methods and probability theory are utilised, as time to failure and time to repair are some of the most important parameters in CM applications (Barlow and Proschan, 1981, Gunawan, 2014) using Economic Engineering and Monte Carlo simulation (Shadab Far and Wang, 2016, Zio, 2013). The thesis does not focus on advancing machine learning or predictive maintenance for CM thus a thorough review of the methods is not presented. An open-ended system which can accommodate a number of these methods would be able to address the requirements of any stakeholder; as different methods may be utilised.

However, to complete a CM system the information extracted through analytics needs to be presented to the maintenance engineers in a manner that addresses the need for direct business impact identification. DSS systems have been investigated over the past 20 years. DSS is often utilised in creating maintenance schedules, optimised maintenance records, and efficient maintenance action decision making (MoD, 2006a, 2006b, 2006c, Smith, 2001). However, for the system to be accurate the reliability and maintenance actions any one component need to be viewed as impacting on interlinked to other components/subsystems/systems (Carretero et al., 2003). According to Peters (2015), 60% of these applications have failed to mature to successful implementation.

Complex approaches have based the DSS development on analytical results (Jardine et al., 1997). In this case, a proportional hazards modelling method, incorporating age, cost modelling, and maximum likelihood is adopted for independent components. However, the outcome is either performing or not performing a replacement action of a component. In contrast, a control state space model, and a typical Kalman Filter approach is utilised by Christer et al., (1997). Again, the approach is predicting actions for independent systems to suggest replacement actions. Another approach is presented by Khac Tuan et al. (2014). Here, the degradation of the system is compared to thresholds and to dependent and competing failure modes. When multiple failure modes are considered and interactions between systems are important, a reliability approach is identified by the authors as more appropriate.

Moreover, it is not possible to generalise a DSS approach for every domain, as the design of such a system relies on deep understanding of the decision making process and the specific constraints applicable to each organisation (Makowski, 2011). In that respect, the trend in many industries is to develop expert systems based on Data Fusion and Big Data analytics, through highly specified optimisation modelling, to assist in decision making (Vallerio et al., 2015). In maintenance action suggestion within shipping applications, the reported approaches are presenting the DSS as a tool where the parameters to be optimised are of a singular nature – cost or planning optimisation.

In conclusion and according to the literature review, a CM system that simultaneously addresses all the identified needs, constrains and inhibitors (Section 1.1) is not available thus far. The following section presents the key findings of the review and highlights the contributions of the proposed research.

1.4 Contributions

Maintenance is mandatory for the shipping industry but is often performed in a counterproductive manner. Minimum CM requirements for critical systems involve vibration and temperature measurements while pressure is also important. The thesis proposes a modular and wireless system that extends the edge processing paradigm to provide low cost data acquisition for CM applications; meeting industry requirements within a constrained context. Benefits include cost saving, reduction of risk, increased productivity, reduction of human error and efficiency of energy use. The highlights of the literature review are:

- *Monitoring targeted to specific manufacturer machinery/equipment not overall ship strategy especially for older vessels.*
- *Software is necessary for effective CM and regulation compliance due to the large data generated and complexity of the ship system. Better software systems are required.*
- *Slow industry uptake due to cost of implementation, direct benefit obscurity and trust issues.*
- *Commercial CM systems prove that wireless data transfer is possible, though raw data transmission significantly strains the infrastructure, and published work is not available on reliability and suitability.*
- *Large scale application is possible as identical components exist in many ships and thus statistical profiling is already available.*
- *Computational capabilities of the selected system components affect the data processing method selection.*

Through the literature review it is demonstrated that there is a gap in current research regarding condition monitoring for the shipping industry. A CM system that fully incorporates all the needs of the naval industry may be both complex and difficult to implement but is much needed. This gap is identified in the implementation of edge processed wireless data transfer onboard ships and the extraction of key information to be transferred to shore for decision making. The thesis demonstrates that it is possible to bridge the identified gap through the following:

1) The cost for CM can be reduced through appropriate application of wireless data transmission and edge computing onboard vessels.
2) The initial prohibiting investment in training can be addressed through a Decision Support System that refers to onboard engineers.
3) It is possible to minimise the necessity of large data transfer to shore through transmitting key information necessary for effective maintenance management, utilising on-board edge computing and machine learning.

The main gaps identified through the review, that this thesis will address are:

- *Edge processing can reduce network traffic.*
- *Transmitted data volume reduction and identification of events is necessary to support maintenance action decision support.*
- *Processing at the device recording the data is a new area of computing systems research and is not yet proven in industrial applications.*
- *Internet on ships is expensive and often access is limited or not available.*
- *Centralised onshore analytics significantly increase Internet usage.*
- *CM systems produce large amounts of data that need to be processed to infer higher-level information.*
- *Data gathering is fundamental not only for condition monitoring but other business purposes.*
- *Direct association with benefit does not exist in current CM systems.*
- *Better condition of ships, reduced maintenance cost, efficiency of ship operation and savings are desired and can be achieved through a CM system used to its full potential.*
- *The system should not require significant training to be useful for decision*

making.

- *The system should be low cost to install and operate.*
- *The system should be modular and able to extend to all critical machinery and equipment throughout a ship.*

In that respect, the first research question outlined in the next section is already partially answered through the review. However, there is no published work to prove suitability and effectiveness of wireless transmission onboard. Moreover, there is no work addressing the big data challenges that widespread use of CM will generate; being adaptable and scalable for the range of ships within big data environments.

The complexity of the problem demands a hardware/software co-design investigation approach. To assess the details of this complex problem and develop a suitable system, a systems' engineering process is adopted. The methodology to be followed is presented in the following chapter.

To address the shortfalls in current shipping CM through advancing edge computing in this application domain (Section 1.3) and to provide the added value for shipping industry stakeholders (Section1.1), the contribution of this thesis is a novel integrated system (Chapter 2) developed under constrains. The system combines several algorithms implemented simultaneously at the edge of the network, utilising minimal resources, enabling flexible, remotely controlled, and remotely managed enhanced CM using a purpose-built communication protocol.

Compared to the state of the art the proposed integrated system advancements as applied to ship CM in the maritime domain are:

1) The development of portable algorithms extending the edge processing paradigm through multi-sensor parallel data mining to minimize wireless data transfer and to provide reliable data without compromising the decision-making process; utilising the capacity at the edge of the CM node network for: data compression and event extraction, flexible interfacing to several sensors, scalable and reliable data transfer, and remote system management, while reducing hardware requirements (Statement 1 and 3).
2) Development of modular and adaptable hardware using commodity hardware in the constrained industrial environment of the ship to achieve low cost, on a

Linux platform (Statement 1 and 3).

3) Development of an open-ended data acquisition system that can interface on a variety of reliability centred maintenance software solutions
4) An optimised multiple constraint Decision Support System for condition monitoring on ships, using reinforcement machine learning to optimise maintenance action suggestions in real-time onboard, and non-real-time onshore (Statement 2 and Research Questions in Section 1.2).

Thus, the contribution to knowledge is achieved through:

1) The integrated system, its performance and usability.
2) The validation and verification of the system's applicability for CM.

1.5 Disertation Layout

The thesis is structured in five additional chapters. Figure 1:8 presents the layout of the dissertation and the links between chapters.

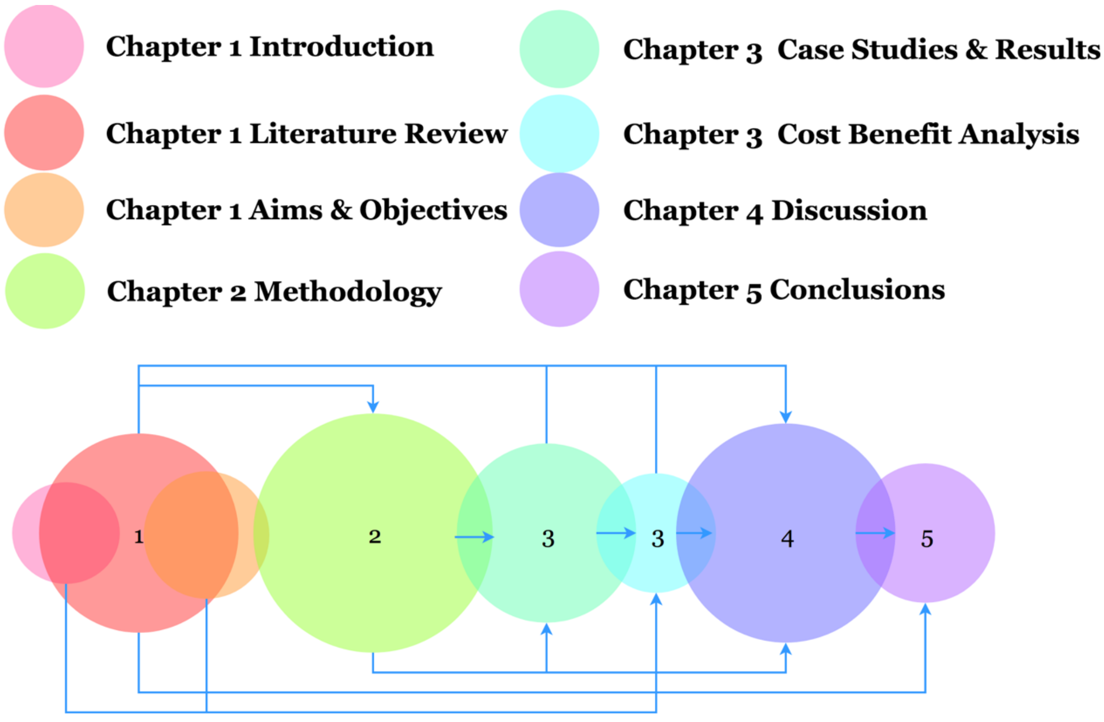


Figure 1:8 - Dissertation layout diagram.

Chapter 1 presented an introduction to the maritime sector, a literature review, the research question, the aims and objectives, and the contributions of the thesis. Chapter 2 presents the methodology to develop the solution that meets the aims and objectives presented in Chapter 1. This chapter is divided into sections covering the complete system starting with an overview of the methodology.

Chapter 3 presents the evaluation strategy, the implementation of the proposed solution, the designed case studies, and the results and findings of the case studies, along with the analysis of results of the evaluation strategy. Chapter 3 also presents a cost benefit analysis of the proposed methodology based on the review, the performed case studies and the resulting findings. A discussion of the findings of Chapters 2, and 3 is presented in Chapter 4 and the conclusions and future work in Chapter 5.

Chapter 2: Methodology

No computerised system can be developed without an application in mind. This chapter will present considerations that affect system design in a ship CM application. An overview of the methodology is presented in the first section. The approach followed in this thesis is a top-down development strategy starting from requirements of the application, according to systems engineering principles (Section 2.2). Sections 3 to 6 discuss the analysis and development of the system components, as well as the algorithms and DSS. Finally, section 7 presents the proposed integrated system and chapter summary.

2.1 Overview

Based on the key findings of the literature review, condition monitoring is necessary to improve the maintenance strategy utilised in shipping. At the moment, no widely accepted preventive maintenance approach utilises a cost effective continuous CM method. Moreover, such a method that is also easy to deploy on older vessels and utilises decentralised data processing is not found in conventional wired installations. Finally, available methods do not provide clear benefit identification for the company operating the vessel and trust/data-confidentiality issues are not addressed to a satisfactory level.

This chapter will review the detailed design and development of the complete system from the point of collecting data to the point of presenting it to the user. The novelty of the final proposed system lies in the cooperation of several methods in a full system approach, which provides solutions to the existing problems identified in Chapter 1. This is achieved through the development of a system to satisfy the research questions (Section 1.2) and outlined aims and objectives, in so doing, covering the gap identified through the literature review (Section 1.4).

According to the International Council on Systems Engineering (INCOSE, 2016): *"A system is a construct or collection of different elements that together produce results not obtainable by the elements alone"* and *"Systems Engineering is an engineering discipline whose responsibility is creating and executing an interdisciplinary process to ensure that the customer and stakeholder's needs are satisfied in a high quality, trustworthy, cost efficient and schedule compliant manner throughout a system's entire life cycle"*.

The complexity of such systems often necessitates an interdisciplinary process. As will be evident through the following sections of this chapter, the proposed system is highly complex with several requirements and constraints.

Figure 2:1 presents the methodology followed, aligned with the Systems Engineering principles, as presented by INCOSE (2016). However, it was further adapted to reflect the requirements of this thesis and extended to incorporate the academic approach necessary. As the issues that the proposed system is addressing reflect existing problems faced by the industry today, the systems engineering approach is considered appropriate, if not necessary. Similar approaches have been used in the past to develop systems (Dhukaram, 2016, Tomotsugu, 2013, Gangadharan, 2013).

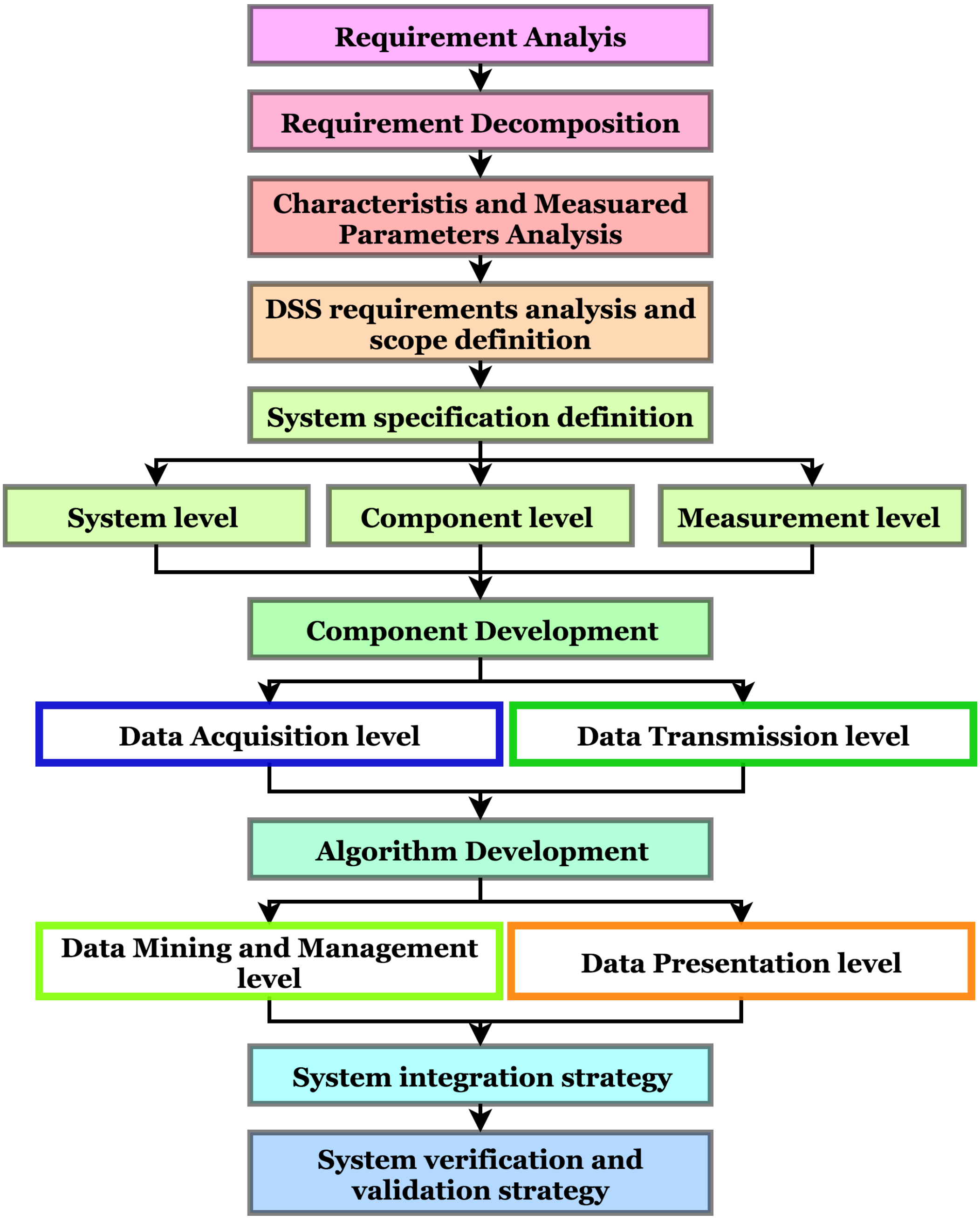


Figure 2:1 – Methodology.

The methodology[3] follows a waterfall model of systems design up until the DSS

[3] Published in: MICHALA, A. L. & VOURGANAS, I. 2017. A Smart Modular Wireless System for Condition Monitoring Data Acquisition. *Proceedings of the 16th International Conference on Computer and IT Applications in the Maritime Industries, Cardiff, 15-17 May*, Technische Universität Hamburg, Harburg, ISBN 978-3-89220-701-6, 212-225.

requirements analysis and scope definition stage (Figure 2:1). However, an agile development and implementation model was used for stages after (and including) the system specification definition[4]. The method is not fully agile as according to feedback[5] the requirements were not iteratively reviewed, whilst the data acquisition, software, DSS and user interface were iteratively reviewed and developed. The waterfall and agile methods are not novel. However, through the definition of requirements in the following sections and identified gaps in Section 1.4, the novelty comes from the proposed system development and application in the maritime domain. This approach is further discussed in Section 2.2 and the requirement for agile development is further analysed in Appendix A.

This method was adopted as it provided sufficient time to understand the maritime requirements of this cross disciplinary system development. However, after the initial design, several iterations led to re-evaluation and re-development and allowed for extended feedback, in particular from the industry experts and other stakeholders. The steps presented in Figure 2:1 are followed in the sections of this chapter in the same order.

2.2 Requirements

Initially, the findings of the previous chapter were categorised to identify commonalities and the system components. Figure 2:2 presents a Venn Diagram grouping the considerations identified in Chapter 1. These considerations are grouped according to the area they impact the overall system; Business Targets presented as Key Performance Indicators (KPIs) (MARINTEK, 2010), Maintenance Targets, Installation Requirements and Provided Services Requirements. The combination of Business and Maintenance Targets identifies the selected maintenance strategy. Similarly, the combination of Maintenance targets and Installation Requirements provides constraints and requirements for the selection of suitable hardware. Finally, the combination of

---

[4] A comparison of waterfall and agile models in systems development is presented in https://www.seguetech.com/waterfall-vs-agile-methodology/

[5] **The requirements were published** in all publications listed in page xvi. **The system was published in**: Michala & Vourganas, (2017), Michala & Lazakis, (2016), Michala, Lazakis, Theotokatos & Varelas, (2016). **The DSS and GUI were published in:** Michala, Lazakis & Theotokatos, (2015), Lazakis, Dikis, Michala & Theotokatos (2017), Dikis, Lazakis, Michala, Raptodimos & Theotokatos (2016), Lazakis, Dikis & Michala (2016), Dikis, Lazakis & Michala (2015).

Supported Services and Installation Requirements shapes the requirements for suitable software functionality.

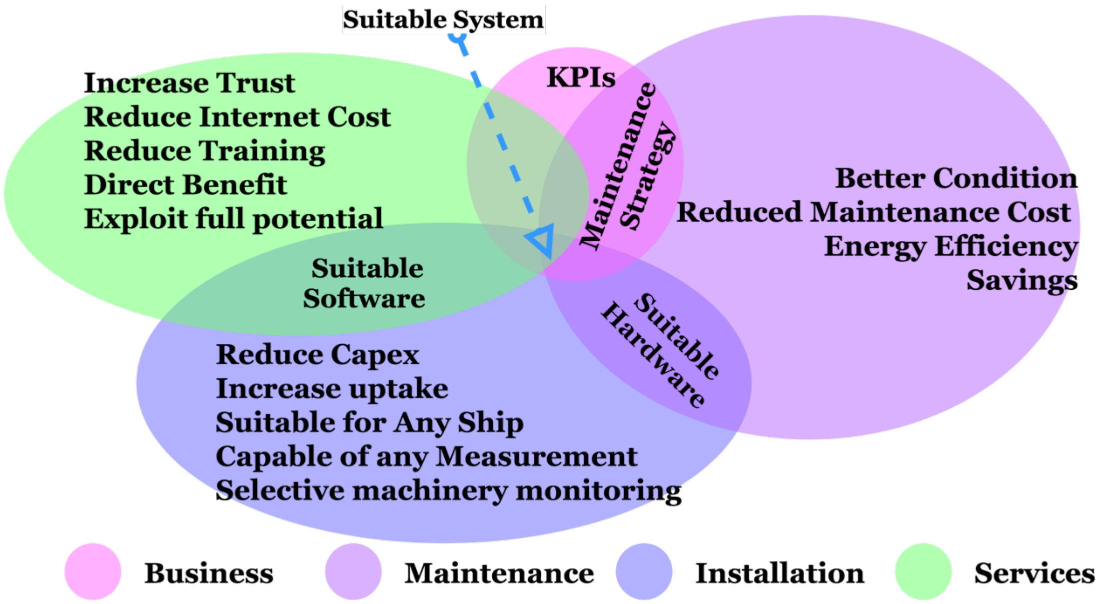


Figure 2:2 – System Requirements Categorisation. Key Performance Indicators (KPI) sourced from MARINTEK, (2010).

Overall, the union of all the areas represents the combined strategy, hardware and software development that meets system requirements and provides a suitable application. As dictated by the literature review the most suitable strategy demands CM, the goal that predominantly drives the system development.

The requirement analysis identified the high-level objectives of this system in four main categories. The decomposition to a low level hierarchical list of requirements follows a four-quadrant strategy to represent the development of this system (Figure 2:3). The four quadrants interact and define the system through an iterative process. This iterative process was necessary to meet the system development requirements according to cyber security regulation (Appendix A). Hardware is represented at the top in Figure 2:3 to highlight that the hardware requirements impose constraints on the software development.

Each of these quadrants addresses a set of considerations and collectively, the full system addresses all four requirement categories. Figure 2:3 represents the suitable hardware requirements as two subsets, the first addressing the method for providing inputs to the system and the second addressing the data flow through the system. These two quadrants successfully meet the requirements of the selected maintenance strategy through CM, while at the same time targeting all the considerations of the installation requirements. In particular, the reduced CapEx is one of the primary benefits to increase industry adoption of CM systems, met through the utilisation of wireless communication. A cost-benefit analysis of the proposed system is presented in Chapter 3.

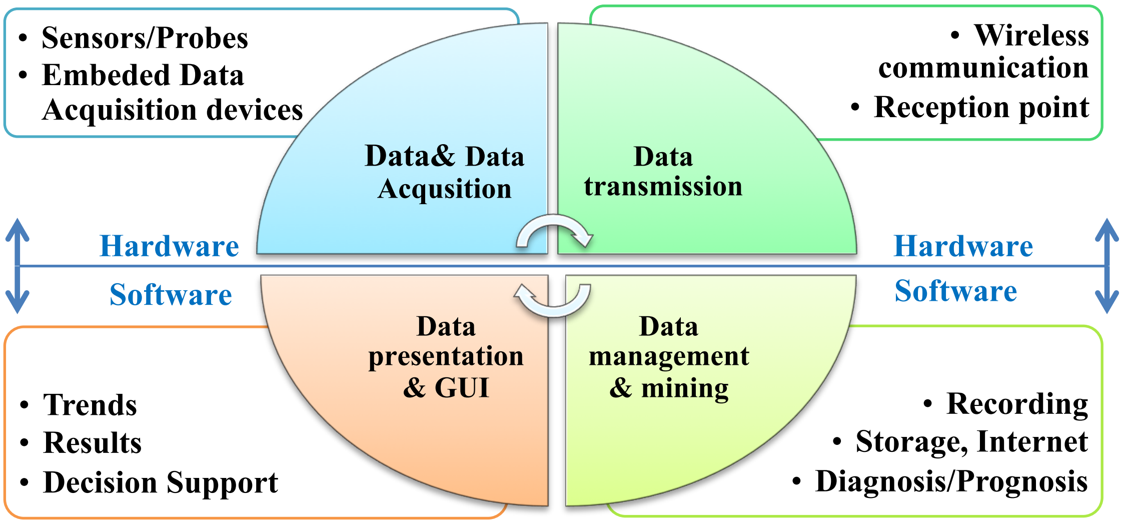


Figure 2:3 – Strategy for novel maintenance system development.

Software development is also represented by two distinct quadrants, the strategy for information extraction (mining) and data management followed by the strategy for data presentation. The requirements for functionality and services are the most important drivers for those quadrants combined with the installation requirements. Decomposing the requirements to tangible development quadrants, results in a clear understanding of the system's components. There are four major components which are further divided to sub-components (Figure 2:3). The correlation of requirements, literature gaps and system components is summarised in Figure 2:4.

In Figure 2:4 the requirements identified from the literature review are presented as cloud shapes and the decisions made derived from the methodology as parallelograms. Requirements can be directly related to constraints for the proposed system (Figure 2:4) These led to the design decisions that shaped the development of the proposed system. To facilitate this system, specialised hardware and software co-design investigation was necessary. The system design decisions, fall in two categories; the physical system development – reflecting hardware decisions – and the software development. These are further divided to correspond to the four quadrants of Figure 2:3.

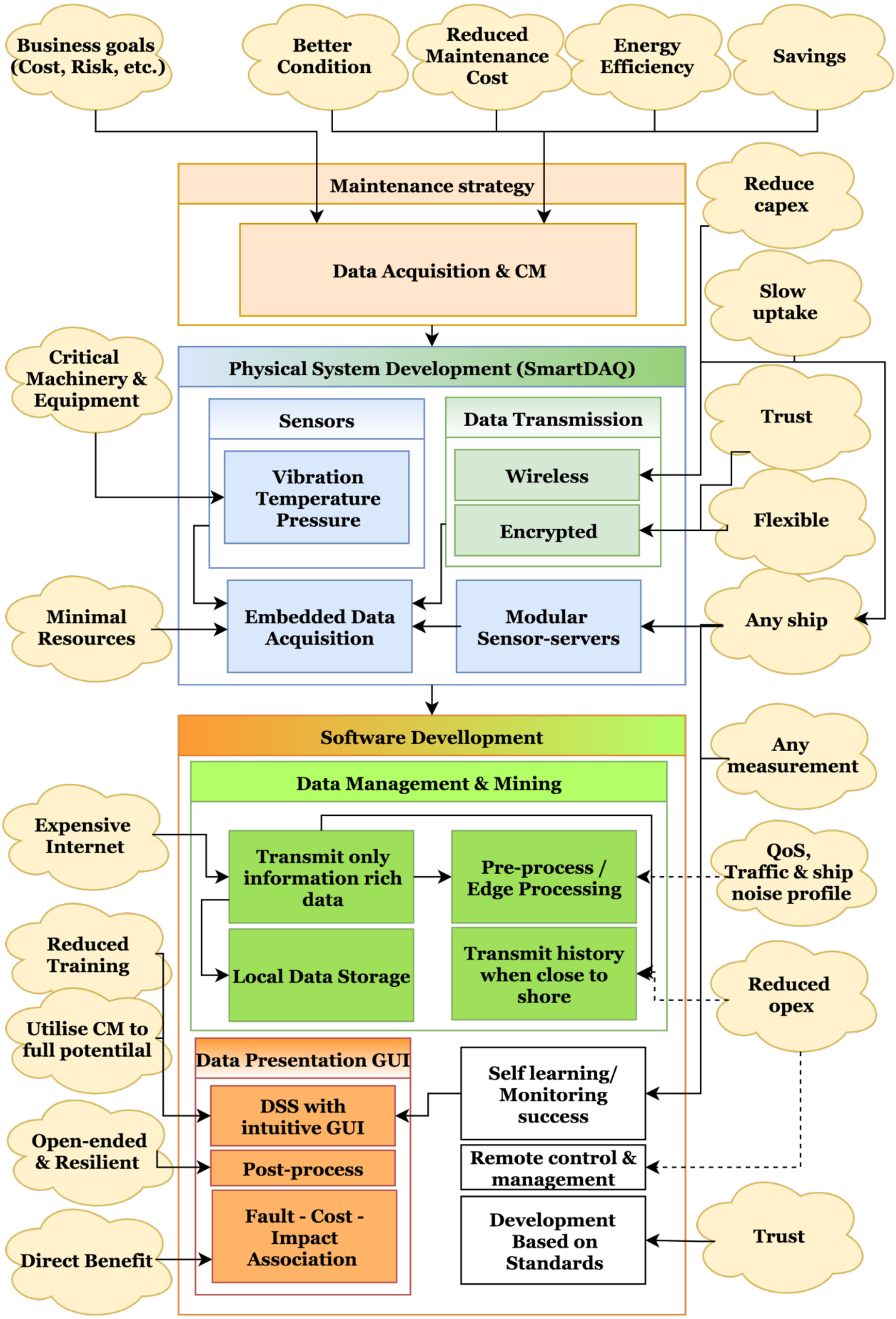


Figure 2:4 – Data management system needs based on literature review identified considerations.

The requirements identified in a hierarchical list according to the level of importance for the industry stakeholders mapped to the four quadrants are:

1) *Low capital investment and low operational cos.- Transmission & Acquisition.*
2) *Minimal satellite Internet usage but full visibility to shore – Management & Mining.*
3) *Easy installation with minimal requirement for out-of-service hours – Transmission & Acquisition.*
4) *Flexible deployment to cover a large variety of machinery and equipment – Acquisition.*
5) *Utilisation of wireless technology where possible – Transmission.*
6) *Data translated to useful maintenance decision support – Presentation & Mining.*
7) *Data linked to direct benefit for the stakeholders – Presentation & Mining.*
8) *Input interface that can support a variety of industrial sensors - Acquisition.*
9) *Increased data protection strategy to enhance trust in technology – Transmission & Management.*
10) *Prognosis of failures and long-term condition management visualisation – Presentation & Mining.*
11) *Access to computers is possible only in the control room which is a different physical room adjacent to the engine room – Acquisition & Transmission & Presentation.*
12) *Data acquisition near the sensor location is a physical requirement as engine rooms are physical structures that cover a very large area – Acquisition & Transmission.*
13) Data acquisition of measured parameters must comply with requirements imposed by Class and regulation – Characteristics & Measured Parameters Analysis (Table 1:4).

To identify the required scope for DSS and address points 6 and 7 of the above list, the minimum necessary number of monitored machinery and equipment must be identified. According to the findings of Chapter 1, the selection is based on importance and criticality of ship systems (Figure 2:5). Fire and Alarm systems are excluded as they require current monitoring which is out of the scope of the thesis.

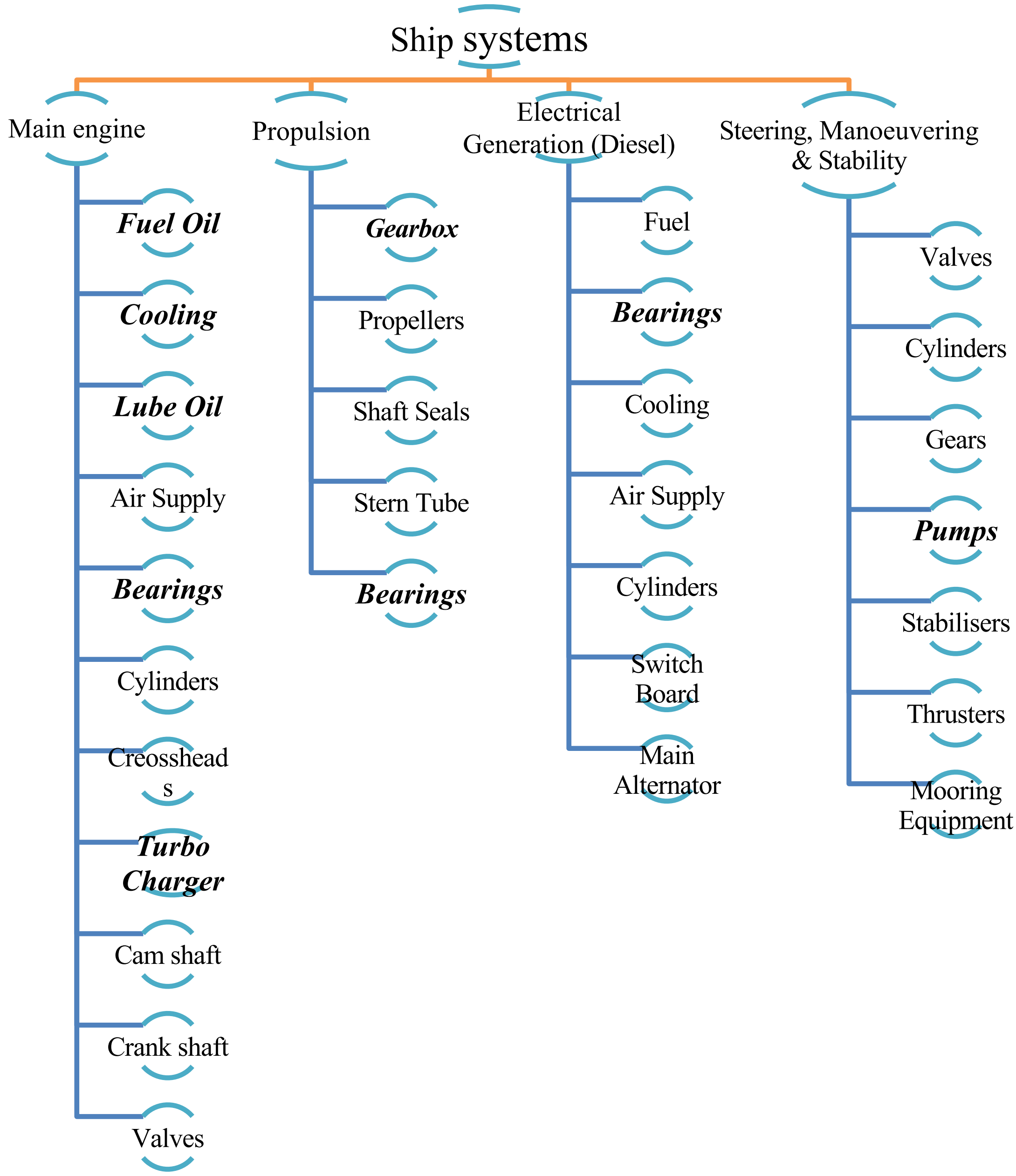


Figure 2:5 – Ship selected critical systems and resulting subsystems.

Figure 2:5 presents a more detailed classification of systems and subsystems for the critical machinery and equipment requiring CM. Additionally, the subsystems in some cases incorporate components such as pumps, filters and motors which often require to be monitored separately to assess the condition of the subsystem. According to a review of the CM data requirements for tankers, bulk carriers and container ships, presented in INCASS (2014b), some of the components and subsystems require to be monitored more frequently. These are highlighted in Figure 2:5 in bold.

Where possible the pre-installed commercial sensors should be utilised. If that is not applicable for reasons of insurance and warranty, the data collected from the existing sensors may be directly transferred to the post processing unit. In that event, there is a requirement for specific interface development, to be discussed in the following sections of this chapter.

If no sensors pre-exist, temperature, pressure and vibration sensors will need to be installed with minimal intervention to the machinery. Pressure sensors require intrusive installation, and thus will require a cost/benefit analysis to determine whether it is a viable investment; discussed in Chapter 3. In that respect, installation on both new-built and existing ships will require the same minimum effort. Additionally, sensors can be selectively deployed in stages based on the extent that the ship operator wants to invest in CM.

2.3 System Component Analysis

To evaluate if the proposed system is applicable in CM for on-ship machinery and equipment, the necessary inputs must be connected to appropriate acquisition and transfer equipment and presented to users. In that respect, this section will investigate the specification for data acquisition, transmission and presentation.

2.3.1 Data Acquisition

Several hardware architectures exist today for use in 'smart' devices. These include microprocessors (e.g. x86, ARM architectures (TI, 2016)), CPUs (Saecher and Markl, 2012), combinations of the two (e.g. Big-Little (Chung et al., 2012)), and accelerators (e.g. GPUs and FPGAs (Saecher and Markl, 2012)). Currently, the use of accelerators is a vibrant research domain especially in low power applications. However, they are difficult to program, software is not portable between architectures or vendor implementations and time consuming to re-program (e.g. upgrades, serve different CM inputs). The same applies to mobile device architectures such as Big-Little.

The use of embedded systems in data acquisition is well established. Using sensors effectively and understanding the hardware in an embedded system is key to development (Costillo, 2015). Commercial systems are available for a variety of industries including marine and maritime (NI, 2016a, Humphreys et al., 2014, Cheng et al., 2013, AVL, 2013, Vasilescu et al., 2005, Wärtsilä, 2012, eGreenShip, 2013, Lilas, 2009, Nemarich et al., 1990). Embedded is defined as: *"systems which utilise microprocessors to perform a number of actions, manage input signals and provide the desired output with minimal resources"*.

After the input measurements are selected, several other design decisions need to be made. For instance, electronic interfaces need to be created between the sensor and the embedded system processor. Moreover, depending on the processor selection and its capabilities, software development resources may be limited. Hence, hardware may be the only possible solution for Analogue to Digital Conversion (ADC) or Digital Signal Processing (DSP). However, if the processor has sufficient memory and processing power these can be implemented largely in software. The trade-off between processing power, battery consumption and sampling frequency ultimately determines the software development for a particular application. In order to apply the best system design strategy, the processor, the sampling and real-time monitoring requirements must be examined. The power supply and consumption requirements were not the primary focus of the thesis and are discussed in Section 5.2.

Single Board Computers (SBCs) use CPUs instead of microprocessors. They are flexible, easy to manage remotely and can deploy many algorithms in parallel to serve several CM inputs (Molloy, 2015c). Examples include the Raspberry Pi, BeagleBone, Galileo and Arduino (Lewis, 2015). The Linux processors combine low power consumption, microprocessor and mini OS capabilities (Molloy, 2015c). Major vendors such as Silicon Labs and Texas Instruments provide a large variety of *'plug and play'* hardware and software, specifically developed for the IoT generation (Weisman, 2016). As the focus of this thesis is on higher processing on the data acquisition unit, Linux processors are a compelling foundation. At the same time, development time is reduced as software is in languages such as C, C++ and Java instead of processor specific embedded C. For the proposed methodology, the available solutions are compared (Table 2:1).

Provided that no OS exists, Arduino was ruled out. Moreover, the lower processing capacity of Arduino was a limiting factor. The RPi was not a viable option as the continuous writes to the SD-Card limit its lifetime and thus reduce the robustness of the system. As the BeagleBone Black (BBB) had a more powerful processor and already available internal storage, it provides a more compelling option for this application. Also, the readily available access to a Linux Kernel and other peripherals was instrumental to the decision. Unlike standalone embedded processor chips, or Systems on a Chip (SoC) solutions, the more powerful processors of this generation of SBCs give fertile ground for network edge programming; the focus of the research.

Table 2:1 – Comparison of Linux quick start development boards (values marked with * indicate that the option is not readily available and would require significant software development overhead).

Parameter	Raspberry Pi 2/B	BeagleBone Black	Arduino UNO R3
Embedded Processor	0.9 GHz ARM A7	1GHz ARM A8	ATmega328
RAM	1 GB	0.5 GB	2 KB
Storage	SD card, external	4 GB, internal	32 KB, Flash
USB ports	4	1	1
Peripherals	HDMI, Ethernet	HDMI, Ethernet	0
OS	Yes	Yes	No
Real time	No*	Yes	No*

The reliable OS allows easy access to hardware through command line and scripting (Molloy, 2015b). BBB is equipped with Analogue Ports, ADCs and is designed to allow monitoring applications in contrast to its other counterparts, providing a great advantage to embedded development especially in the early stage. Another benefit of this platform is that it comes complete with a variety of stackable daughterboards referred to as capes; allowing modular development (Molloy, 2015a).

Finally, the most significant advantage of BBB is that it is fully open source. In that respect, information and support for development is easily accessible. That also translates to access to hardware designs. Hence, all the components can be easily transferred to their miniature counterparts and Printed Circuit Board (PCB) design, for the final stages of the development. BBB is an excellent proof-of-concept development board and is suitable for less demanding deployments; however, there are other more robust systems that could be used in production. There are numerous embedded system development boards that are specifically intended for industrial use, providing features like robustness to heat, vibration, etc., and run Linux; these are not reviewed here as development of a proof-of-concept was the aim of the thesis.

The disadvantage of SBCs versus microprocessors is the ability to process input and react in real-time. Linux processors are not as easily used for real time monitoring. Real-time monitoring refers to data collected under certain timing constraints with decisions made within that time frame. The Linux operating system increases complexity in scheduling of real-time tasks to meet the defined timing constraints (Liu, 2000). For example, there are specifically developed microprocessors such as Texas Instruments ARM platforms (TI, 2016) for specialised real-time applications.

To address this shortcoming of Linux processors and to reduce complexity of scheduling, BBB offers two additional micro-processors on board, specifically dedicated to real-time monitoring and interfacing to sensors (Molloy, 2015b), i.e. two Programmable Real-time Units (PRUs). To be able to provide real-time monitoring on the other SBCs, significant software engineering would be required to keep within the time constraints, which translates into increased development overheads, possible race conditions, or other deadlock conditions, not easily identified and rectified.

Also, BBB uses server time synchronisation through Ethernet to establish the correct synchronisation of time. Synchronisation implementation could be achieved through the data transmission channel. In this approach, the real time could be reset through data received from the central collection hub, reducing the hardware and implementation cost at the expense of increased network traffic.

Several real time monitoring applications have been reported in the literature for industrial condition monitoring (Yang et al., 2012) proving that wireless network nodes can be used in such applications (Cheng et al., 2013). Moreover, the same work presents the use of wireless nodes for not only monitoring but also control. In that respect high dependability, reliability and quality of service of the communication is proven. That work uses ZigBee, further elaborated in Subsection 2.3.2.

2.3.2 Data Transmission & Management

The data transmission component facilitates the wireless communication between the point of data acquisition and central data collection. For wireless communication, several parameters need to be considered (Gardner, 2012). Wireless networks are, by definition, prone to electromagnetic interference and are affected by any obstacle that disturbs the RF signal path. However, several advances in the technology have allowed for the successful application of Wireless Multihop Networks (WMNs) in modern industrial setups (Badis and Rachedi, 2015, Ming et al., 2012). The engine room of a ship is similar to an industrial unit in the type of equipment and machinery used, and their noise profile (brief review in Appendix B). Alternative technologies are ultrasonic and optical communication distributed networks (Vasilescu et al., 2005). However, ultrasonic applications may not perform well in noisy environments such as a ship's main engine room. Also, optical technologies require a line of sight between the nodes of the network and small distances between the nodes.

Other parameters to be considered are the time synchronisation method, network deployment, QoS, message routing, network reliability, network fault identification and recovery mechanisms, data rates and frequency of data transmission (Nandi et al., 2014, Kiyang and Van Zyl, 2014, JaeHyuk et al., 2013, Zhao et al., 2013, Xu and Liu, 2012, Ralston, 2007); addressed in this thesis through industrial communication protocols and software implementation.

The Institute of Electrical and Electronics Engineers (IEEE) has issued the IEEE 802.15.4 standard in the 2.4 GHz ISM band (Wagner and Barton, 2012, IEEE Computer Society, 2003). Industrial application Protocols based on the IEEE 802.15.4 standard are: Wireless Highway Addressable Remote Transducer (WirelessHART), International Society of Automation (ISA) ISA100-11a, 6LoWPAN, and ZigBee/ZigBee Pro (Shelby and Bormann, 2009b).

The 6LoWPAN standard is specifically developed for low power wireless sensor networks using embedded systems for industrial applications where monitoring and/or control are of interest (Shelby and Bormann, 2009a). ZigBee has been extensively used in a variety of industrial applications such as electrical power sub-station condition monitoring (Baker, 2010) and bearing condition monitoring (Feng et al., 2015). WirelessHART claims to use lower power than ZigBee and provide similar service (Myhre et al., 2014).

Even though WirelessHART, ISA100-11a and 6LoWPAN could have been candidates for the application they have a disadvantage compared to ZigBee. ZigBee provides the ability of full *ad-hoc* path identification and *mesh* routing. Also, it is fully compliant with IEEE 802.15.4, provides full flexibility for the application layer, and allows for higher level of data security. ZigBee has incorporated the IEEE 802.15.4 MAC layer security and provides data encryption in three distinct layers (Lennvall et al., 2008). Table 2:2 presents a comparison of the three most established protocols.

Research supports that ISA100-11a may be more robust in high noise interference.

As data need to be verified for transmission, it increases power consumption and delays delivery (Wagner and Barton, 2012). However, the most significant interference that affects the performance of wireless networks is noise generated through Wi-Fi traffic – often present in land based industrial environments (Grami, 2016). In the case of ships, such interference is only present when in port, at which point most machinery and equipment is not in operation. Other sources of interference outside the Wi-Fi band are more prevalent in this environment; further discussed in Appendix B. Also, the possible loss of data does not significantly affect the reliability profile of machinery or equipment (Baker, 2010). Thus, the extra cost for ISA100-11a is not justifiable for this application. In contrast, a low-cost ZigBee Pro with a software defined delay tolerant networking approach guarantees delivery of all data regardless of the transmission medium but could have an effect on real-time decision making onboard (Section 2.6).

Table 2:2 – Comparison of Industrial Wireless Protocols.

	WirelessHART	**ISA100-11a**	**ZigBee Pro**
Power consumption	Lowest	Lower	Low
Mesh	Power optimised, Frequency hopping	Coordinated Frequency Hopping + Node Hopping	Ad-hoc Distance Vector Node hopping
Channel	Dynamic	Dynamic	Static
Modulation	TDMA - DNT-SMP	TDMA - DNT-SMP	TDMA(optional slot)
Channel selection	Dynamic + Blacklisting	Dynamic + Cycling + Blacklisting	Optimised + Blacklisting
Devices	Routers	Routers	End Devices + Routers
Security	Authentication + Encryption, Node-to-Node	Authentication + Encryption, Node-to-Node	Authentication + Integrity + Encryption, Node-to-Router
Cost	~100 $	~100 $	~10 $

*Time Division Multiple Access (TDMA) modulation (JaeHyuk et al., 2013). Very low power wireless transmission is possible (Bongjae et al., 2014) but depends on the desired transmission range (Mehta and Reddy, 2015).

As discussed in Chapter 1, ZigBee Pro would not be able to perform under the volume of raw measurements. Also a topology of the network with maximum separation of 6m is necessary according to Kiyang and Van Zyl (2014), increasing the number of sensors that can be attached to each unit. Thus, a data management strategy was proposed based on the edge-processing paradigm; distributed in storing and sensing. The data is transmitted to the central collection point where it will be post-processed, utilising the full processing capabilities of the onboard computer (Figure 2:6). To enable further onboard analytics for condition prediction, the central collection point will acuminate all the post-processed data, storing the data in a structured format.

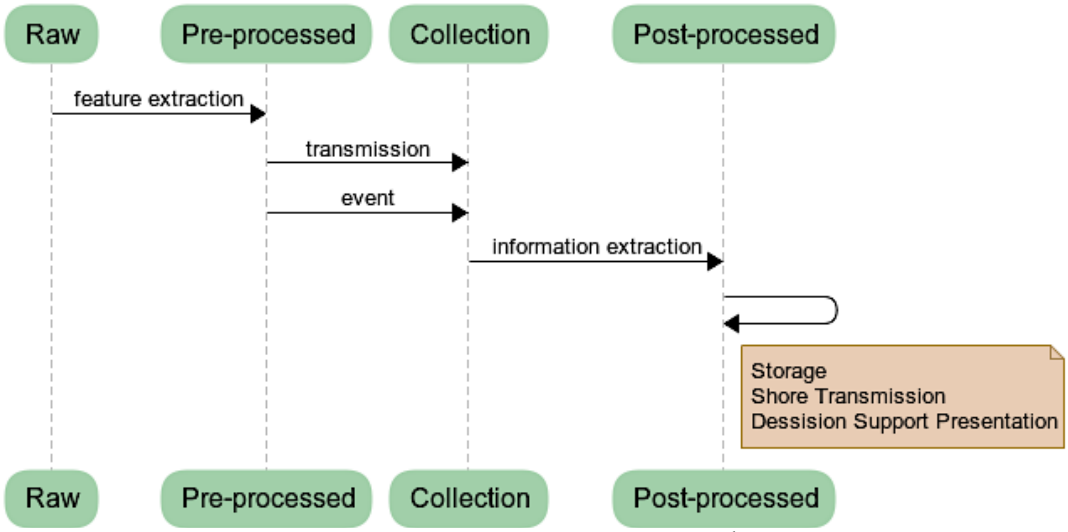


Figure 2:6 – Data management sequence[6].

In this thesis a set of storage files in simple CSV format are utilised which could be easily imported to a shipping commercial database at a later date, such as the one presented by Taheri et al. (2015), Adamson (2016b) or even Cloud Computing platforms (Xia et al., 2016, Uhlmann et al., 2015). This allows the system to be open ended in terms of storage options and analytics. CSV files were used as the data volume generated by the case studies was not substantial. Moreover, this approach allowed for standard tools such as `bash scripts, awk scripting` etc. to be utilised for analysis of results.

As it is outwith the scope of the thesis to present a novel approach in CM data analytics, condition and fault diagnosis, a proven state-of-the-art method will be used based on a Bayesian Network representation of the monitored system for fault extraction (Lazakis et al., 2017, 2016a, 2016b, Dikis et al., 2016, Michala et al., 2016b, 2015). This method provides an ideal analytics component for the proposed system as it is compatible in input/output requirements and is validate for use onboard ships. The results of the reliability analysis method will be used by the proposed DSS to provide maintenance action decision support onboard (discussed in the following subsection).

---

[6] created using the tool www.websequencediagrams.com

Finally, to complete the data management strategy a method for on shore visibility must be proposed. A consideration is the operational cost of the system especially in terms of satellite data transfers. For this reason, the required analysis is executed onboard and the resulting information in the form of actions, warnings or failures are the only data transmitted to shore.

2.3.3 Data presentation

One of the inhibitors in Chapter 1, is that users do not identify the immediate benefit from using CM technologies. In that respect, this section discusses data presentation in a manner useful to the end users including both onboard and on shore personnel.

The reliability analytics component presents condition information in degradation curves. The reliability, failure modes, along with other inputs such as the actions that can/cannot be performed onboard are necessary DSS inputs. Information from expert users is important in the interpretation of the reliability of the system in each condition (Dikis et al., 2016, Lazakis et al., 2016a, 2017). Additionally, most approaches are presenting the DSS as a tool where the parameters to be optimised are of a singular nature – cost or planning optimisation (Section 1.1.2). But maintenance action suggestion is not considered as a multiple parameter problem where constraints apply (Tsang, 1995); such a method is not available for onboard real-time maintenance decision support to the best of the author's knowledge. Thus, this thesis will present a method which addresses all these requirements. Moreover, this DSS approach will implement a reinforcement machine learning method to individualise decision support for each vessel through time.

Another important parameter in data presentation, apart from the actual data and information extraction, is the Graphical User Interface (GUI). A plethora of studies have discussed the feedback of users to GUIs and the usability of software design. According to current guidelines for GUI development, the design should always consider the user experience, the user expectation and user knowledge so that the it is tailored to provide the most useful information in the most appropriate manner (Gray and Salzman, 1998). According to recent trends, the optical artistic presentation of the GUI is no longer relevant. Functional GUIs have been regarded as outdated. Most importantly, since the era of iOS, simplicity and intuity, as well as obstruction have been driving GUI designs (Morgan, 2014). The target of GUI is to present the information when it is needed through basic interfaces. Firstly, user feedback and use cases are the only real measure of success. Secondly, simplicity is a key requirement.

The GUI which will be used in this thesis was developed, following these principles and presented in several publications, workshops and conferences (Lazakis et al., 2017, 2016a, 2016b, Dikis et al., 2016, Michala et al., 2016b, 2015). Through the public showcasing and consultation with industry stakeholders, extensive feedback was acquired from potential users and experts in the field, used in refining the GUI.

The outcome of the design analysis presented in this section is a concise system, that harvests the benefits of a powerful and smart data acquisition unit. For the development of the methodology four areas are proposed in Figure 2:7, corresponding to the layers presented in Figure 2:3.

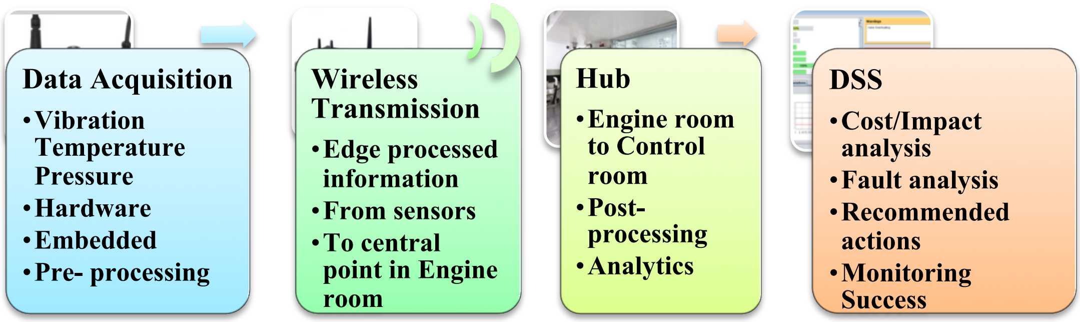


Figure 2:7 – Proposed methodology implementation overview.

The specification of the proposed system is versatile and modular, based on edge processing and wireless transmission, representing a system beyond the current state-of-the-art of ship CM. In contrast to existing approaches the proposed system advances the state-of-the-art through decentralised data management on a low-cost wireless platform that supports real-time onboard DSS. The system can be applied to new and existing vessels alike, at minimum installation cost and intervention. Also, through correct data management, and security, the customer sensitive information can be hidden, improving trust of the system. Through associating impact of condition with cost, the benefit of CM is more direct. Minimising the data transmitted to shore, when the ship is sailing, further reduces cost, while providing non-real-time visibility to the shore-based business functions.

2.4 Component Development

This section will further elaborate on development, based on the discussed constraints, considerations and design specifications (Section 2.3). The final integration of the components in presented in Section 2.7.

The Data Acquisition (DAQ) component is developed according to the identified capabilities (Sections 1.1.2 and 2.3) using a BBB (Section 2.3.1). However, to interface the BBB platform to the selected range of input sensors the DAQ unit needs to incorporate hardware to translate the analogue input to compatible BBB input. The implementation and hardware interface to BBB is discussed in Section 3.1 using a globally recognised interface for coaxial cables; a Bayonet-Neil Concelman (BNC) connector along with signal conditioning electronics. The selected infrastructure satisfies all the design constraints and requirements outlined in the physical system – sensor and data acquisition (Section 2.2).

For the system to be modular, it must be able to permit different settings. Table 2:3 presents a summary of the configuration settings available at commission defined by the physical connection to sensors. A summary of all the configuration settings and the selected values will be presented at each experimental setup in Chapter 3.

Table 2:3 – Configuration settings.

Parameter	Setting
Measurement	Temperature, Pressure, Vibration
Type	Value, Signal

The overview of the DAQ component is presented in Figure 2:8. This component contributes to the proposed system in combining the processing unit, the embedded Linux platform, its capability to be adjusted to different sensor requirements, and the algorithms developed to manage both the input and the operating routines of the system (Section 2.5). Thus, advancing ship CM through decentralisation of processing under domain specific constrains and advancing the edge computing paradigm via single-pass 0-hop lightweight and portable processing of CM data for feature and event extraction.

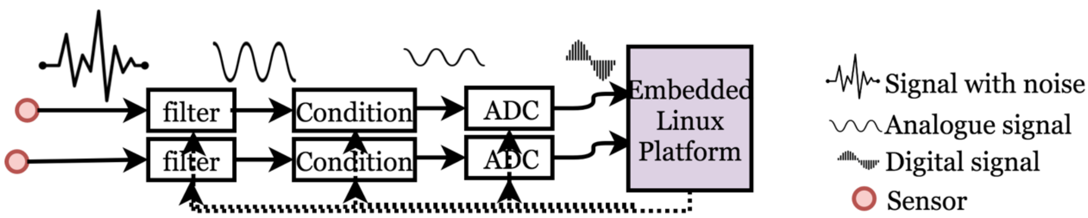


Figure 2:8 – Integrated DAQ component for signal harnessing.

Figure 2:9 presents the most significant characteristics of this system to reduce wireless traffic. This approach can increase the QoS and reliability of the network.

Based on Sections 2.3, the proposed system uses ZigBee Pro wireless transmission. This approach meets the needs and constraints identified in the literature review of reduced capex, enhancing industry adoption and providing security to boost trust. Unique encryption keys are generated at commission so that other wireless systems can not breach the system. The protocol has embedded encryption mechanisms, which can be further enhanced through additional message encryption prior to transmission, if necessary.

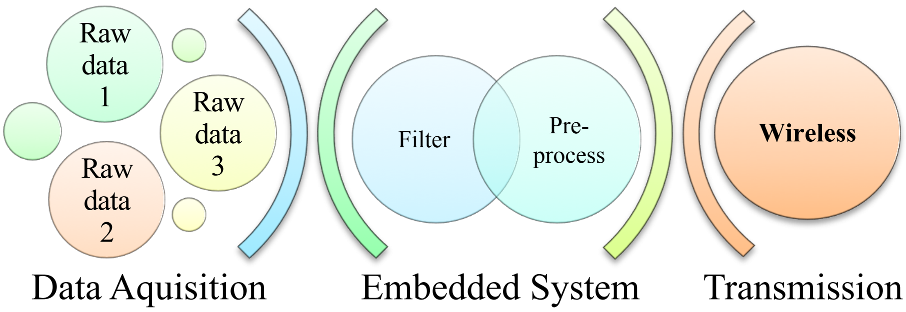


Figure 2:9 – Pre – processing and filtering raw data to reduce wireless network traffic.

The key points affecting the algorithm development that drives this wireless communication system are :

- *Reduction of traffic to increase reliability.*
- *Verification of data transmission and encryption, authentication, and integrity security utilisation.*
- *Investigation and documentation of system performance (not documented in the literature).*
- *Delay tolerant networking and mesh remote management and self-healing is not available in existing systems.*

These can be addressed through the management method. Moreover, this method considers other requirements such as low power consumption. The performance validates the suitability of this novel system and the method for assessing this is presented in the Chapter 3.

For the embedded system to be able to drive the wireless communications, several configurations need to be considered. Table 2:4 presents additional configuration settings required for the wireless network. These must be setup at commissioning, similarly to other settings discussed in the previous section, governed by the decision that ZigBee Pro will be used.

Table 2:4 – Additional configuration settings (continues from Table 2:3)

Parameter	Setting
Encryption	Generated Encryption Key

To meet the requirements of the system, five operating modes are necessary (Figure 2:10). Table 2:5 presents these operating modes and their requirements in in terms of execution time and data rates.

Table 2:5 – Default operation modes timing and indicative data requirements.

Mode	Value Type		Signal Type	
	Sec	Bytes	Sec	Bytes
Sleep	58	0	59	0
Record	2	16	1	16
Failure Onset	20	160	100	1600
Attempt Join	∞	1	∞	1
Error	∞	1	∞	1

The system is initially in Sleep mode (Figure 2:10); then, it cycles through Record mode for healthy system conditions and can also enter Failure Onset mode if abnormalities in the data are identified. When an abnormality is identified, the system increases the sampling period and frequency to identify if the recorded values are relevant to failure or just noise.

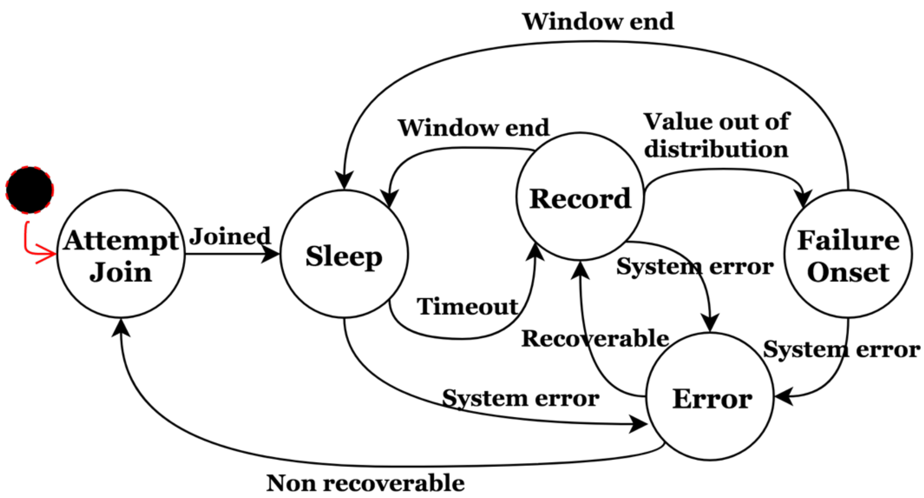


Figure 2:10 – Embedded and Wireless system state machine.

To establish that abnormalities in the data are not related to internal errors, the system has several internal error identification mechanisms. When such an error is identified, the expected behaviour cannot be guaranteed, and the system goes into Error mode. A self-healing process is assumed at this stage, if possible, and the general system is notified of the condition. If the error is non-recoverable, the device enters sleep after producing a distress signal. Such signals are referred to as *events*. An event posting mechanism is also in place to manage the propagation of these events. In this eventuality, when the device is healed, it moves into Attempt Join mode to reconnect to the mesh. The state machine of Figure 2:10 presents the connection between modes. The conditions of the transitions between states are dependent on time constraints and state identification.

In order, to make maintenance of the proposed system more manageable, a set of commands can be transmitted from the central collection point through a user interface (Table 2:6). These commands can be used to alter the configuration settings of any DAQ deployed, but do not allow change of the encryption key parameter. So, every sensor can be signalled to start recording more frequently, move out of sleep mode or even change the parameters to allow different sensors to be attached. Test and fault-finding commands are also available for diagnostic purposes and network management.

Table 2:6 – Commands for network management, diagnosis and configuration setup.

Command	Description
Join	Tells any devices to join the mesh if they have the correct encryption key
Remove	Deletes a device from the mesh and forces it to sleep
Command	Protocol for custom command, used to allow expansion of the system
Mesh	Reports the status of the mesh
Channel	Custom change to the channel setting
Refresh	Removes and re-joins all devices (heal)
Reset	Resets the device to configuration parameters
Test	Forces a device to send a test message with information on statistical performance
Sleep	Forces a particular device to sleep
Wake	Forces a device to wake but does not alter the recording settings
Record	Forces a device into Recording mode
Failure Onset	Forces a device to record with Increased sampling rate
Event	Special command initiated by the node in distress. Different events can be recorded

Additionally, other events related to data are available such as: Data value with 20% increase in standard deviation, Data outside limits and Data close to alarm thresholds. This approach resembles the 'If This Then That' framework (IFTT, 2017), utilised to support posting events to Tablets and Smartphones in conjunction with this system. Machine learning approaches are the state-of-the-art in detection of patterns or events from historical data. Some of these approaches can be executed at lower power and computational computation (e.g. forward phase of SVM) as discussed in Chapter 1. However, they require training/learning based on classification of the particular input. Hence such approaches are not portable and cannot be uniformly applied to all ships, systems, subsystems and components.

To implement these commands and remote control of the system, a communication protocol was created. This protocol utilises a unique identification byte to determine which command is sent between devices or if data is transmitted. The second byte is representative of the length of the message from 0 to 255 bytes. The following bytes carry the actual message (Figure 2:11). These messages are Cyclic Redundancy Code (CRC) checked for success of message transmission and an Acknowledgement (ACK) is then propagated back to the sender (delay tolerant networking). As a result, only successfully delivered messages are erased from local memory, minimising the loss of data.

Command Byte	**Length of following message Byte**	**Message bytes**

Figure 2:11 – Format of communication protocol.

The management methodology and the message exchange protocol contribute to the completion of the novel edge processing system advancing shipping CM under the reviewed constrains. Particularly the ability to monitor the condition of the network, remotely configure the network, and acquire condition and data relevant events in parallel with information extraction is a unique combination of functionalities that empower the system compared to existing approaches. The evaluation, Case Studies and results presented in Chapter 3 investigate the performance of the developed system as well as the utility and efficacy of the communication protocol.

2.5 Algorithm Development

In the previous sections the analysis and identification of the system in terms of component development, constraints for software development and system management, data collection, and transmission were presented. This section demonstrates the part of the methodology that relates to software development for data management and processing. This development as well as the development of the components presented in the previous section of this chapter has followed the software development standards. The development strategy and risk analysis are available in Appendix A.

The selection of pre-processing algorithms was based on the findings of Chapter 1. The pre-processing algorithms are verified and validated through the evaluation strategy presented in Section 3.3.2.

As the system needs to be versatile, it must be able to accommodate recordings from a variety of machinery and equipment. For machinery and equipment different ranges are applicable. Hence, it is not possible to specify these in advance, as it would reduce the versatility and adaptability of the system. For these reasons, the range of values would need to be an additional input parameter to the system specified at commissioning. Table 2:7 reflects this by presenting additional user configured parameters for the proposed system. These will be necessary for the system to evaluate if the readings are within range and/or if errors/events have developed in the data acquisition system. This versatility is a key contributor to the system development versus existing approaches.

Table 2:7 – Data-specific system configuration settings for any sensorial input.

Parameter	Setting
Measurement site	Text description of installation site
Range maximum limit	Highest acceptable reading
Range minimum limit	Lowest acceptable reading
Upper threshold	Highest acceptable, indicating normal operation
Lower threshold	Lowest acceptable, indicating normal operation

Additionally, the pre-processing algorithm needs to be able to identify when equipment is not in operation. Most data recorded in that period will need to be optimised out of context through the pre-processing software. This technique retains only relevant data in the database and periods of no operation can still be deducted from the data time-stamps. In that respect, a gap in the data of one hour would equate to one hour of the specific machinery/equipment being switched off only if a synchronous event exists. As three types of measurements have been identified, the algorithms used for each case are presented.

For the vibration measurements, the selected approach was discussed in Chapter 1.

Fast Fourier Transformation (Hou and Bergmann, 2012) utilises minimal resources in processing the data to extract the frequency domain characteristics of the vibration signal. Additionally, information for the time domain signal must be collected, such as mean, standard deviation, peak-to-peak amplitude, RMS and variance (Chapter 1). This algorithm processes a window of the vibration signal, at a time which coincides well with the cyclic operation of the embedded system. Thresholds of the statistical properties are determined to indicate onset of failure and trigger higher sampling rates. The approach is presented in Pseudo code 2:a.

Pseudo code 2:a – Signal type data pre-processing algorithm.

```
process: Normal_Sampling_State
  while recording_window ≠ 0  and  number_of_windows > 0 do
     Read data in normal_sampling rate          //User parameter
  end
  for each_record do
     calculate new_FFT
     calculate new_peak_to_peak_amplituted, μ, σ, RMS
     calculate new_variance
  end
  if new ≫ old or                               //first old extracted from thresholds
     new ≪ old or
     new_FFT_components ≠ old_ FFT_components then
        go to Failure_Onset_Sampling_State
  else
     for (number_of_windows) do
        Transmit ( time_of_first_record, length_of_window, new,
                 new_ FFT)
     end for
     Update (old)
     go to Sleep
  end if
end process
process: Failure_Onset_Sampling_State
  Increase sampling_rate
  Reduce recording_window
  Increase number_of_windows
  go to Normal_Sampling_State
end process
process: Sleep
  Prepare device to enter low power/sleep mode
  Sleep for sleep_period of time                //User parameter
end process
```

Reducing the sampling rate is very common to obey the system constrains of processing capability, memory allocation, and power (Nachman et al., 2008). Additionally, each DAQ unit has a local memory capable of storing several months of unprocessed data (SD-Card), which can be easily extracted if needed at regular intervals. If a failure of the DAQ transmission network occurs, the raw data could be used.

Pseudo code 2:a was selected for its simplicity, time, power efficiency, and as it provides sufficient feature extraction for the selection of operating modes. Moreover, the transmitted data is significantly reduced while the post-processing method can still extract important information to identify the condition of the equipment/machinery. Finally, FFT component analysis is available from a variety of other commercial systems. Thus, this pre-processing method could provide data compatible with many existing analytics tools. The signal recorded by pressure sensors in diesel engines (Bertola et al., 2006) follows a sinusoidal behaviour due to the palindromic nature of the change in pressure according to the revolution of the engine. Hence, it is similar in nature to the vibration signal. In this case, the feature extraction is dependent on the analysis of the frequency domain response, as well as the mean amplitude and variance of the time domain signal (Wang et al., 2014, Thurnheer and Soltic, 2012, Wu and Huang, 2011). The application of the information extraction phase combined with event extraction at the edge of the network in a single algorithm contributes to the implementation of the proposed system.

Pressure measurements can also apply to other machinery and equipment such as pipes. Those measurements would require a different pre-processing approach, following the same principles as temperature processing. These measurements tend to be different in that they are (1) not required to have such high sampling rates and (2) no frequency analysis is necessary according to the engine revolution cycle (eGreenShip, 2012a, Wang and Gao, 2006). However, the engine speed would normally influence the maximum applicable temperature threshold of normal operation.

Hence, the earlier pre-processing approach is no longer relevant and simple statistical feature extraction approaches suffice combined with event identification (Loiselle et al., 2015, Goodman, 2015, Zhao et al., 2014). Also, this approach has no negative impact on the utilised post-processing method and t is easy to provide estimations for missing data, either due to errors in the network or temporary faults affecting the data acquisition process (Simunek and Pelikan, 2008). The algorithm selected for the implementation of this pre-processing method is presented in Pseudo code 2:b. However, as the data is regenerated from statistical profiles and partial information, the system would not provide a reliable input source for algorithms that require high fidelity such as ANNs.

Pseudo code 2:b – Value type data pre-processing algorithm.

```
process: Normal_Sampling_State
  while recording_window ≠ 0  and  number_of_windows > 0 do
    Read data in normal_sampling rate            //User parameter
  end
  for each_record do
    calculate new_mean_value
    calculate new_deviation_value
  end
  if new_mean_value ≫ old_mean_value or   //first old extracted from thresholds
    new_mean_value ≪ old_mean_value or
    new_deviation_value ≫ old_deviation_value or
    new_deviation_value ≪ old_deviation_value then
      go to Failure_Onset_Sampling_State
  else
    for (number_of_windows) do
      Transmit ( time_of_first_record, length_of_window, new_mean_value,
                 new_deviation_value)
    end for
    Update (old_mean_value, old_deviation_value)
    go to Sleep
  end if
end process
process: Failure_Onset_Sampling_State
  Increase sampling_rate
  Reduce recording_window
  Increase number_of_windows
  go to Normal_Sampling_State
end process
process: Sleep
  Prepare device to enter low power/sleep mode
  Sleep for sleep_period of time                 //User parameter
end process
```

The system thus far presents an output that is encrypted, transmitted through a purpose built communication protocol, and as such is not yet open-ended. However, by post-processing the data to regenerate a sequence recovering the original raw data, the system becomes open-ended to any information extraction tool. Thus, an additional step needs to be integrated into the process to translate the pre-processed data generated by the embedded system.

The overview of the post-processing and analytics methodology for one possible analysis tool is presented in Figure 2:12, viewed as a black box for the purpose of the thesis. The data presented to the reliability analysis tool is expected to be raw not pre-processed; an implementation constrain addressed through post-processing algorithm.

Post-processing received data, recreates the raw information. The pre-processed information includes statistical profiles as well as events used to recreate a measurement for the monitored period and following the given profile. For value type data (temperature, pipe pressure), this is implemented through reverence engineering of the statistical properties of the received message (mean, deviation) and injecting the event information. For signal type data (vibration, engine related pressures), this is implemented through reverse FFT, statistical properties and injection of the event information. The post-processing step is presented in Figure 2:13.

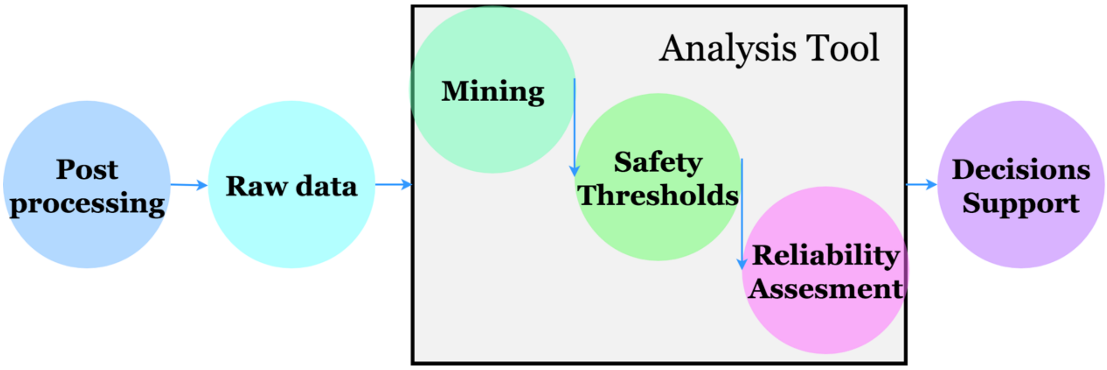


Figure 2:12 – Data flow through Post-processing and into analysis tool and DSS. The tool data flow internal sequence was adapted from Lazakis et al. (2017).

The added benefit of using post-processing is that it adds resilience to the system for missed data due to network faults/failures or other errors resulting from noisy transmissions (Yang et al., 2012). Finally, it enables the system to be open ended.

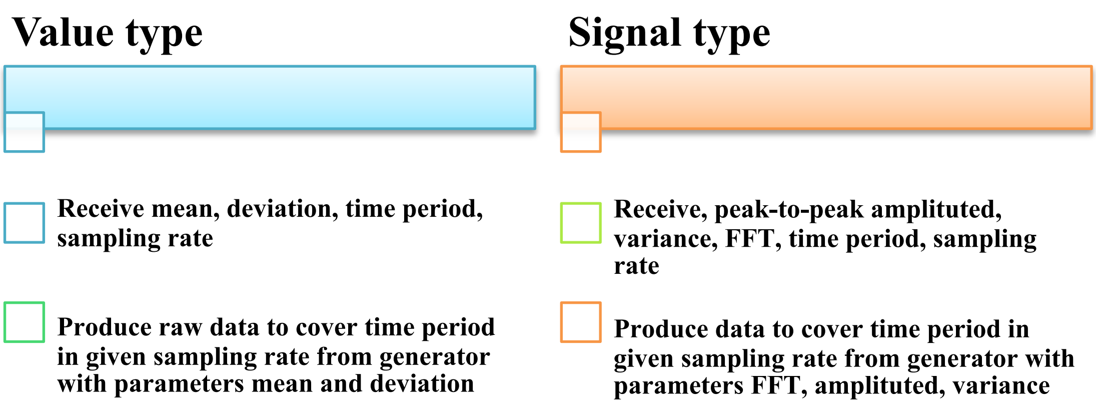


Figure 2:13 – Post processing received data method to provide open-ended output for compatibility.

The selected reliability analysis tool, used as an example, processes the data to extract their reliability performance, through a data mining approach which calculates failure rates (λ), Mean Time Between Failures (MTBF), and Probability of Failure (PoF). This reliability analysis tool provides suitable inputs for the decision support system (Section 2.6). The reliability analysis tool has no mining capability for signal type data. Therefore, alternative tools had to be used for this task, discussed in Section 3.3. The proposed DSS method is further discussed in the following section.

Finally, to complete the data management strategy discussed in the requirements, an algorithm was developed for transmission of the DSS output to shore. This is presented in Figure 2:14, and its implementation in Section 3.2.

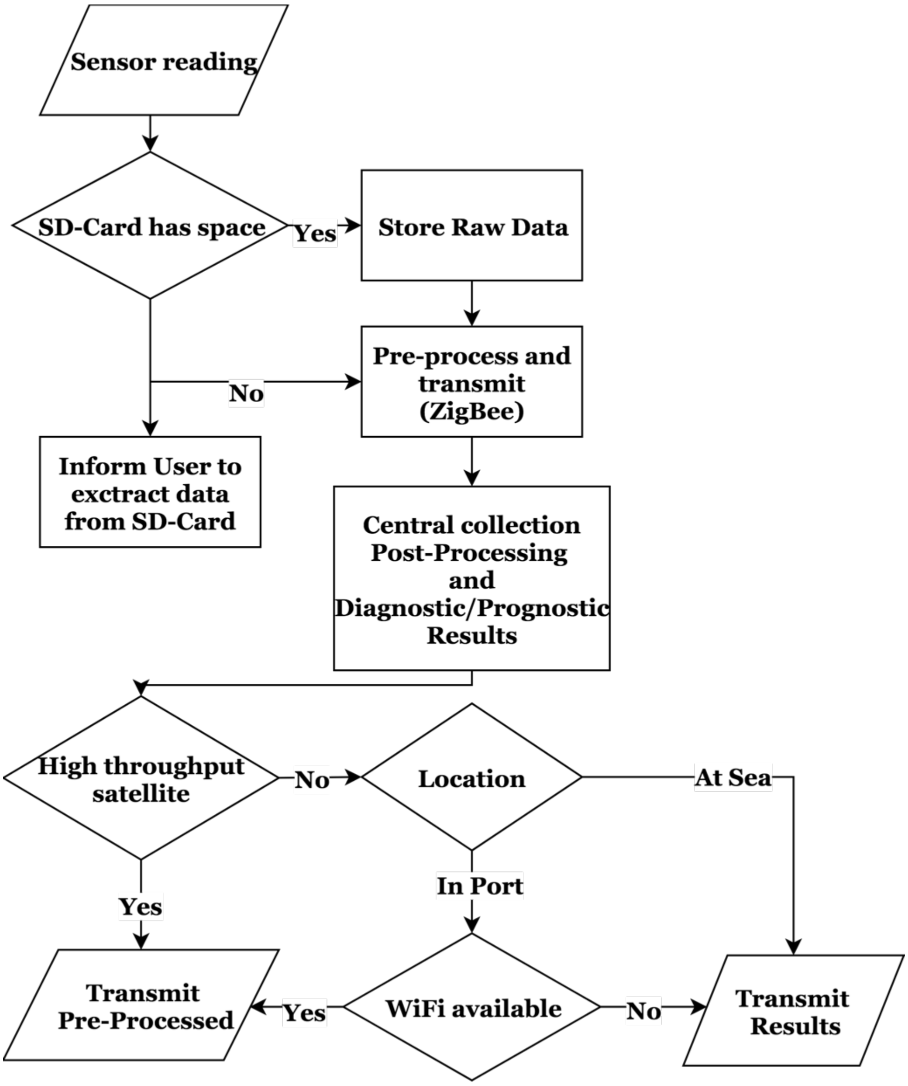


Figure 2:14 –Data transmission decision algorithm to minimise bandwidth use when at sea.

Real-time visibility is not possible as it depends on the location of the ship and satellite coverage. As a result, the proposed approach allows data to be transferred to shore based on conditions. The aim is to remove the obstacle of low connectivity when it exists and utilise high connectivity when available. Through selective transmission of data to shore, based on available connectivity, at any location the algorithm can provide the best service with the lowest cost. Overall, the system advances the state-of-the-art as it provides real-time CM onboard and visibility to shore (with delay) while removing the infrastructure strain created by transmission of raw data for centralised processing.

2.6 Decision Support System

As discussed in Chapter 1, the DSS problem onboard a vessel is often a multiple-parameter multiple-constrain optimisation. Such an approach is not documented in the literature. The state-of-the-art for onboard maintenance action decision support only considers singular optimisation parameters and a subset of constraints. Constraints such as availability of parts, crew expertise and weather conditions are only the most prominent. Others such as regulatory requirements and maintenance planning in preferred locations further constrain the DSS. Thus, a novel approach must be formulated for a multi-optimisation, multi-constraint problem. The proposed method achieves the optimisation of suggested actions based on constraints.

As an outcome of the proposed methodology data are available in many forms. Initially the raw data can be either collected from remote sensor locations or extracted from the post-processing phase. Additionally, the analysis tools used can translate these into reliability values expressed as percentages. However, most non-expert users would not be able to relate these values to actual issues, or sources of issues, in the physical systems. In that respect, these values should be presented in a manner that is assistive in decision making, clearly demonstrates the issues, and correlates to a clear operational and cost impact.

In the case of the analysis tools used, the output is the degradation associated to known failure modes for each system, sub-system, and component. The DSS tool can directly evaluate the likelihood of each failure mode and only suggest maintenance tasks/actions that are relevant to the most likely failure mode at each given moment. Thus, the suggested maintenance action is optimised towards the most likely failure cause for each part of the ship machinery and equipment.

The component, system, or subsystem likelihood of failure (L) is based on the reliability output (R) (Equation 2:1).

$$\mathrm{L} = 1 - \mathrm{R} \qquad (2:1) \quad (\mathrm{Lees}, 2012)$$

Each component/system/subsystem can have more than one failure mode (Kritzinger, 2017), so the calculated failure likelihood set $\{\mathrm{L}_1, \mathrm{L}_2, \ldots, \mathrm{L}_\mathrm{n}\}$, for a set of failure modes $\{M_1, M_2, \dots, M_n\}$, is calculated, where L_1 is the probability of M_1 and so on.

The overall probability of failure of the component is also returned by the reliability analysis tool and is a single value (L_c) (Dikis et al., 2016). Similarly, for every sub-system and system these are L_{ss} and L_S respectively.

To identify the probability of a specific failure mode being the cause of low reliability, the DSS calculates the weighted probability of all failure modes. The contribution of each component to the probability of failure is calculated using the standard method (Equation 2:2). Then, the probability of failure due to a specific failure mode for a specific component is calculated as presented in Equation 2:3. These equations were adapted for the DSS based on weighted probability theory principles (al-Nowaihi and Dhami, 2010).

$$W_{c_k} = \frac{L_{c_k}}{\sum_{i=1}^{m} L_{c_i}} \quad (2:2) \quad (\text{al} - \text{Nowaihi and Dhami, } 2010)$$

where W_{c_k} is the weighted contribution, $k = 1 \dots m$, and m is the number of components contributing to the sub-system under investigation.

$$N_j = \frac{L_j \times W_{c_x}}{\sum_{i=1}^{n_1} L_i \times W_{c_1} + \sum_{i=1}^{n_2} L_i \times W_{c_2} + \dots + \sum_{i=1}^{n_m} L_i \times W_{c_m}} \qquad (2:3)$$

where N_j is the contribution of the failure mode, $j = 1 \dots l$, l is the total number of failure modes of all the components contributing to the sub-system under investigation, m is the number of components contributing to the sub-system under investigation, W_{c_x} is the weighted contribution of the component under which failure mode j is listed, and $n_1, \dots, n_m$ are the numbers of failure modes listed under each component $c_{k=1\dots m}$.

If the contribution N_j exceeds a predefined threshold, the responsible component and failure mode are presented as an alert (warning). A second higher threshold exists for failure identification. Thresholds are based on manufacturer data, expert judgement data and historical data. However, there may be a variety of actions relevant to each failure mode. Some actions could not be possible on the ship due to lack of parts or expertise.

The DSS tool is developed to incorporate multiple-constrain analysis, to optimise the proposed decision onboard the ship through Constrain Programming. This approach has been successfully applied in other applications to maximise system reliability, or availability, or to minimise cost, but not with multiple objectives or conflicting objectives (Feng et al., 2017, Meneghetti and De Zan, 2016, Li et al., 2016b, Khalili-Damghani et al., 2014). The same DSS can be used both for onboard and onshore CM. The following paragraphs will formalise the problem for the onboard application. However, different constraints can be parametrised into the system for onshore assessment, given that onshore personnel usually handle long term maintenance planning as opposed to an immediate response to maintenance actions more relevant to onboard crew. To the best of the author's knowledge this approach has not been previously published or documented in the literature.

To formulate the problem, the failure mode set $M_h = \{m_1, m_2, \dots, m_n\}$ and the action set $A_h = \{a_1, a_2, \dots, a_g\}$ associated with a failure mode of component/subsystem/system $K_h \in K$ was defined, where K is the set of monitored components, subsystems and systems on the ship. The function $L(a, m)$ is true if an action a is associated with a mode m. Also, the set of available parts $P_h = \{p_1, p_2, \dots, p_j\}$ associated with K_h was defined and the function $U(a, p)$ is true if and only if a part p can be used within action a in order to perform the action successfully.

The problem is to find a feasible solution to the partial function F (Equation 2:4).

$$F: A_h \rightarrow \{E, C\} \rightarrow L \wedge U = 1 \qquad (2:4)$$

where $E = \{a_1, a_2, \dots, a_l\}$ is the set of actions for which there are expertise available on the ship, and $W = \{a_1, a_2, \dots, a_z\}$ the set of actions that can be executed under the specific weather conditions.

F is an assignment of actions for each component/subsystem/system, that demonstrates degradation close to the defined threshold values, while obeying the constraints. As F is a partial function, the actions that belong to the domain $dom(F)$ are the selected actions. The first constrain of the system is that it needs to select one and only one action from each set A_h to identify as the most appropriate action (Equation 2:5).

$$\forall a_i^h, a_j^h \in A_h, \quad \left(a_i^h \in dom(F) \wedge a_j^h \in dom(F)\right) \Rightarrow i = j \qquad (2:5)$$

The ability to execute an action a_h was defined through Equation 2:6.

$$\forall a_i^h \in A_h: \left(L\left(a_i^h, m_i^h\right) \wedge U\left(a_i^h, p_i^h\right) \wedge \left(\exists\, a_i^h \in E \cap W\right)\right) \Rightarrow a_i^h \in dom(F) \qquad (2:6)$$

The optimisation algorithm achieves the minimisation of the total cost (C_T) of the operation of the ship as a primary target (Equation 2:7). Moreover, a secondary target is the minimisation of each individual cost in six major areas. The estimated cost for each of the areas is based on fees, that apply to the shipping industry, or known average costs for parts or maintenance. The areas are 'Environment' (C_E), 'Safety' (C_S), 'Asset' (C_A), 'Maintenance and Operation' (C_M), 'Performance' (C_P) and 'Commercial Penalties' (C_C).

$$\min(C_T) \qquad (2:7)$$

where $C_T = C_E + C_S + C_A + C_M + C_P + C_C$,*.but the individual costs may have competing conditions. For example, reducing* C_A *may lead to an increase of* C_E.

The third goal of the tool is to optimise action planning. However, this is based on failure mode likelihood resulting from the reliability analysis and through linking action selection to the most likely failure cause (Equation 2:6).

Moreover, the DSS tool is extended to incorporate a reinforcement machine learning technique (Varone, 2017, Morgan, 2014). Hence, the DSS tool is updated to be able to record which suggested action was taken by the engineers on board (Figure 2:15).

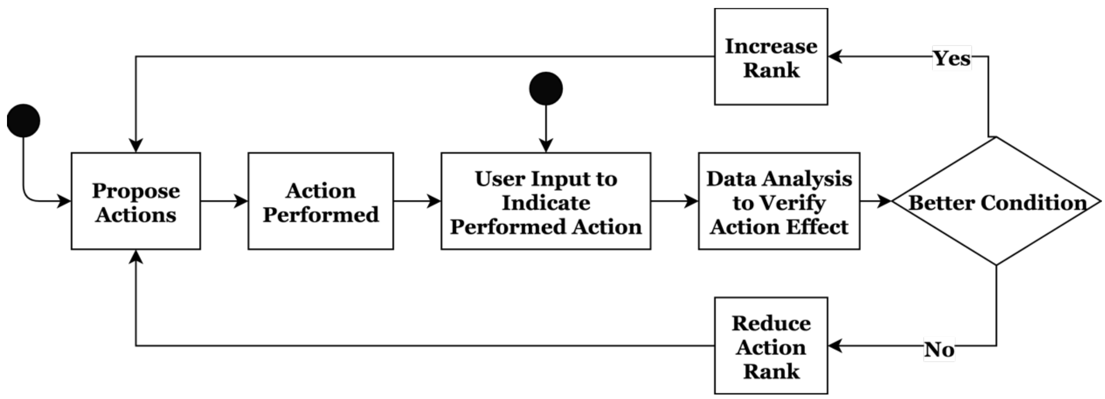


Figure 2:15 – Algorithm used to incorporate basic Machine Learning in DSS.

If that suggested action demonstrates an improvement of the predicted reliability, then the action is identified as successful. On the other hand, if the action taken resulted in no improvement, then the action is identified as unsuccessful. Successful actions for a specific component are promoted higher up the suggestion list. Unsuccessful actions are ranked lower in the suggestion list. This list is dynamically updated based on historical information available regarding actions suggested and actions take for each system, sub-system, or component of the system (Figure 2:15). The implementation of the DSS is presented in Section 3.2.

Finally, to present the extracted information to onboard engineers the GUI was developed. The design of the DSS GUI[7] considered input from seafarers and shipping industry stakeholders. An Agile development approach allowed for progressive incorporation of the suggested changes, to conclude with a GUI that is most appropriate. Moreover, the GUI development stripped out all the data mining information from the immediate view but making it available in easily accessible ways. The original DSS GUI was presented in Michala et al., (2015) and was expanded for this thesis based on collected feedback from the relevant conferences and workshops (Lazakis et al., 2017, 2016a, 2016b, Dikis et al., 2016, Michala et al., 2016b, 2015). The updated GUI implementation is presented in Section 3.2.

2.7 System Integration[8]

The earlier sections have discussed the methodology for developing components and algorithms. This section presents the system integration strategy to achieve the aims and objectives of the research. Figure 2:16 presents the system in overview. The implementation of the integrated system is presented in Section 3.1.

The data transmission component is integrated with DAQ and can support up to 8 sensors for each Unit. Cables connect the sensors to the DAQ which then edge-processes the data, manages the unit local storage and transmission, and supports incoming control and monitoring messages. The proposed system can accommodate all the needs of an industrial application as identified in Chapter 1 and requirements identified in this chapter and provides a novel solution to problems faced today.

The Receiver Unit comprises of a single receiver connected to the local PC along with the post-processing component that analyses and conditions the incoming data. Other software needs to be installed on the Local PC to provide the reliability analysis

---

[7] Published in Michala et al., (2015), Michala et al., (2016b), Dikis et al., (2016), and Lazakis et al., (2017, 2016a, 2016b).

[8] Published in MICHALA, A. L. & VOURGANAS, I. 2017. 'A Smart Modular Wireless System for Condition Monitoring Data Acquisition', *Proceedings of the 16th International Conference on Computer and IT Applications in the Maritime Industries, Cardiff, 15-17 May 2017*, Technische Universität Hamburg, Harburg, ISBN 978-3-89220-701-6, 212-225.

and decision support necessary, as the outcome of this system. The DSS and transmission to shore algorithm is also deployed on the local PC. Supplementary software manages the installed system but is further discussed as part of the validation and verification method (Chapter 3).

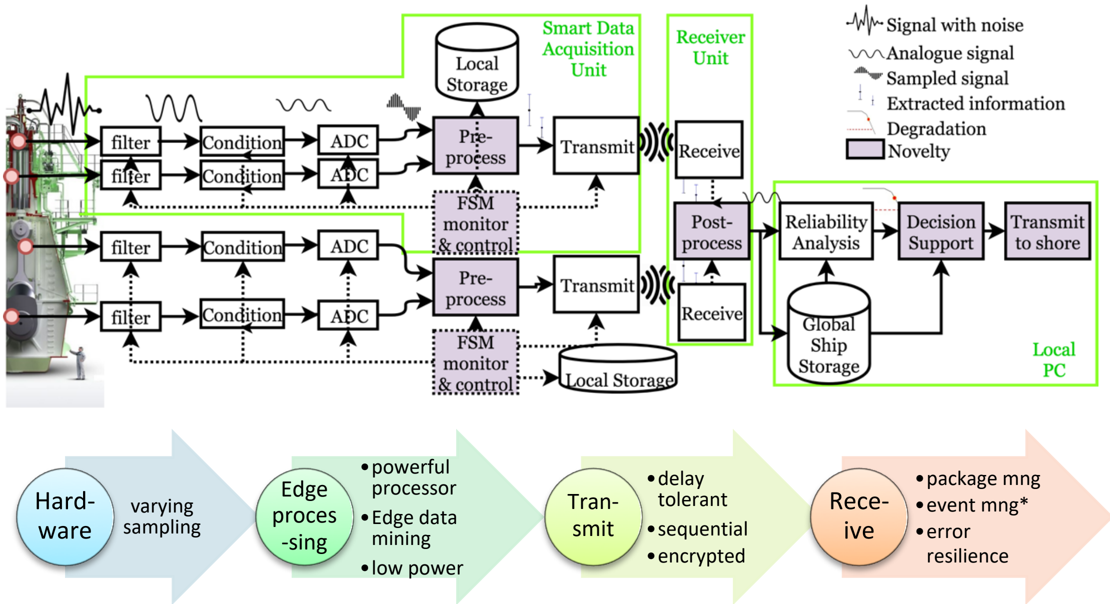


Figure 2:16 – Integrated system overview illustrating the DAQ and the collection point along with the data flow block diagram (*mng stands for management).

As demonstrated in the first section of this chapter several diverse requirements were identified as relevant to the aims and objectives of this thesis. A novel system applicable to shipping CM was identified and developed to address those requirements and the resulting specifications. The system development process was presented, and the decisions taken in this process elaborated through in Sections 2.2 and 2.3.

The requirements for pre-processing and appropriate algorithms were presented. The resulting system supports low traffic and information loss, custom event/error identification and remote management commands advancing applied research in ship CM. Condition identification was based on an existing tools, but post-processing algorithms were defined to make the data compatible with any tool. The system addresses the needs of ship CM with the goal of providing better condition, reduced maintenance costs, increased savings, and an evidence-based approach to efficiency through the association of maintenance actions with operational costs.

The proposed approach was based on wireless, modular, embedded, and encrypted principles (Figure 2:17). This approach provides benefits that meet industry needs such as increased trust, availability of the system to be installed on any ship for any measurement, and scalability of the system. Through the proposed DSS optimisation method and the machine learning algorithm, the system provides the most relevant maintenance actions for the particular ship. The system is flexible so that only a few critical parts could be monitored, while the operator gains trust and identifies the benefits of using the system. Further upgrades could up-scale to a full CM platform that supports any maintenance strategy. A significant addition to the proposed system is the algorithm for selective data transmission to facilitate onshore visibility, but with reduced satellite communication costs.

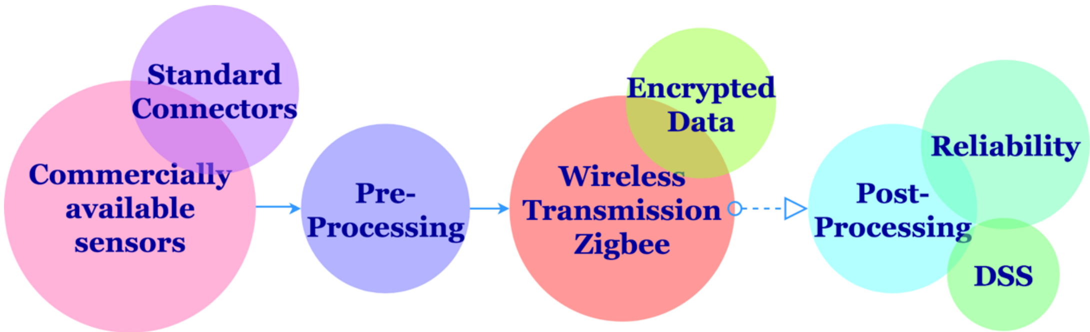


Figure 2:17 –System Overview.

In conclusion, the proposed approach utilises CM to its full potential and provides a direct cost-benefit to the user, as the costs relevant to a maintenance action suggested but not executed are directly visible. The following chapter will present the implementation of the system and the evaluation through the application to particular case studies and cost/benefit analysis.

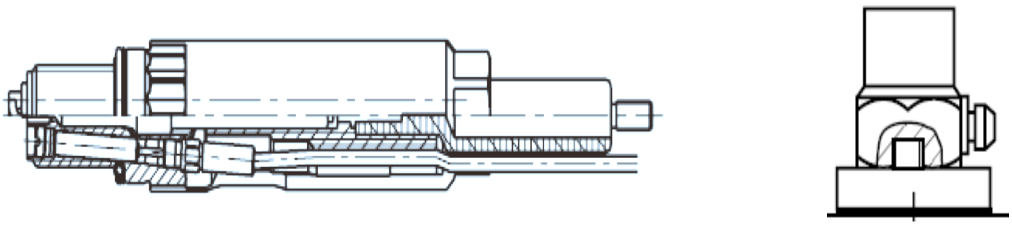
Chapter 3: Evaluation

This chapter presents the evaluation of the proposed system. Sections 3.1 and 3.2 describe the hardware and software implementation respectively. Section 3.3 aims to showcase the application of the proposed system in case studies and the evaluation of relevant results. The section initially presents the description of the experimental setup, followed by the verification and validation strategies used in the case studies. Section 3.4 presents the evaluation of the system in business impact addressing the second aim of the thesis. The benefits of the system along with the impact in cost reduction are discussed and a cost/benefit analysis is presented. The results and findings will then be discussed in the following chapter (Sections 4.1 and 4.2).

3.1 Hardware Development

The constraints and implications that the proposed approach for the ship CM has, on both hardware and software design were examined in Chapter 2. Also, in the previous chapter, the adopted approach for the development of the identified system was presented. This section presents the implementation of the hardware and discusses the installation and commissioning stages of the system. Appendix C presents a brief manual for the user interface. It must be highlighted that the benchtop model is not the miniaturised final version of the hardware as it was chosen for software/hardware verification. The description starts from the presentation of selected sensors, followed by the implemented interface to BBB.

The pressure sensor for combustion engine pressure measurements was selected from the KISTLER (2016) range of products for its measurement and the temperature range. Also, the dimensions were important so that it can be installed in the available engine. Moreover, the sensor follows the desired certification (Appendix A) and specification identified in the previous chapter. The vibration sensor selected was supplied by Brüel & Kjær (2016), and again the same considerations were taken into account. However, this sensor was only used in the initial development of the device as a source of input and was not utilised in the case studies due to technical issues. Instead the NASA IMS vibration data set was used (Section 3.3.5). Finally, the temperature sensor was the pre-installed sensor from the CM12 Automotive Diesel Engine measuring the cooling water temperature outlet of the heat exchanger. Figure 3:1 presents the selected sensors. The datasheets of the selected sensors and the engine pre-installed sensor are available in Appendix D.



(a) (b)

Figure 3:1 – Selected sensors for installation on the engine (a) pressure sensor (b) vibration sensor.

The length of cable from the sensor to the pre-processing unit was determined based on access and was the minimum possible, to avoid noise generation or pickup. All sensors were provided with a maximum cable length by the manufacturer and this length was not exceeded under any conditions. The installation of the sensors was based on manufacturer guidelines and performed by the laboratory staff. Even though every care was taken to minimise the cable lengths for the case studies discussed in this chapter, it is acknowledged that potential issues with the installation of sensors may be encountered at installations in ships. The proposed system targets ships that have sensors already installed within equipment, perhaps from manufacturers or other survey activities. In that scope, the sensors will have a high likelihood of being installed with the required cabling in place and not being used continuously for CM. As such, the installation of sensors and cables does not fall within the scope of the case studies.

In order to ensure very low Electromagnetic Interference (EMI) the majority of manufacturers choose to use BNC connectors and coaxial cables to connect sensors to the data acquisition equipment (EE, 1998) and particularly for vibration monitoring where the initial signal is prone to noise (Brüel & Kjær, 2016, NI, 2016b, Tyco Electronics, 2016, TI, 2015, Measurement Computing, 2012). For pressure and temperature applications, other interfaces are also used and several connector types are available (Judd, 2016). However, for transducers operating in conditions of very high temperatures or pressures, BNC connectors are the most well established (NI, 2016a, AVL, 2013, KISTLER, 2016, Bertola et al., 2006), being an ideal interface for a modular system. An example of how BNC connectors can be incorporated into an embedded system, particularly for vibration monitoring, is displayed in Figure 3:2. Analogue electronics were necessary to ensure that the input signal is in the desired voltage range and will not harm the integral digital electronics.

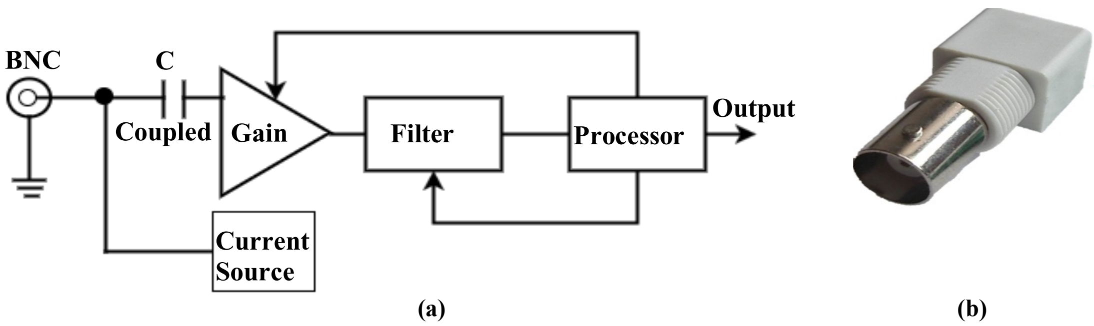


Figure 3:2 – (a) BNC connector to embedded system wiring diagram redesigned based on Measurement Computing (2012) and (b) typical BNC connector for PCB layout with bayonet lock to secure the cable (photograph of purchased part used for system implementation).

According to the requirements of industrial applications, sensors are most often equipped with either charge or voltage amplifiers. The selected sensors for the implementation of the proposed methodology fall within this category. An example of the configuration of such a sensor is presented in Figure 3:3. The figure was adapted from Levinzon (2015) based on the equivalent circuit of an accelerometer transducer, used for single axis vibration measurement. The principle is applicable to all similar transducers (Weber 2002, MIP, 2000). Also, the Signal Condition Unit (SCU) was adapted to the needs of the proposed development.

The SCU, through analogue electronics, provides the required power supply to the sensor and transforms the data signal to a useful voltage range. A Continuous Current Source (CCS) was also necessary because a single coaxial cable was used, for both the supply to the sensor and the data read through DC voltage changes. The output of the signal conditioning unit was then passed to the voltage divider circuit, then onto the ADC, the BBB and the PRU, so that the signal was converted to digital data.

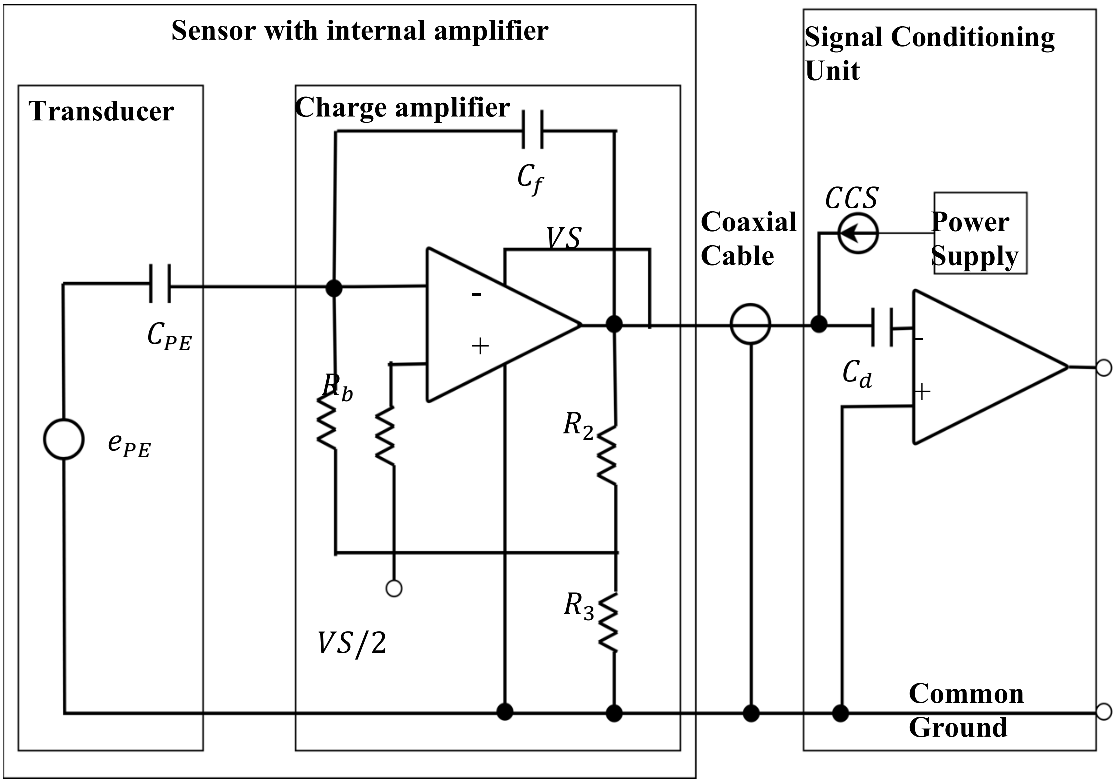


Figure 3:3 – Electronic configuration of the sensor with an internal amplifier connected to signal conditioning circuit.

The shield of the coaxial cable was connected to ground, providing a common ground between the transducer, charge amplifier and SCU. This was particularly important for the cancellation of noise and the avoidance of grounding issues often encountered in hardware development.

The voltage divider circuit was necessary to transform the output of the transducer into a voltage range, that is acceptable for the digital electronic circuits of the system, such as the operational amplifiers used for the protection of BBB and the BBB itself. All the sensors used in these case studies ranged for voltages over 10V (e.g. 0 to 12V output). However, the BBB analogue input General Purpose Input/Output (GPIO) pins operating ranges are 0V to 1.8V; thus the requirement for voltage division. The circuit used is presented in Figure 3:4 and was designed based on general analogue electronics' design guidelines (MIP, 2000, Serridge and Licht, 1987). Moreover, an ADC was selected that supports up to 100 Ksps sampling rates which is higher than the built-in ADC of the BBB.

The values of the decoupling capacitor C_d and the resistors were calculated using the standard equations (Molloy, 2015b). The values of the resistors R_1 and R_2 determine the gain of the signal. The values of R_3 and R_4 determine the offset of the signal. Additional connections (eliminating floating pins) to eradicate switching noise were considered; omitted from Figure 3:4 for simplicity.

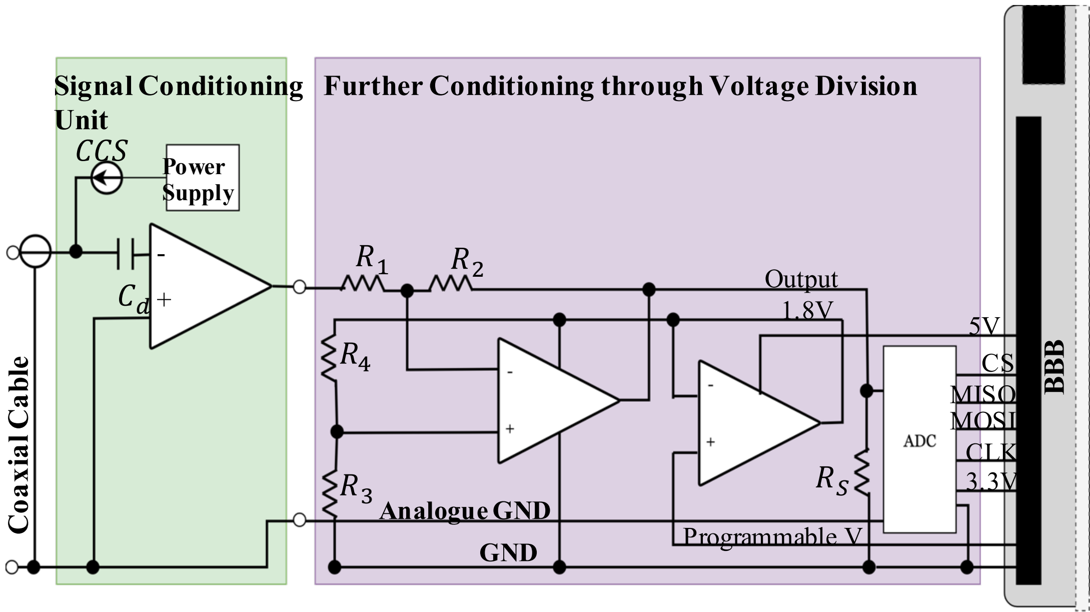


Figure 3:4 – Analogue and digital electronics for the connection of the sensors to BBB.

The three main hardware blocks required for the implementation of the device are presented in Figure 3:5. The sensor connection and related signal conditioning circuit, the BBB with connections to the battery power supply, and the wireless chip development board. In the miniaturised model, the wireless chip development board can be removed to reduce space and the USB serial connection replaced by UART serial connection through GPIOs. This is not presented as it is standard practice.

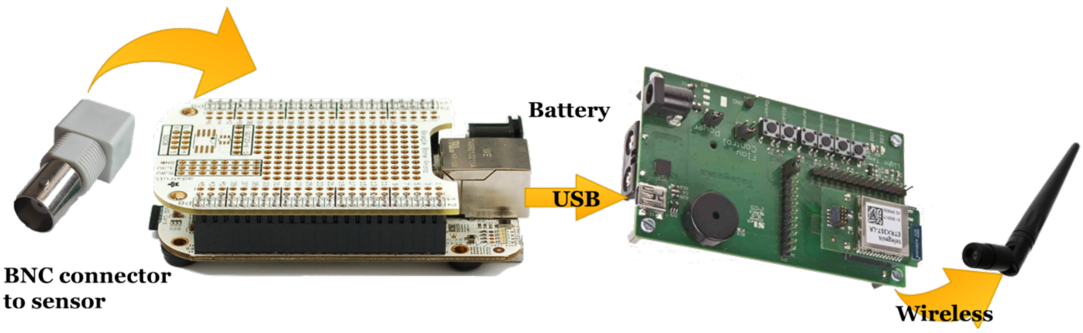


Figure 3:5 – Main hardware blocks and connections used for the benchtop model device.

The photographs in Figure 3:6 are from the initial breakout model, using a breadboard the BBB and the ZigBee Pro development board. The benchtop and the laboratory deployments are presented the following sections while Figure 3:7 presents the proposed installation layout onboard ships.

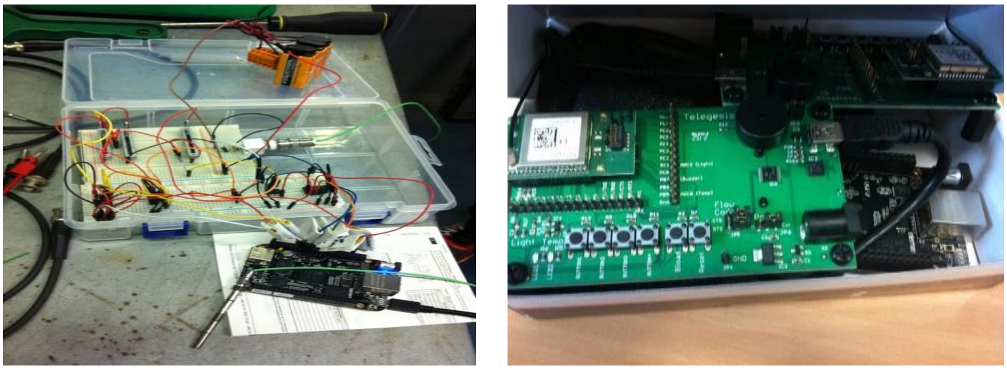


Figure 3:6 – Initial break-out model with battery support for the connected pressure sensor and micro-USB connection to power-bank for BBB (left) and USB connection to Wireless breakout board in card-board housing (right).

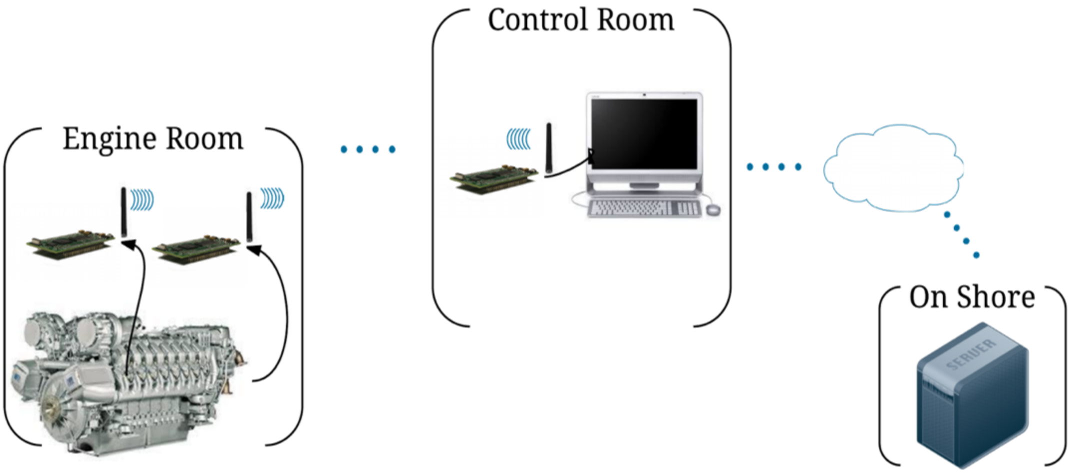


Figure 3:7 – Layout of the system and wireless data transmission node proposed ship installation.

3.2 Software Development

The inputs and outputs of BBB were programmatically controlled at the installation of the developed software, and the configuration was set to default parameters. The default configuration can be changed at run-time through altering the configuration file. The configuration file consists of a field for each of the parameters described in the Chapter 2. An example of a field in the configuration file is presented in Pseudo code 3:a.

Pseudo code 3:a – Example of entries in the configuration file.

```
1:TIME_ZONE=Europe/London
2:#This is an example comment
3:#MEASUREMENT_TYPE=signal
4: MEASUREMENT_TYPE=value
…
```

All the services executed in BBB used the default system docking service to create, set, and maintain services in the kernel domain. So, the system can easily be expanded. Files stored in the user space facilitated inter-service communication and local data storage. Depending on the configuration file, different services were invoked for the different pre-processing algorithms. A general service was deployed to maintain the system in accordance with the configuration file and to manage which services are active or inactive. The wireless transmission was operated through a separate service that sources information from the output file of the pre-processing service. All the components were independently tested and verified.

Issues with any one of the services could be easily corrected through the maintenance and management service, without affecting the overall system performance. The management service was also responsible for implementing the state machine of the system, described in Chapter 2. Figure 3:8 presents the system architecture utilising the capabilities of the BBB Linux OS.

The process-value and process-signal services accessed information from PRU, while the wireless service reported information to the wireless chip through USB serial interface utilising the special input/output ports available on BBB. The library developed for the wireless chip enabled both receiving and transmitting messages, parsing, and queuing, as well as delay tolerant transmission (Section 2.4).

The central collection point had additional services for post-processing information received and storing information. The wireless service was responsible for managing the load of information in a manner compatible with the network capacity available, so no data loss is allowed.

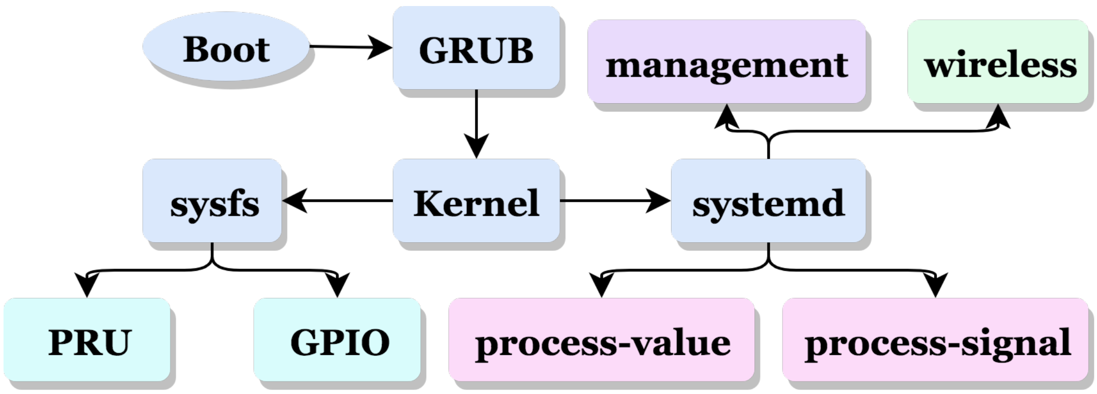


Figure 3:8 – Linux system architecture using sysfs, systemd and system kernel utilities.

The algorithm of the management routine is presented in Pseudo code 3:c, a requirement of the functionality of the state machine presented in Section 2.4. The output of the recording state was stored in the local data base. The wireless routine operated independently requesting data from the local database that correspond to a recording window. This was then transmitted, and the wireless routine returned to ‘sleep’ for a period equal to the length of the window. This algorithm is presented in Pseudo code 3:b.

Pseudo code 3:b – Wireless transmission routine.

```
process: main
    while TRUE do
        Update current time
        Fetch latest data from database
        Call the transmission library, package and transmit data
        Sleep (window)                                    //User parameter
    end
end process
```

The algorithms for process-value and process-signal have been presented in Pseudo code 2:a and Pseudo code 2:b of Chapter 2 respectively. For the FFT the FFTW open C library implementation was used (Frigo and Johnson, 2005).

The wireless library was deployed with several functions available to the user. A UML diagram representation of the developed library in C is presented in Figure 3:9. There are four main categories of functions; setup, error handling, message handling, and network management.

Pseudo code 3:c – State Machine.

```
process: main
    while TRUE do
        Execute ( state )   //Global variable holding pointer to next state process
    end
end process
process: Execute
    go to state
end process
process: Sleep_state
    Prepare device to enter low power/sleep mode
    if  error then
        Set state as Error_state
    else
        Sleep for sleep_period of time                    //User parameter
        Set state as Record_state
    end
end process
process: Record_state
    switch input_type                                      //User parameter
        case signal:
            if Normal_Sampling_State_signal then // internally set next state
                Set state as Error_State               //executes if an error is detected
            end
        case value:
        default:
            if Normal_Sampling_State_value then //may internally set next state
                Set state as Error_State               //executes if an error is detected
            end
     end
end process
process: Failure_Onset_Sampling_State
    as in Record_state call appropriate Failure_Onset_Sampling_State_xxxx
end process
process:Error_state
    Check global ERROR value
    Call handler for particular ERROR
    if global ERROR value is cleared then
        Set state as previous state               //Global variable maintained by all
    else
        Set state as Attempt_Join_state
    end
end process
```

The library requires the setup functions to be called before any other class of functions can be used. Then once a message is passed to the library for sending, the `pro-`

`cess_timer()` function must be called recursively, to allow for the library to internally manage the segmentation of the message into packages, appending headers, and sending to the central collection point.

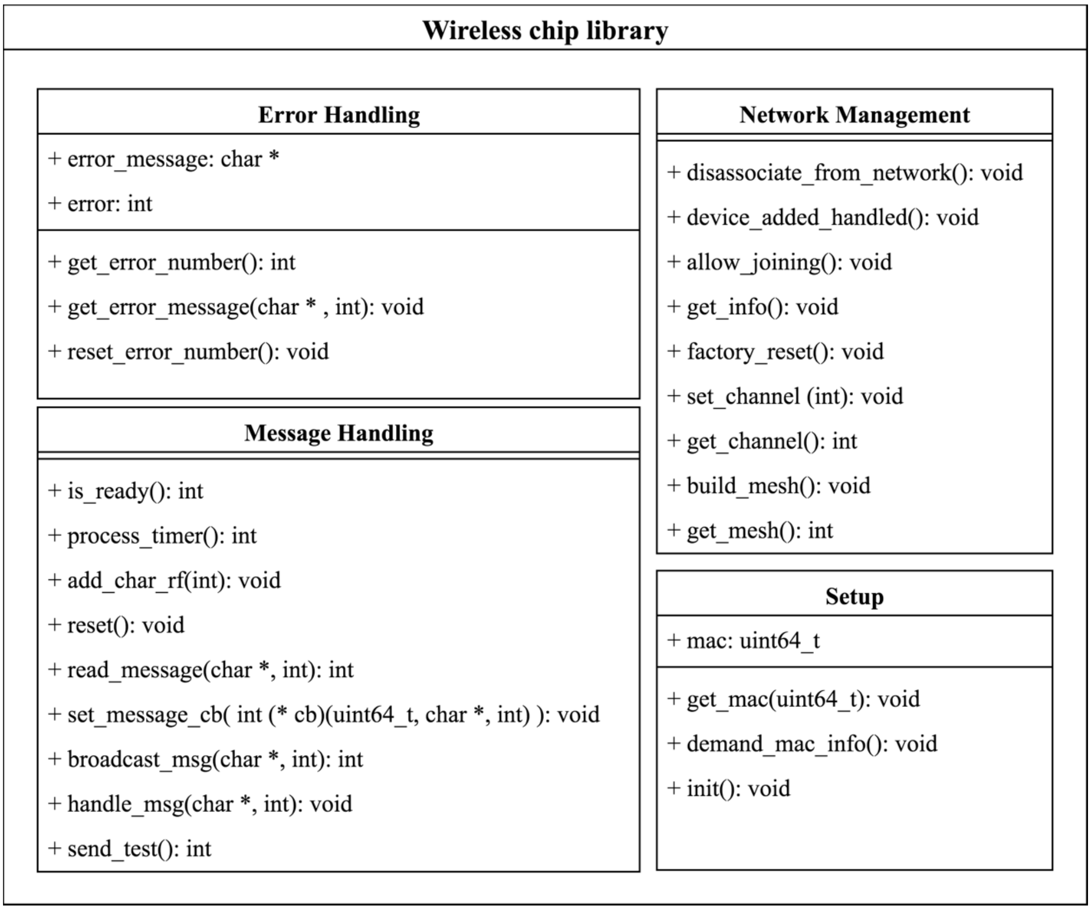


Figure 3:9 – UML diagram of the wireless chip driving library with the added functionality for network and error management both from the local and the remote processors.

GPIO access was directly available through simple file read/write operations from any algorithm; hence they are not discussed separately. PRU programming was necessary to enable real-time response and event extraction from the analogue input signals. This was developed in processor specific assembly and was based on guidelines published by (Molloy, 2015a). In effect, the code developed reads a pin and sends the read value to a register. Then, to pass that reading to the main processor, it stores that value in the shared memory location which is predefined by the hardware architecture. The second PRU is also used to generate an accurate clock for sampling the input signal (Figure 3:10).

The Device Tree Overlay (DTO) is the BBB implementation to enable GPIOs and other pins in certain I/O modes. This is particularly necessary in BBB because pins are often assigned to different functionality in a multiplexed way, and clarification is needed from the main core to differentiate between setup options for each application. For the ADC the SPI communication protocol is needed. To enable the SPI an overlay is uploaded. It informs the BBB that specific pins are going to be used as a communication channel, and the default functionality of those pins (HDMI header) is disabled.

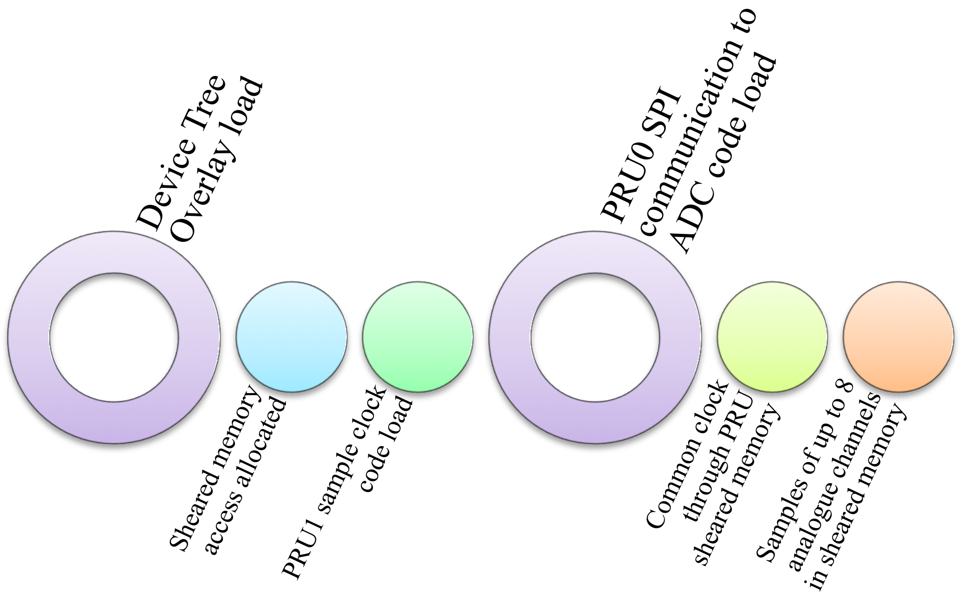


Figure 3:10– Process to setup PRUs for ADC sampling of any desired sampling rate up to 100Ksps based on BBB specification and guidance from (Molloy, 2015a).

Additionally, the pre-processing the code reads from a shared memory location where data are stored by the PRU within a time window. Moreover, the Sleep state was also responsible for disabling the PRUs for preservation of energy when the device was not recording.

For the central collection point the software implementation (Figure 3:11) involved several processing steps. The collector software was implemented as a `systemd` service. This service was permanently operating, as there are no energy conservation requirements for the collector point, which is attached to a local PC and powered through it. This service was also using the Wireless Communication Library (Figure 3:9). The additional functionality of this service was re-generating the post-processed data stream from the received information, and storing the outcome in the local PC database for the information to be utilised by the rest of the tools. The information was outputted to a Microsoft Excel document in a CSV format (Coma Separated Values), an option to provide output in other formats exists when database installation is possible.

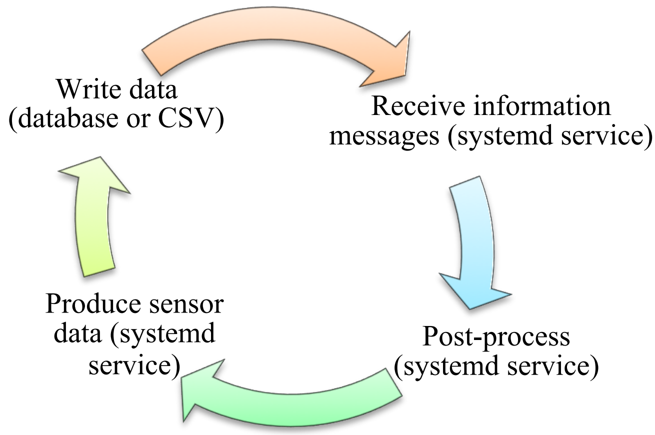


Figure 3:11 – Flow of central collection point DAQ software implementation.

To regenerate the data an implementation of pseudo-random values generated based on a Gaussian distribution function was used in C Programming Language. The C version of the Ziggurat Random Number Generator method was used from open source code as presented by Marsaglia and Tsang (2013). The library was utilised for Normal distribution random number generation and the equation $X = (Z * \sigma) + \mu$ was used to retrieve values within the characteristics reported by the received information for each value type input. Moreover, when events were received, the event value, if necessary, was used to overwrite particular values or to make sure that wrong data were not inserted in the local database. In the case of signal type the inverse FFT algorithm from the FFTW open C library implementation was used (Frigo and Johnson, 2005).

A black box reliability analysis tool was used for value type data. For signal type data Python Sci-Py and NumPi libraries were used to identify the condition of the machinery for these cases through a simplistic algorithm (Quezada, 2017). The former was implemented in JAVA while the latter in Python. The output was then passed to the DSS software.

The transmission to shore algorithm was developed as a simple `bash script`. The script executes a standard Linux `df` command to identify the remaining capacity of the SD-card and returns this value to the calling C program. Then the program can decide if there is sufficient space (first decision, algorithm in Figure 2:14).

To determine the condition of the network, the configuration file (Pseudo code 3:a) is checked to determine if a high throughput satellite connection is available. Returning the result as a `Boolean` value, the C program (`systemd` service) manages the wireless transmission accordingly. The configuration file is changed by user input at the onset.

High throughput satellite connection does not change dynamically as it requires specific contractual agreements and specialised hardware to be installed on the ship.

Finally, to determine if the ship is in port or at sea the DSS software checks the operating condition of the engine. If all engines are switched off, then it is assumed that the ship is in port and the user is prompted to ask if data transmission should commence. This algorithm was developed in three separate components and utilised in different stages of the system accordingly.

The implementation of the DSS in JAVA using NetBeans as an IDE was revised after having been tested on both Windows OS and Mac OS to be portable. Moreover, the system was designed to be able to support multiple ships so that it is scalable and usable in broader applications.

The architecture of the classes used, and their interconnections are presented in the UML diagram in Figure 3:12. A detailed presentation of all classes and their internal fields and methods is presented in Appendix E. There were two central classes in this implementation; the `UserInterface` class and the `ShipStructure` class. The first was responsible for presenting the data to the user and for input/output operations whilst the latter was responsible for data handling, storage, processing, and management.

The `UserInterface` class used classes `ProgressListener`, `ProgressRender`, `GradientPallet`, `Graph` and `StatusTree` to present the various information required. Moreover, it used the classes `DBComms` and `ParseExcel` for database communications and input from excel files respectively. The `ShipStructure` class relied on the `TreeObject` class to hold information for each system, subsystem, and component of the ship.

As the ship systems and subsystems needed to record additional information and hold lists of `TreeObjects`, they were implemented as separate classes, viz `ShipSystem` and `SubSystem`. Finally, a `HumanAction` class was used for the set of actions that the DSS can propose for each `TreeObject` and a `FailureMode` class to represent each of the possible failures and their associated costs. This is a significant expansion to the development reported in Michala et al. (2015) which presents a first approach to the development of the GUI, is limited to the `UserInterface` related classes and did not support Excel file inputs.

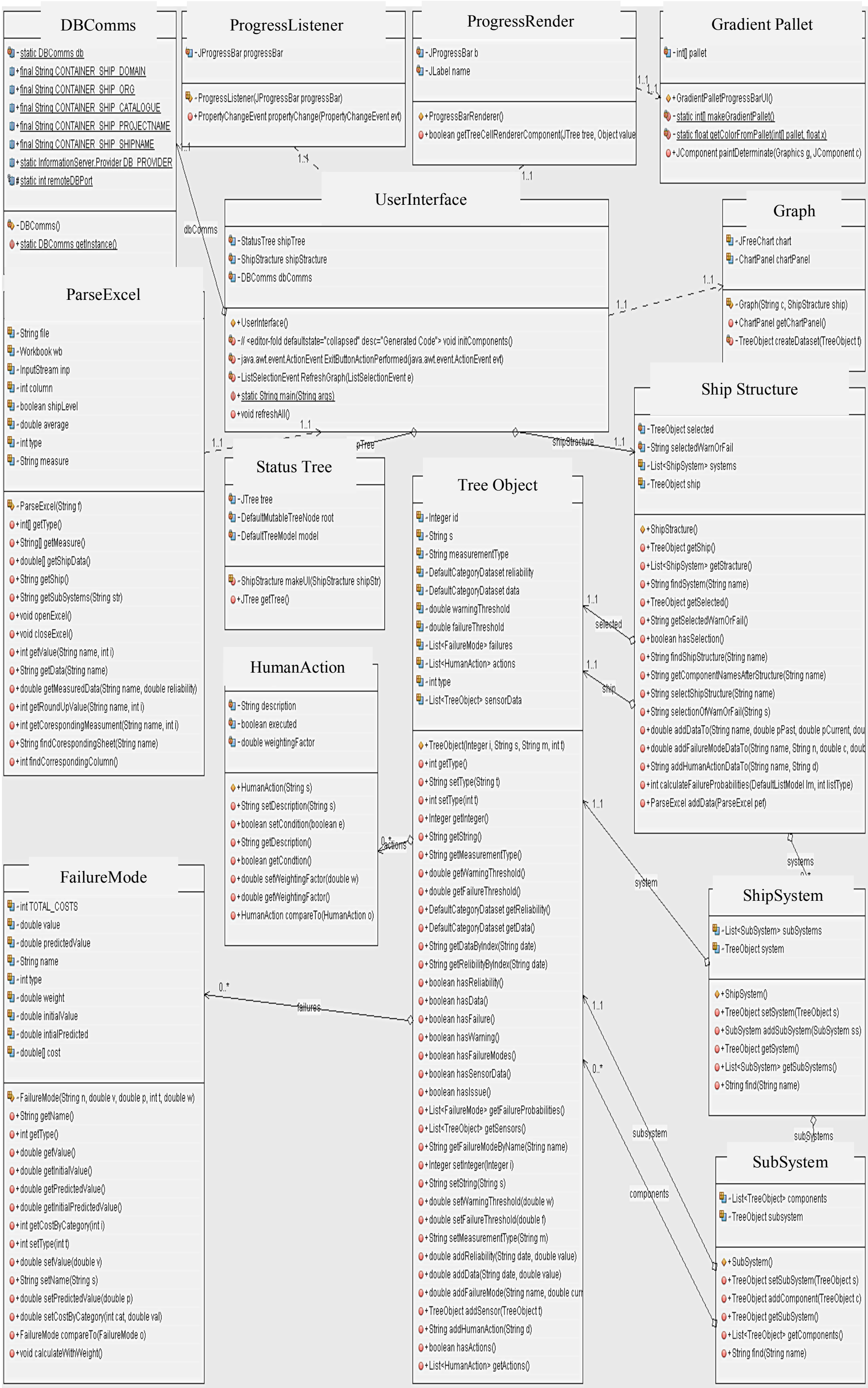


Figure 3:12 – DSS Java program represented as a standard UML diagram.

In addition to those developments, the GUI was updated compared to the initial implementation[9]. In *Analysis Tab,* the presentation of numbers was updated to be in tables allowing for a maximum of two digital points representation (Figure 3:13). Moreover, the implementation of the calculation of these values was introduced (Chapter 2), through the `FailureMode` class in the method `calculateWithWeight()`. Furthermore, as actions were now suggested based on the optimisation requirements, the costs predicted in the *Cost Analysis* tab were also related to the most appropriate action being recommended i.e. if the action is <u>not</u> taken, the resulting cost is estimated in the *Cost Analysis* tab.

Figure 3:13 presents a set of fictional data, adjusted so that the tool predicts significant degradation on Crosshead Bearing 1 to the extent that a warning is raised. Also, Camshaft Bearing 1 is predicted to demonstrate a failure within 5 days but the two possible failure modes associated with this are almost equally contributing to the upcoming failure. It is however understandable that overloading would create overheating. So, this is not an unexpected condition.

The *Actions Tab* of the case presented in Figure 3:13 was also update (Figure 3:14). Here, the user has clicked the first checkbox to indicate that "Check for Excess Wear" was performed. The DSS recalculates the condition of the system based on the incoming readings from sensor and re-estimates the warning condition of the camshaft bearing. If the data demonstrates a change for the better, then the warning will be removed. Otherwise, the user will be presented with a suggested action at the top of the list. The order of actions in this tab depends on the DSS's estimation of which action is more likely to help resolve the issue. The ranking actively changes depending on actions being recorded as successful, or not.

---

[9] MICHALA, A. L., LAZAKIS I. & THEOTOKATOS, G. 2015. 'Predictive maintenance decision support system for enhanced energy efficiency of ship machinery', *International Conference of Shipping in Changing Climates 2015 Conference proceedings, 24-26 November 2015*, Glasgow.

DIKIS, K., LAZAKIS I. & MICHALA, A. L. 2015. 'D4.5 (WP4): Architecture, framework and development of Decision Support System', *Inspection Capabilities for Enhanced Ship Safety Consortium*, EC FP 7 (FP7/2007-2013). Grant Agreement No 605200.

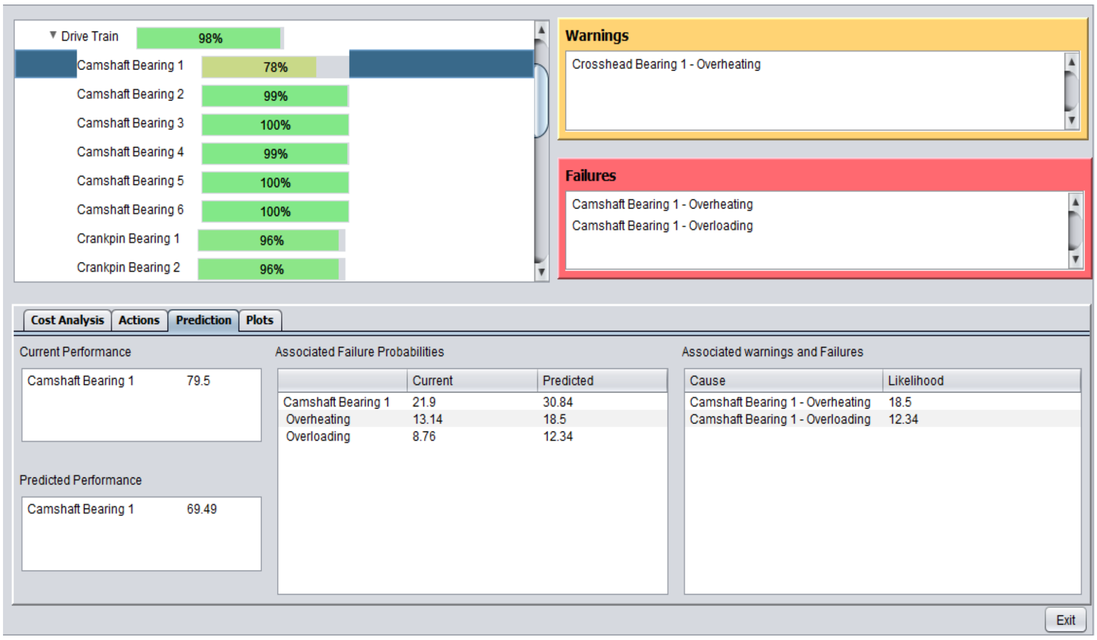


Figure 3:13 – Updated prediction analysis tab of the GUI presenting the statistical degradation analysis used for the DSS on a camshaft bearing which is found to be in a warning condition.

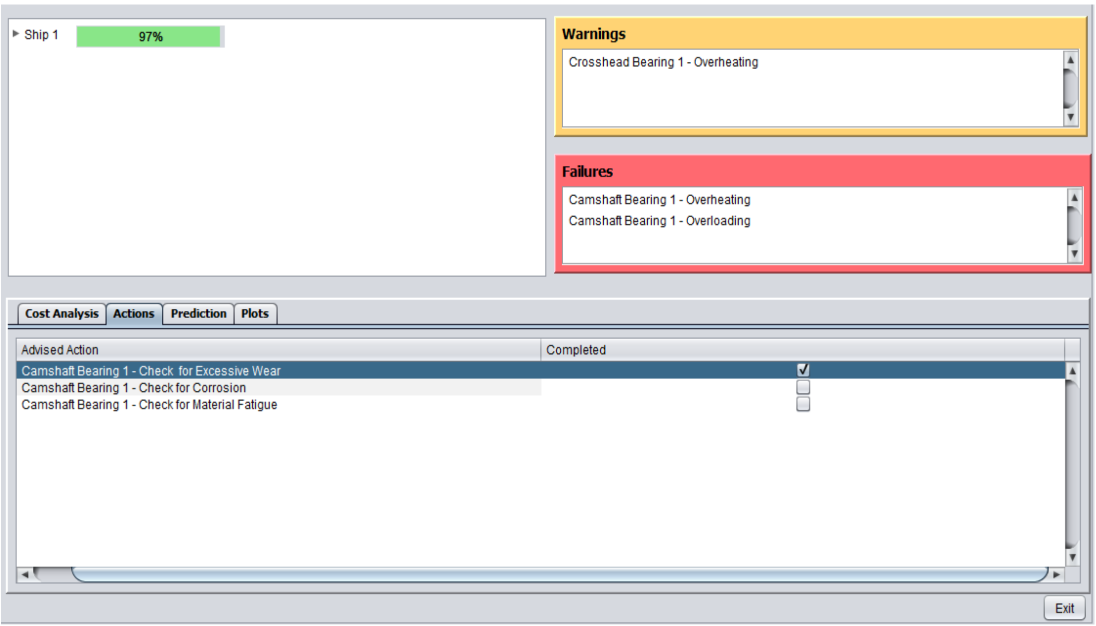


Figure 3:14 – Updated actions tab of the GUI presenting the additional functionality for completing an action which is suggested for a warning raised by the DSS for a camshaft bearing.

3.3 Technical Evaluation

3.3.1 Experiment Setup

To evaluate the methodology and the presented implementation, the system was experimentally set up in two locations. The same laptop was used in both cases for collection of data, post-processing, reliability analysis, and DSS analysis. The software was installed once at the beginning of the first case study and used in all subsequent case studies.

The initial model allowed for software and functionality evaluation through a benchtop setup (Figure 3:15 – Left). This was deployed under normal office conditions and allowed for an initial evaluation of a single sensor being read and processed. The figure demonstrates the connections between the analogue electronics on the top and right segments of the breadboard and the digital electronics on the lower segment. The connections to batteries, ZigBee Pro and BBB are also presented. Two options were evaluated for battery connection: (a) a battery bank through micro-USB (b) a Li-Po battery through a shouldered connector. The wiring diagram for the Li-Po battery connector is presented in Figure 3:15. The provided connection for the onboard rechargeable power supply was used, and the required resistors were added to the system to provide a reliable connection to the battery. Initially, a Lithium Polymer (Li-Po) single cell 6600mAh was used.

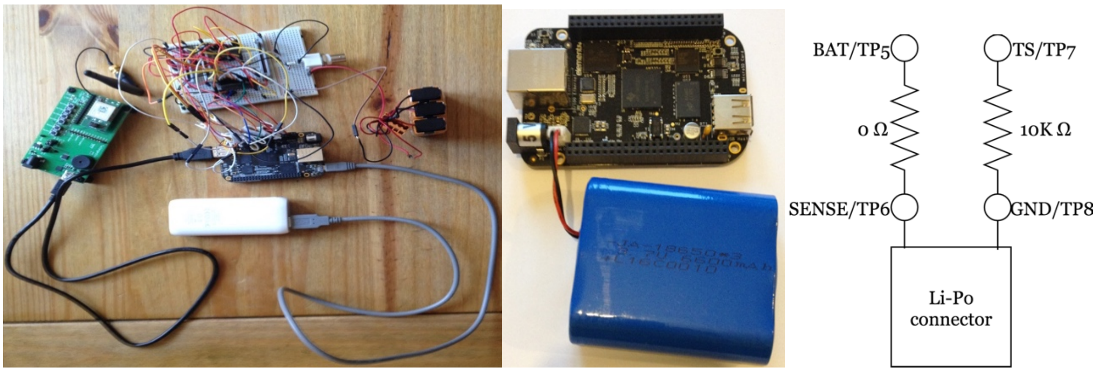


Figure 3:15 – Benchtop model of the DAQ measurement unit powered by a battery set for the sensor and a battery bank for the BBB board (Left). BBB to Li-Po battery photograph (centre) and connection diagram (right).

A laptop was used to connect the receiver unit. Output and input was also monitored at times via an SSH connection through the Ethernet port of the BBB directly via the same laptop. A single pressure sensor was attached to the BNC connector to measure atmospheric pressure at a constant level. Then, an automatic air pump was attached to a tube. The pressure sensor was connected to the same tube. This tube became a variable air pressure environment to allow for controlled variations in pressure. The initial proof of concept only requires the installation of a sensor at such a controlled test facility. This set up was used for the first case study (Figure 3:20).

The second location was the Engine Laboratory of the Naval Architecture Ocean and Marine Engineering Department of the University of Strathclyde. This location allowed for the evaluation of the system under realistic conditions. The engine is far smaller than a ship engine. However, the room provides conditions that have a potential for high interference, generation of electromagnetic noise, and sensor installation sites that mimic the targeted application. This location was used for the second and third case study presented later in this chapter.

The engine room is an approximately 3x3 meter metal box. A glass window is installed on one of the sides to allow visual access from the control area. When the door of the engine room is closed, the room is isolated from the control area. This creates higher interference and cross-talk conditions, as the signals can reflect on the metal surfaces. The Engine room is presented in Figure 3:16 where a CM12 Armfield automotive four-cylinder, direct injection, high speed diesel engine is located (Table 3:1).

Figure 3:16 - The Engine Room in the Laboratory, image captured from control area through the glass window.

Table 3:1 – Characteristics of the diesel engine in the marine engine laboratory at the University of Strathclyde.

Engine Specification*	Model Volkswagen SDI 1896cc
Engine type	4 stroke
Cylinders	4
Speed (rpm)	3600
Max power (kW)	55 kW for 20 mins

* http://discoverarmfield.com/en/products/view/cm12/automotive-diesel-engine

The DAQ system connected to a pressure sensor and battery bank is presented in Figure 3:17 (left). This box was placed inside the Engine room and the sensor connected to the engine’s first cylinder. This setup is one of the two possible deployments for the DAQ units. The wireless transmitter connection is via the USB cable and the battery is located under the BBB board in this picture (battery bank option). Figure 3:17 (right) presents the central collection unit connected to a laptop, located outside the Engine room.

The second possible deployment of the DAQ unit for this location is presented in Figure 3:18, where four DAQ units are displayed. In this case, the unit only comprises the BBB and the Wireless transmitter boards. This configuration allowed for multiple BBB boards to be deployed without physical connections to sensors. The purpose of this deployment is twofold; firstly, the generation of predefined and hence controlled inputs to the system; secondly, the generation of high wireless traffic without the necessity of expensive sensor hardware.

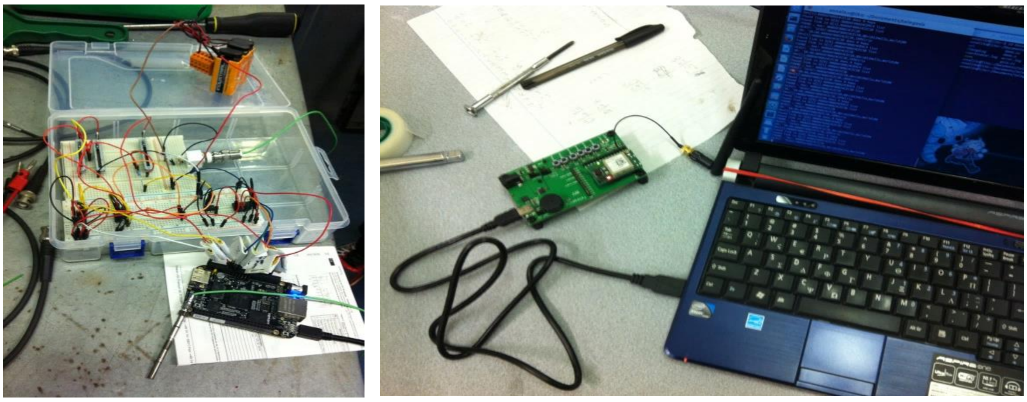
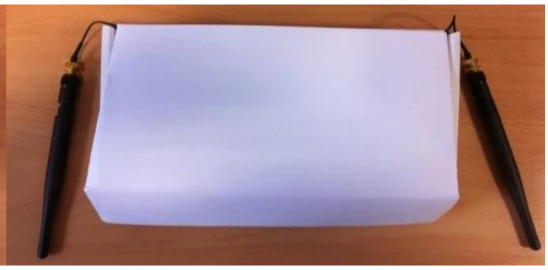
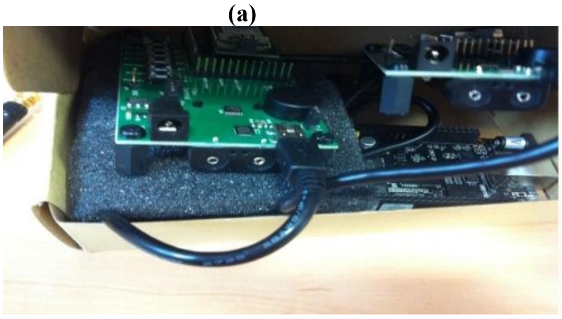
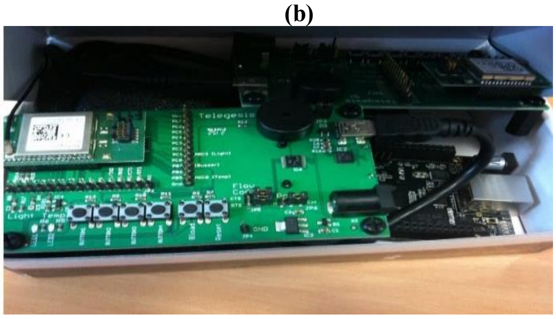


Figure 3:17 - Board connected to signal conditioning circuit and sensor (left) and receiver board connected to local PC (right).



(a) **(b)**





(c) **(d)**

Figure 3:18 - Four DAQs with virtual sensors: (a) and (b) housing and antennas, (c) and (d) wireless transmitter development boards and embedded BBB Linux boards, battery powered.

The next section will elaborate on the validation method proposed which will be used to verify that the system is indeed capable of producing the required output and satisfies the aims and objectives of this thesis.

3.3.2 System Verification and Validation Strategy

To validate the system and methods presented in Chapter 2, there were several aspects of the system that had to be verified, including the performance of the network within the experimental setup presented in Section 3.3.1 and the validation of the pre and post processing algorithms to identify if the regenerated data streams were a true representation of the original recorded data. Finally, the DSS had to be verified. The methods presented in this section are used in the case studies (Sections 3.3.3 to 3.3.5).

The first metric that was identified for the evaluation of the network was the number of attempts made by the sending unit, important as the system was designed to perform several attempts until a message was acknowledged by the receiver (delay tolerance). This feature ensured that the messages will be delivered successfully, and no data is lost due to the Acknowledgement mechanism. However, it can create an overload of the network and significant lag in the delivery of data. Finally, it can become problematic if data require several attempts, as the DAQ unit will have a large bottleneck in outgoing traffic. As a result, the sum of attempts per message package was recorded when the network library was compiled in debug mode.

Apart from the verification strategy to assess the suitability of the system, a method for accessing the validity of the pre and post-processed data is presented in Figure 3:19. The raw data was collected from the sensor prior to pre-processing. This dataset was not yet processed through any algorithm or other part of the system that could invalidate it. As the sensor used was trusted to provide correct readings, the raw data was also considered correct. At this stage, the system stored the unprocessed data locally prior to mining or management actions. This data set (D_1) was identified as the valid data set for any period of measurements. The data was then pre-processed locally at the DAQ Unit, transmitted, and post-processed upon collection. The result of the post-processed data was identified as the second data set which is not yet validated (D_2).

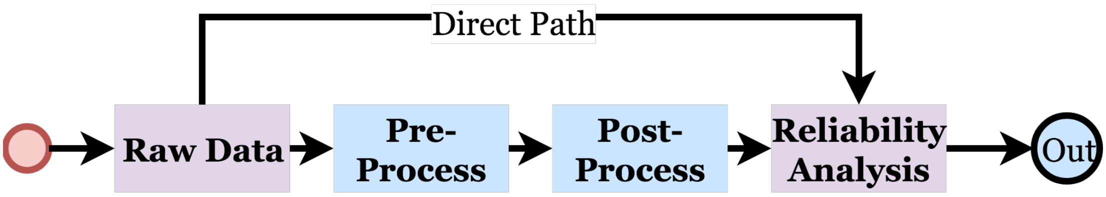


Figure 3:19 – Methodology and direct path produce two different outputs from the reliability analysis tool.

These two datasets were assumed comparable. As a result, a correlation of the two data sets should have a high coefficient of determination (R^2). As linear regression was used the coefficient of determination is equivalent to the square of the correlation coefficient. If no information was lost the two outputs of the reliability analysis component should also be highly correlated (Equation 3:1).

$$R^2 \cong 1 \; \forall \; (D_1, D_2) \qquad (3:1)$$

Finally, to validate the DSS, a comparison of suggested actions was performed between the novel DSS and the original DSS (Michala et al., 2015). The results of the tools were compared both in content and order. In every case, the suggested actions were compared against the existing expert opinion recorded when initially developing the first version of the DSS. During the development of the initial version the actions suggested for each failure were provided by the maintenance department of a shipping company and validated against Class requirements and regulation[10]. This was assumed to be the correct suggested action set. Each action set was validated against the correct action set.

3.3.3 First Case Study: Pressure Measurements[11]

The purpose of this experiment was to create the conditions that would lead to events being registered and to identify if the variation in data was closely followed by the extracted features and recreated data streams. Thus, this case study displays the proof-of-concept and investigates the validity of the data processing method, utilising the benchtop model. Based on the specifications of the pressure sensor, the calculated values for the resistors were R1 = 3.09 kΩ, R2 = 213 Ω, R3 = 150 Ω, and R4 = 1 kΩ. The variable resistors presented in Figure 3:15 were set to these values using a voltmeter to verify the settings. The pressure sensor was connected to the DAQ to record value type data.

The configuration of the system parameters was made directly through the Ethernet SSH connection and the values "Value Type" and "Pressure" were stored in the configuration file respectively. Also, the encryption key was manually setup, after being

---

[10] MICHALA, A. L., LAZAKIS I. & THEOTOKATOS, G. 2015. 'Predictive maintenance decision support system for enhanced energy efficiency of ship machinery', *International Conference of Shipping in Changing Climates 2015 Conference proceedings, 24-26 November 2015*, Glasgow.

[11] Published in: MICHALA, A. L. & LAZAKIS, I. 2016. 'Ship machinery and equipment wireless condition monitoring system', *Proceedings of the International Conference of Maritime Safety and Operations, 13-14 October 2016, University of Strathclyde, Glasgow*, ISBN No 978-1-909522-16-9, 63-69.

generated by the coordinator board via the random generator. A sampling rate of 100 KHz was used for all sensors as the maximum ADC setting; sufficient for every input, considering current value type measurements are recorded once in 4 hours onboard, while vibrations are sampled at approximately 10 KHz in the laboratory.

For this case study, the air pump was used, presented in Figure 3:20. The pump had three settings; off, on at low pressure, and on at high pressure. The states were changed by pressing the button once for low pressure, twice for high pressure and once again for off. When off, the pump was not increasing the pressure in the tube and allowed it to be reduced as the air was naturally leaking out of the tube. When on at low pressure, the pump would steadily increase the pressure in the tube as more air was pumped in. Similarly, the pressure increased when on at high pressure, but more rapidly.

Figure 3:20 – Experimental setup with controllable changes to pressure over time: (a) the pump was connected to one end of a hose while the sensor inserted at the other; gaps were sealed, (b) a picture of the sensor inserted into the tube with the far end of the tube sealed on the floor of the engine room.

During the experiment, the tube, the pump, and the sensor were not re-aligned or reconfigured, so that the pressure in the tube would create different patterns as time passed due to changes naturally occurring to the position of all components. Table 3:2 presented the configuration settings.

Table 3:2 – Configuration settings for the first case study. Values -1 were used to indicate that there was no limit or threshold for this case study.

Parameter	Setting
Measurement	Pressure
Type	Value
Encryption	Generated key
Measurement site	Test pipe
Range maximum limit	-1
Range minimum limit	0
Upper threshold	-1
Lower threshold	-1

The experiment started with the pump on low pressure. Then the pump was turned to high pressure for a few seconds, followed by a few second turned to off. The transitions between states was random to generate a variation in the data stream. This sequence was designed so that data would not remain constant and with the purpose of creating spikes and sudden changes to the data stream. The pump was eventually set at low pressure for several hours to complete the 24-hour experimental period. In this study, the DSS component was not considered.

Figure 3:21 presents the data recorded from the sensor at the DAQ unit prior to transmission. This is the primary dataset. The pressure sensor data were generated as the sensor was excited. The picks and valleys in the graph correspond in time with the changes in the operating mode of the air pump.

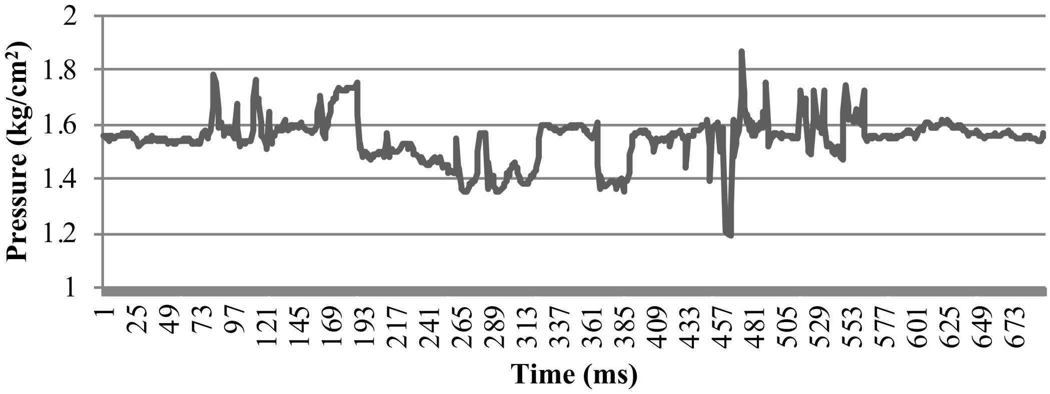


Figure 3:21 - Raw data collected from the sensor without pre-processing.

The pressure was not calibrated as accuracy of the measurement could not influence the result of this study. Nevertheless, the physical pressure dial on the equipment corresponded to the measurements at the DAQ unit; the dial readings were not recorded. Algorithmically, it would be of very low cost, development effort, power consumption, and CPU/RPU utilisation, to incorporate a calibration factor for the measurements; through remote software updates.

For every window of measurements, the pre-processing algorithm generated the extracted features. Figure 3:22 presents just the mean measurements for the defined pre-processed windows of the full experiment session. This is the secondary dataset.

This dataset was transmitted to the collection point along with the standard deviation and length of the window. All other measurement characteristics and events were also transmitted, generated based on the algorithms presented in Chapter 2. The amount of points is reduced by one order of magnitude in the secondary dataset compared to the primary.

Following the reception of the secondary dataset at the collection point, the post-processing algorithm generated a tertiary dataset (Figure 3:23). The aim of the tertiary data set is (i) to provide a comparison point and (ii) to eliminate compatibility issues between the DAQ system and the analysis tool.

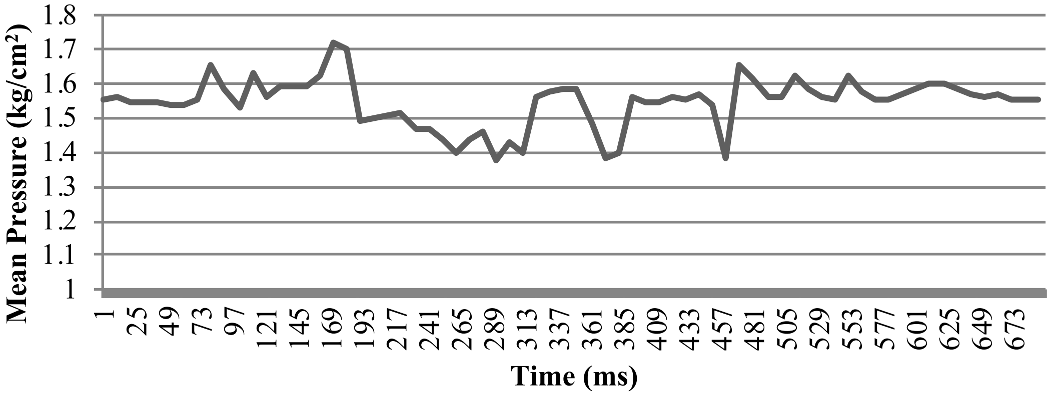


Figure 3:22 – Pre-processed mean pressure data received.

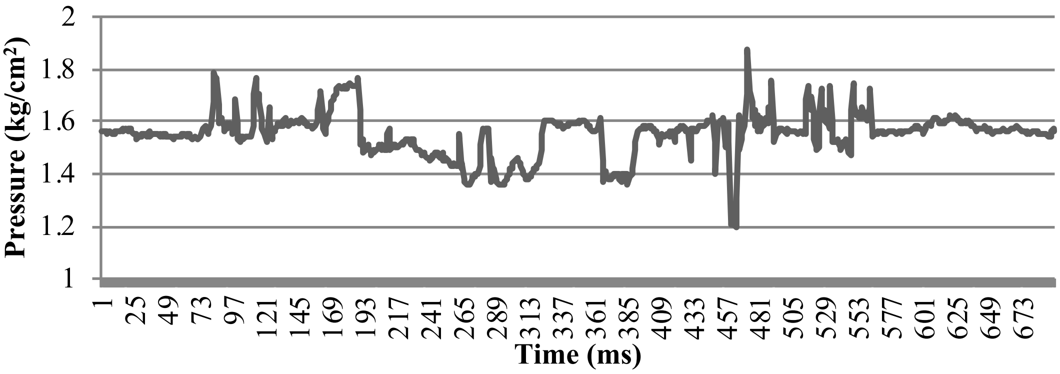


Figure 3:23 – Post processed data generated at the main collection point based on received pre-processed information.

As required, according to the evaluation method presented in Section 3.3.2, the primary and tertiary datasets were statistically analysed (Figure 3:24). Also, for completeness, we statistically compare the primary and secondary datasets (Figure 3:25). The correlation of the primary and tertiary sets is as expected (R^2 = 0.99998). Thus, the pre-processed dataset, even though it is significantly smaller in bytes, does not alter the information contained in the primary set.

As expected the correlation between the primary and secondary set is not as strong. To generate the correlation graph, the two sets had to be of equal length. For this reason, the secondary set was used as a whole. The primary set was reduced by selecting one point in each monitoring window period corresponding to the mean point in the secondary set. The values presented in this graph are reported to demonstrate that if the post-processed values are used for further analysis, is likely to result in statistically significant error in the predicted condition of the monitored equipment/machinery.

To evaluate the performance of the reliability analysis and decision support software, the primary and tertiary sets were both used as input. The aim of this part of the experiment was to identify differences in results produced by the tools due to differences in the two datasets. The dataset was assigned to the air pipe of the main engine for the purpose of the reliability analysis tool and the DSS. This assignment was made by injecting the dataset to the input excel file under the specified name of the input measurement.

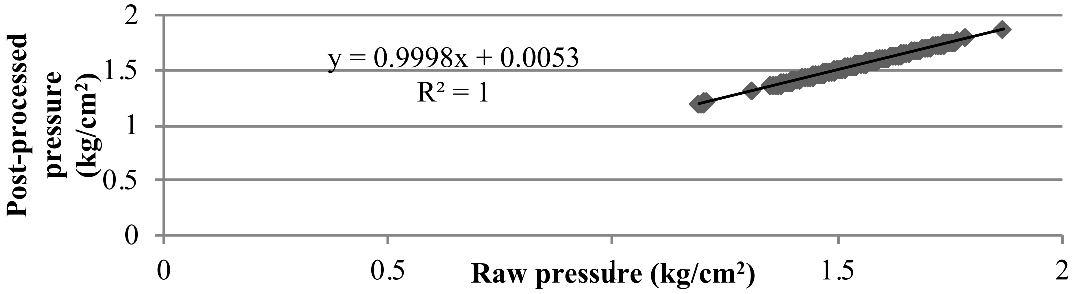


Figure 3:24 – Data set correlation between post-processed values and raw values is at the highest possible value (primary and tertiary datasets).

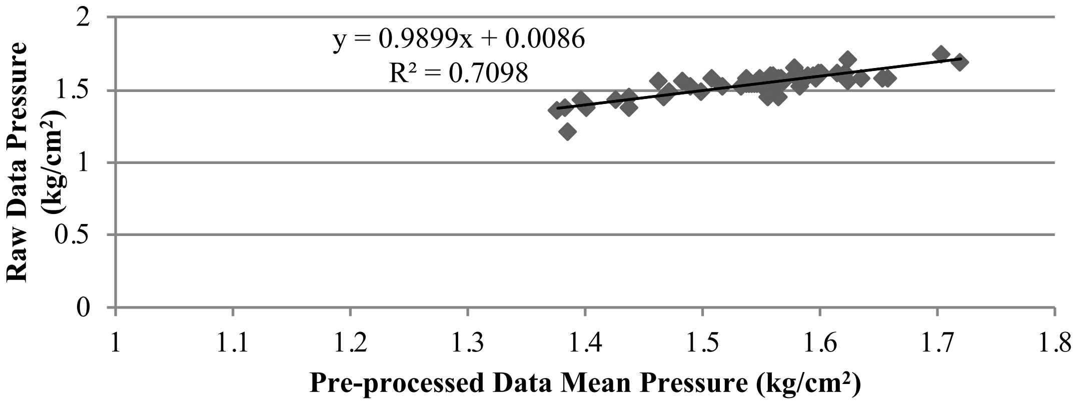


Figure 3:25 – Data set correlation between mean pre-processed values and raw values is low (primary and secondary datasets).

Initially the primary dataset was manually inputted to the reliability analysis tool. The generated reliability graph is replicated in Figure 3:26. The reliability had a falling trend (negative slope) dropping from 100% to 98.8% in five days after the end of the experiment period i.e. drop in reliability by 1.2% in the course of 5 days. The period of prediction was a user defined input of reliability analysis tool.

For the tertiary dataset, the process was automated. The post-processing algorithm saved the values at the correct file for the reliability analysis tool.

The reliability analysis tool and the DSS were executed at the end of the experiment session to view the generated reliability graph, replicated in Figure 3:27. In this case, the reliability value drops to 99.8% (Figure 3:26).

To formally compare the two reliability curves, the correlation analysis is presented in Figure 3:28. As demonstrated, the two curves have no statistically significant differences with R^2 = 0.989. However, there is a small error of the order of 1%.

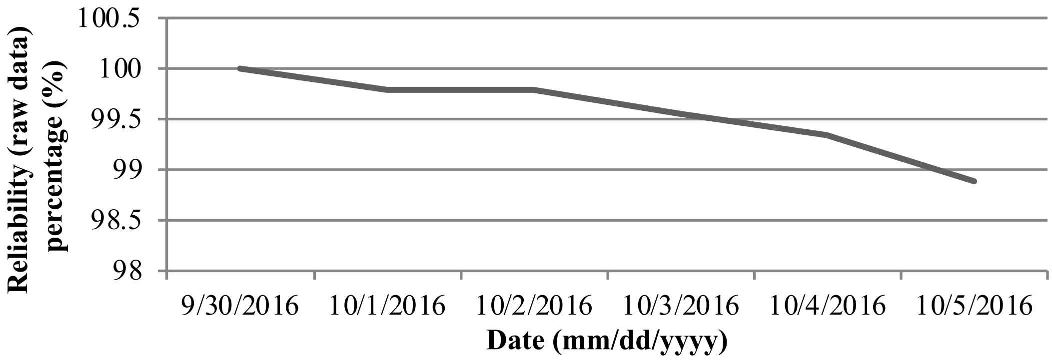


Figure 3:26 – Predicted condition based on first set of data (raw data).

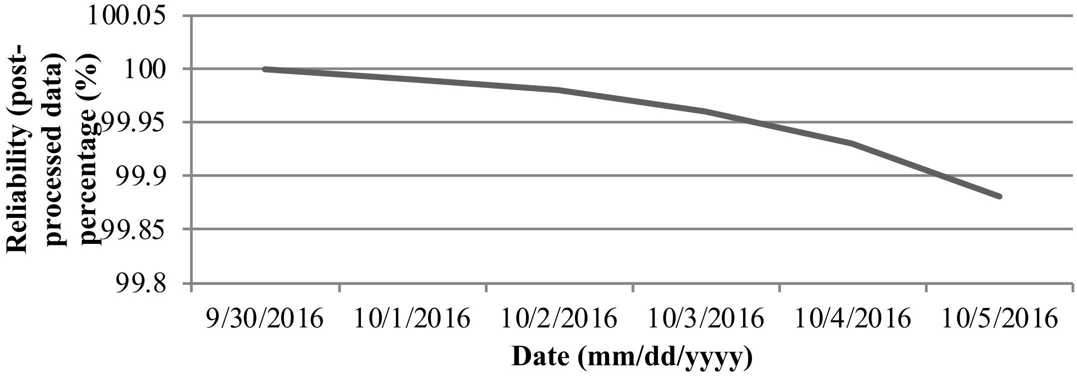


Figure 3:27 – Predicted condition based on second set of data (post-processed data).

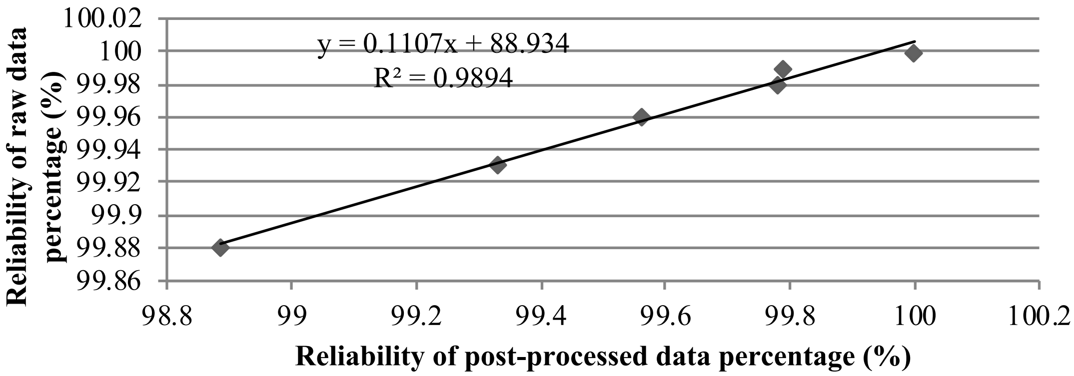


Figure 3:28 – Correlation of the two predicted reliability result sets.

This error was not significant as it did not cause a Warning or Failure to be predicted by the DSS. As a result, in both cases, the DSS did not suggest any actions for maintenance of the main engine or any components related to the measurement. Further, all the components had a reliability value between 99% and 100%, including the main engine. The main engine was the only system that was addressed for reliability analysis in the tool and thus the ship was comprised only of the main engine. Hence, the reliability of the ship as a whole was 100%.

However, the tool has hardcoded thresholds associated with every component. The tool expected readings of approximately 6 kg/cm^2 with a low threshold not defined and a high threshold at 7 kg/cm^2. When the air pump measurements were introduced as main engine air pipe measurements to the tool, it was not able to handle the low pressures appropriately. Figure 3:29 presents a result for the Scav Air Pressure component as presented in the DSS user interface when the tool was executed with the tertiary dataset. This component uses the pressure as input for the reliability calculation.

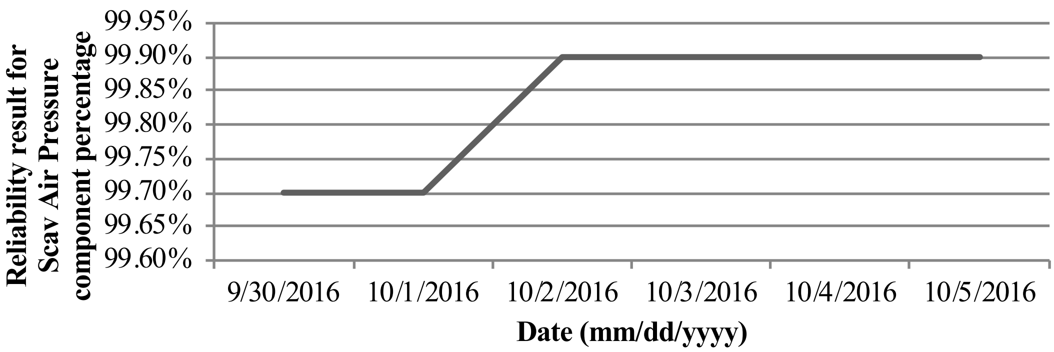


Figure 3:29 – Example of data that has been allowed for processing through the MRA even though they were indicative of a sensor providing erroneous readings (In this case values lower than expected kg/cm^2).

In this case study, the pre-processing unit did not generate an event that flagged the data as erroneous, as it was configured for readings in the recorded band. The output of the tool demonstrates an unexpected rise in reliability which is a wrongly calculated outcome. The impact of non-sanitised input to the reliability analysis tool would be the production of unexpected operational condition estimates, leading to wrong maintenance action suggestions. For example, if the reliability rises software such as the DSS could estimate that a previously raised Warning is no longer a threat and can be removed.

3.3.4 Second Case Study: High Load Performance[12]

The second case study was designed to investigate the performance of the system under large load, several incoming streams of data, and several DAQs connected to the same coordinator unit. The performance of the network is also evaluated through

[12] Published in: MICHALA, A. L. & VOURGANAS, I. 2017. 'A Smart Modular Wireless System for Condition Monitoring Data Acquisition', *Proceedings of the 16th International Conference on Computer and IT Applications in the Maritime Industries, Cardiff, 15-17 May 2017*, Technische Universität Hamburg, Harburg, ISBN 978-3-89220-701-6, 212-225.

this case study.

The evaluation metric recorded was the number of attempts a DAQ had to make before a message was successfully received by the central collection unit, as presented in section 3.2. This metric can provide an indication of the reliability of the network as well as the QoS. To demonstrate that the processing method remains valid even under high load conditions of both the DAQ and the collector units, the same analysis of the data streams is performed in this study, as in the previous.

Because of the shortage of available hardware and accessible sensors, it was not possible to create high load conditions using physical sensors installed on the engine. To approximate connection of the required number of sensors, the following alternative method was used. Physical connections were created between PRU outputs and PRU inputs of the BBB. There are 25 possible PRU connections according to the specification of the BBB, which were sufficient for the required 16 points needed. Data recorded on a ship were read from an excel file and streamed out to one of the analogue output I/Os of the BBB to the ADC (Figure 3:30). The connected input was then read via the PRU algorithm presented in Chapter 2. The input was treated by the BBB as a physical connection to an existing sensor. All seven analogue I/Os were used. When no physical sensor was connected to the BBB, the 7^{th} analogue I/O was used on different time windows to imitate two signals arriving at different times. Thus, a TDMA approach was utilised to create a virtual 8^{th} sensor per BBB. An image of the connected virtual sensors is presented in Figure 3:30. Seven wired connections between the ADC and the BBB boards are visible.

Using this method eight virtual sensors were created for a DAQ unit. The unit was effectively pre-processing and transmitting eight streams of data, as if it was connected to eight physical sensors. The analogue electronics were removed. Also, the data transmitted were valid as they originated from a new-build ship in excellent condition and were cross-validated by the engineers and experts of the shipping company. This set of data was available and used by the author as well as other researchers (Lazakis et al., 2017, 2016a, 2016b, Dikis et al., 2016, Michala et al., 2016b, 2015).

A total of four such DAQs were deployed as presented in Figure 3:18. This setup did not evaluate the capacity of the battery to supply 8 different physical sensors but rather focuses on the capabilities of the DAQ and collector units. Table 3:3 presents the configuration settings.

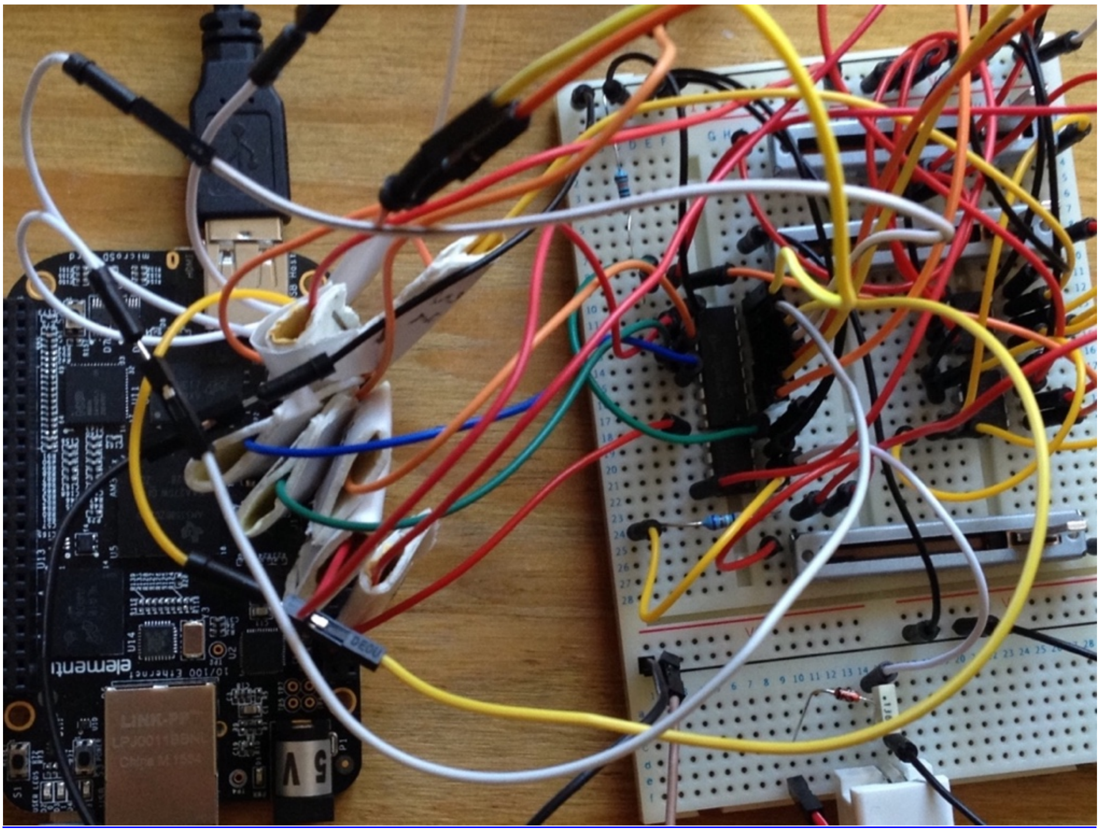


Figure 3:30 – All 7 virtual sensors connected from the Analogue I/O (ports 33 to 40 – refer to Appendix D for additional information on port mapping and connection allocations).

To complement this deployment, an additional DAQ was equipped with 6 virtual sensors and one physical connection to the pressure sensor used in the first case study (with the analogue electronics). The collection point and the connection to the physical sensor was presented in Figure 3:17. The pressure sensor in this case was placed in the mounting point at the top of the first cylinder of the engine where it was initially installed by the laboratory technicians for general monitoring use. Figure 3:31 presents the connected pressure sensor on the main engine and the DAQ unit prior to the deployment of the virtual sensors.

Table 3:3 – Configuration settings for the second case study.

Parameter	Setting
Measurement	Pressure, Temperature
Type	Value
Encryption	Generated key
Measurement site	See Table 3:7
Range maximum limit	Defined in analysis tool
Range minimum limit	Defined in analysis tool
Upper threshold	Defined in analysis tool
Lower threshold	Defined in analysis tool

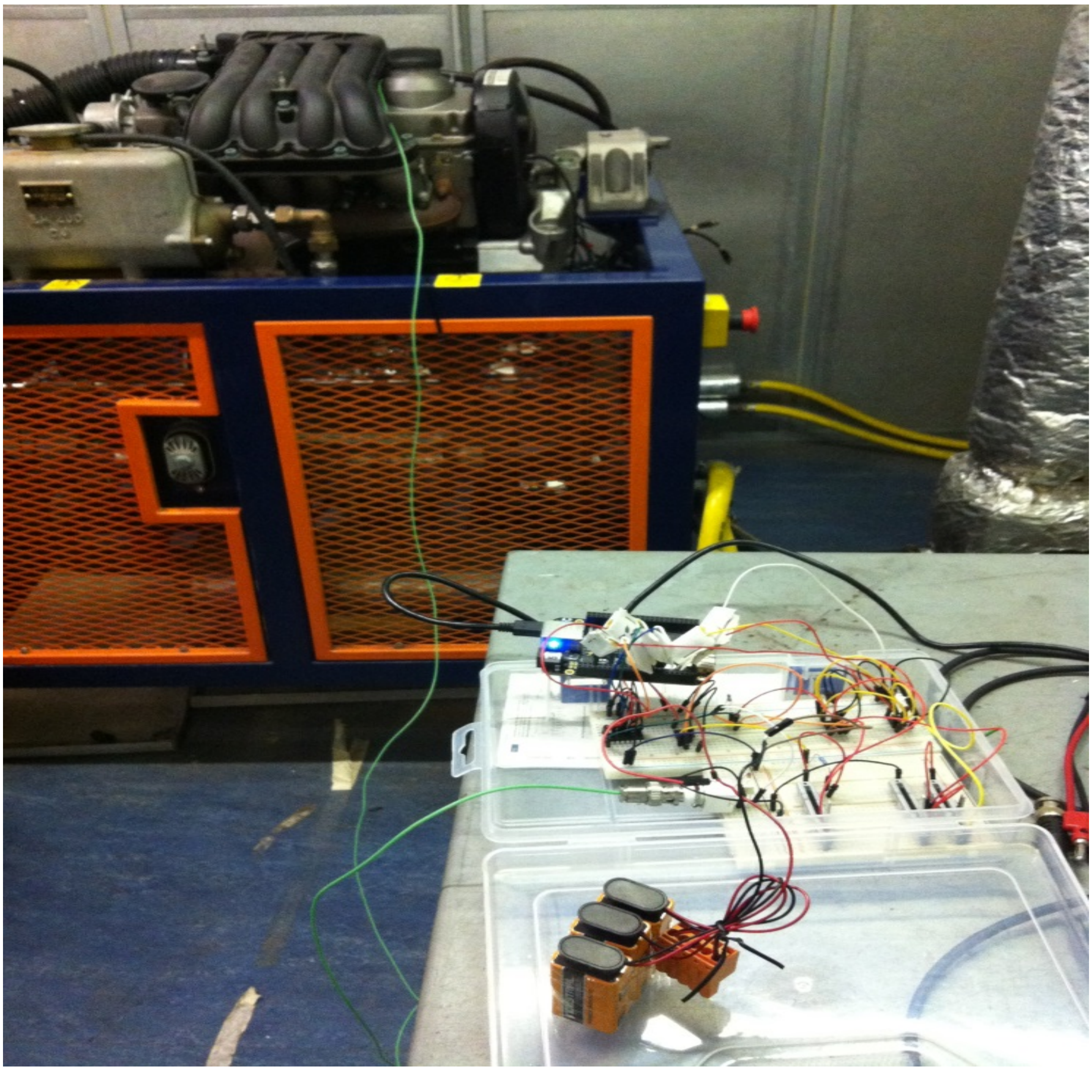


Figure 3:31 – Pressure sensor installed on the machine and connected to the DAQ system.

The installation locations are presented in Figure 3:32. The two boxes housing the four DAQs with virtual sensors were located at the floor behind the engine, to create a further transmission obstacle between that location and the collector hub outside the glass window. The fifth DAQ with the physical connection to the sensor was located on the bench inside the engine room (Figure 3:31). The transmission unit is also visible in this image. The door was closed to increase signal obstruction (as in Section 3.3.3).

In this study two alterations were made to the software: (i) an additional service was created to send readings from the excel file to the relevant output pins for every DAQ unit, (ii) the wireless transmission library was recompiled in debug mode to record more metrics and store the network status at every measurement window.

To transmit the full data set, 38 virtual sensors were created. Each virtual sensor was associated with recordings from a physical measurement of a specific machinery or equipment on ship. The 39th input to the system was the pressure measurements from the laboratory engine. The engine was switched on during daytime throughout the experiment period of a full month depended on laboratory availability. The experiment produced outputs for the duration of one month. The engine was creating electromagnetic noise when operational while no noise generated during night time when the engine was not operated.

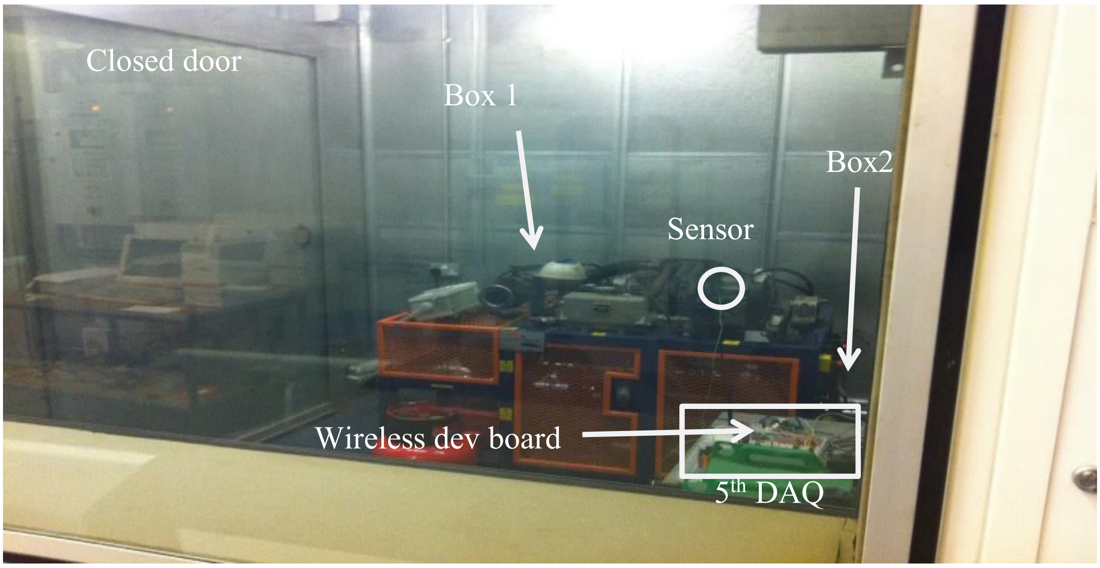


Figure 3:32 - Deployment in Engine Laboratory, image captured from control area through the glass window.

Table 3:4 presents a list of the measurements utilised from the data set. Temperatures were expressed in degrees °C and pressures in Kg/cm^2. A reference number was allocated to each measurement for the purposes of this thesis. Additionally, the physical sensor was allocated reference number 39 and is not presented in the table. The description of each measurement is presented (full description in Nomenclature).

The network was allowed to operate unobstructed by human intervention during the experiment. The analysis of the recorded metrics was conducted after the end of the experiment. The data in regard to transmission attempts, network configuration and performance were recorded locally on every DAQ. The recorded data were then transmitted to the post-processing unit through the ZigBee API request command for the network metrics at the end of the experiment.

One type of event was generated in 153 occasions during the experiment, this was the event generated when values drop to zero. The physical pressure sensor generated such values as the engine was not operating in instances. Also, the dataset had instances of zero measurements when equipment/machinery onboard was switched off.

The event messages were prioritised by the API and sent asynchronously to the recording mode of the state macine, so that the lag between event generation and event post-processing would be minimal and near-real-time. This lag was evaluated to be at the rage of a few seconds but was not recorded formally as part of the experiment. No other issues were recorded and no failures of the DAQ system occurred in the experiment period.

Table 3:4 - Measured parameters from ship's main engine.

No.	Measurement	No.	Measurement
1	Thrust Bearing LO Outlet Temp	20	IntShaft 1 Bearing Temp
2	TCLO 1 Input Press	21	IntShaft 2 Bearing Temp
3	TCLO 1 Input Temp	22	IntShaft 3 Bearing Temp
4	TCLO 1 Output Temp	23	Main Lube Oil Input Pressure
5	TCLO 2 Input Press	24	Main Lube Oil Input Temperature
6	TCLO 2 Input Temp	25	Cylinder Input JCFW Pressure
7	TCLO 2 Output Temp	26	Cylinder 1 Output Exh Gas Temp
8	Scav Air Manifold Press	27	Cylinder 2 Output Exh Gas Temp
9	Scav Air Rec 1 Temp	28	Cylinder 3 Output Exh Gas Temp
10	Main Engine Start Air Press	29	Cylinder 4 Output Exh Gas Temp
11	Piston CO Input Press	30	Cylinder 5 Output Exh Gas Temp
12	JCFW 1 Output Temp	31	Cylinder 6 Output Exh Gas Temp
13	JCFW 2 Output Temp	32	Cylinder 7 Output Exh Gas Temp
14	JCFW 3 Output Temp	33	Cylinder 8 Output Exh Gas Temp
15	JCFW 4 Output Temp	34	Aft Camshaft Bearing Temp
16	JCFW 5 Output Temp	35	Fore Cam Bearing Temp
17	JCFW 6 Output Temp	36	Ex.Gas Out Aft Turbo Charger 1 Temp
18	JCFW 7 Output Temp	37	Ex.Gas Out Aft Turbo Charger 2 Temp
19	JCFW 8 Output Temp	38	Main Engine Control Air Input Press

Figure 3:33 presents the load of the network for each day of the experiment. The load is presented in transmitted Bytes. The variation is due to custom messages such as events, as well as number of attempts for transmitting a packet. The lowest recorded value was 5,616 Bytes on the occasion that all packets carried pre-processed information and were acknowledged directly after the first transmission attempt.

To demonstrate the benefit of pre-processing the information at the edge, the expected network traffic of raw data was also calculated. The calculation was based on the same statistical performance of first, second or more transmission attempts, and on the raw data (primary dataset). For the purpose of this calculation, each raw data point corresponds to one packet. Moreover, packets transferring events and other information were added to the calculation unaltered. In the case of every packet transmitted at first attempt, the network load in bytes was calculated at 43,200 Bytes for the day.

Figure 3:33 presents the actual recorded value for the pre-processed data and the calculated value for raw data for every day of the experiment.

Both the metrics for the network traffic in bytes are based on packets created through the ZigBee API library using the custom protocol. It is however necessary to differentiate the length in bytes of those packets, from the final transmitted length. The latter is longer. The ZigBee protocol attaches information to every packet. This information is used for routing, network monitoring, and characterisation. These bytes are however constant per packet and would thus create the same proportional contribution to both metrics. As a result, they were ignored for the purpose of this comparison and would not affect the comparative outcome of the two metrics.

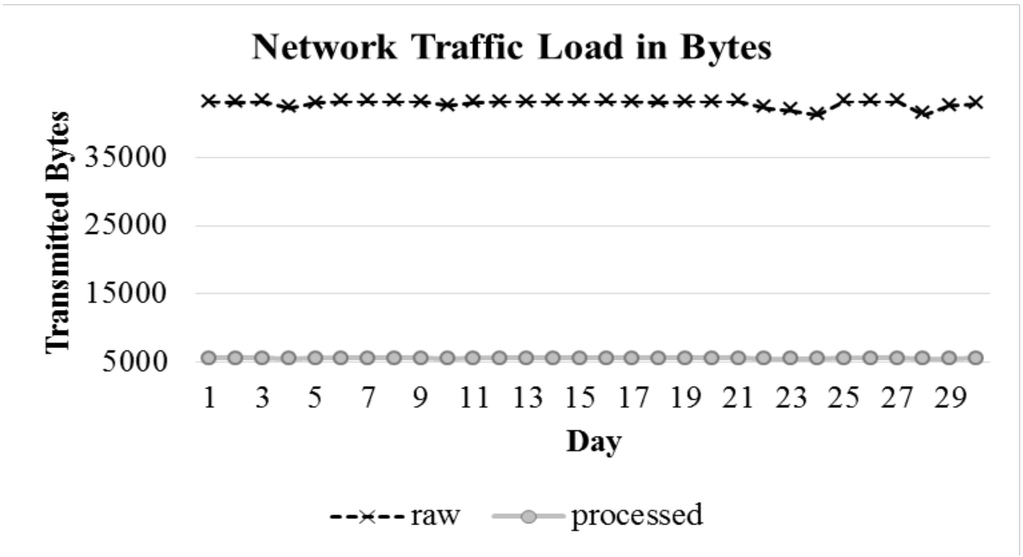


Figure 3:33 – Number of bytes transmitted after pre-processing against raw data bytes throughout the month.

Over the one-month period of the experiment 4,176 packets were transmitted per DAQ device. No packets were lost during this period and all data were transmitted and received successfully (delay tolerant Ack mechanism). The raw data as displayed in Figure 3:33 would be impossible to transmit. In the event of attempting to send the unprocessed raw data, significant delays would lead to transmission deadlocks which eventually overload the DAQ device.

The number of transmission attempts performed for every packet on every DAQ was recorded when acknowledgement or non-acknowledgement was received via the ZigBee API library. This data is presented in Figure 3:34, where total number of packets send per measurement is normalised to 100%. The categories represent the proportion of those packets that were sent and acknowledged during the first transmission attempt, the second transmission attempt, or that required more than two transmission attempts. The sensor instances on the figure correspond to the unique instance numbers associated with each measurement as presented in Table 3:4. Instance 39 is the physical sensor. As the physical sensor was closer to the glass window of the engine room, it required one hop and experienced less interference. This would explain the very low proportion of packets requiring second attempt or more attempts to be received for this sensor.

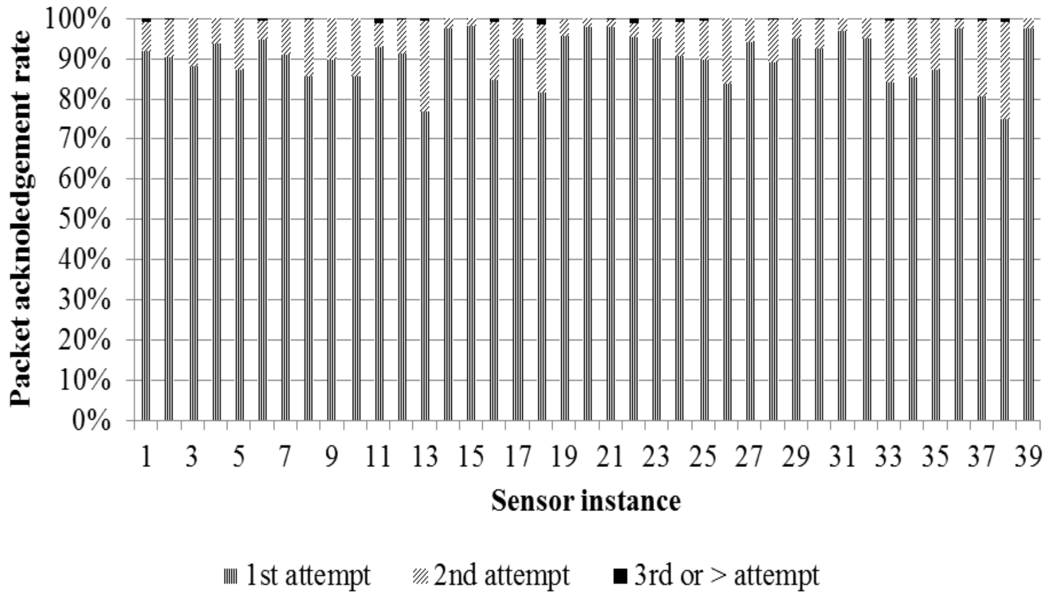


Figure 3:34 - Packets successfully received for each sensor on 1st, 2nd or later transmission attempt.

On average 90.53% of the packets were transmitted and acknowledged on first attempt with a standard deviation of 5.98. Only 9.09% of packets required a second attempt with standard deviation of 5.85. Moreover, the percentage of packets that required more than two attempts was always below 1% with average at 0.38% (st. dev. 0.41). Additionally, due to the acknowledgement mechanism of the API(delay tollerance), all the packets were delivered in the correct sequence and all the messages reconstructed successfully.

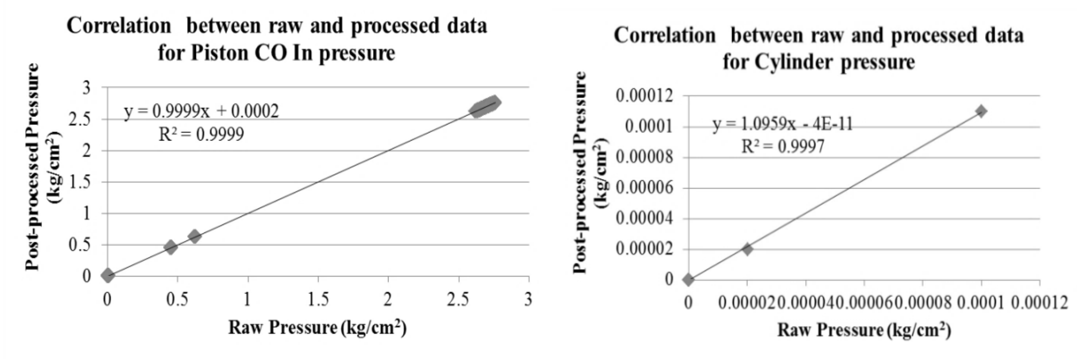
For every measurement, data were collected and post-processed at the control room. Each stream was post-processed independently and results were recorded. Just as in the previous case study a 10-minute window was used for all the sensors. During the 10-minute window the sensor input was sampled for 1 second every minute with the sleep period of 59 seconds. The sampling was performed at 100 Ksps. At the post-processing end, the statistical information of each window was reconstructed to complete one reading per minute (10 readings in total) for the same 10-minute window. The same evaluation methodology was followed as in the first case study and the primary and tertiary datasets were compared for each measurement stream. Table 3:5 presents the correlation analysis between the primary and tertiary data sets.

Table 3:5 – Results of correlation analysis in terms of R^2 values for each sensor instance for Temperature (T) and Pressure (P) measurements.

No	Measurement	R^2	No	Measurement	R^2
1	Thrust B. LO Out T	1	**20**	IntShaft 1 Bearing T	1
2	TCLO 1 Input P	0.999	**21**	IntShaft 2 Bearing T	1
3	TCLO 1 Input T	1	**22**	IntShaft 3 Bearing T	1
4	TCLO 1 Output T	1	**23**	Main Lube Oil Input P	0.999
5	TCLO 2 Input P	0.999	**24**	Main Lube Oil Input T	0.999
6	TCLO 2 Input T	1	**25**	Cylinder Input JCFW P	0.998
7	TCLO 2 Output T	1	**26**	Cylinder 1 Output Exh Gas T	1
8	Scav Air Manifold P	1	**27**	Cylinder 2 Output Exh Gas T	1
9	Scav Air Rec 1 T	1	**28**	Cylinder 3 Output Exh Gas T	1
10	Main Eng StartAir P	0.999	**29**	Cylinder 4 Output Exh Gas T	1
11	Piston CO Input P	1	**30**	Cylinder 5 Output Exh Gas T	1
12	JCFW 1 Output T	0.999	**31**	Cylinder 6 Output Exh Gas T	1
13	JCFW 2 Output T	0.999	**32**	Cylinder 7 Output Exh Gas T	1
14	JCFW 3 Output T	1	**33**	Cylinder 8 Output Exh Gas T	1
15	JCFW 4 Output T	1	**34**	Aft Camshaft Bearing T	0.999
16	JCFW 5 Output T	0.999	**35**	Fore Cam Bearing T	0.999
17	JCFW 6 Output T	1	**36**	Ex.Gas Out Aft Turbo Charg1 T	1
18	JCFW 7 Output T	1	**37**	Ex.Gas Out Aft Turbo Charg2 T	1
19	JCFW 8 Output T	1	**38**	Main Engine Control Air Input P	0.999
			39	Cylinder 1 P	0.999

The values are rounded up to 3 digits. A complete list of the correlation analysis graphs is available in Appendix F. In Figure 3:35, the first graph (Figure 3:35a) is the correlation graph between the primary and tertiary dataset for the Thrust Bearing Lube Oil Output Temperature (instance 1). The second graph (Figure 3:35b) presents the results of the correlation analysis for the physical pressure sensor (instance 39). Both these instances generated 'zero value detected' events.

Similarly, to the first case study the results demonstrate high correlation between the two sets. Events generated by unexpected conditions or large variations in the data are picked up by the pre and post processing algorithms. Thus, no information loss was recorded for any of the instances of this experiment. This holds for both the virtual and the physical sensors. In this case study, events were used to inject points to the dataset, further increasing the correlation between the two sets compared to the initial case study.



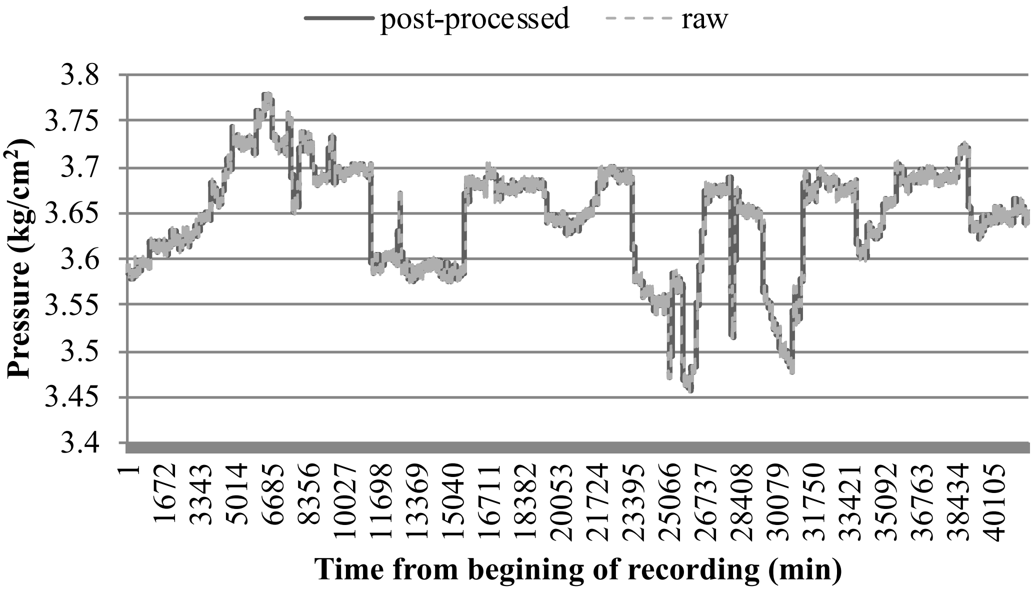
(a) **(b)**

Figure 3:35 - Example of correlation analysis between initial data and post-process generated data for two cases (a) the virtual sensor (No. 11) (b) the physical sensor (No. 39).

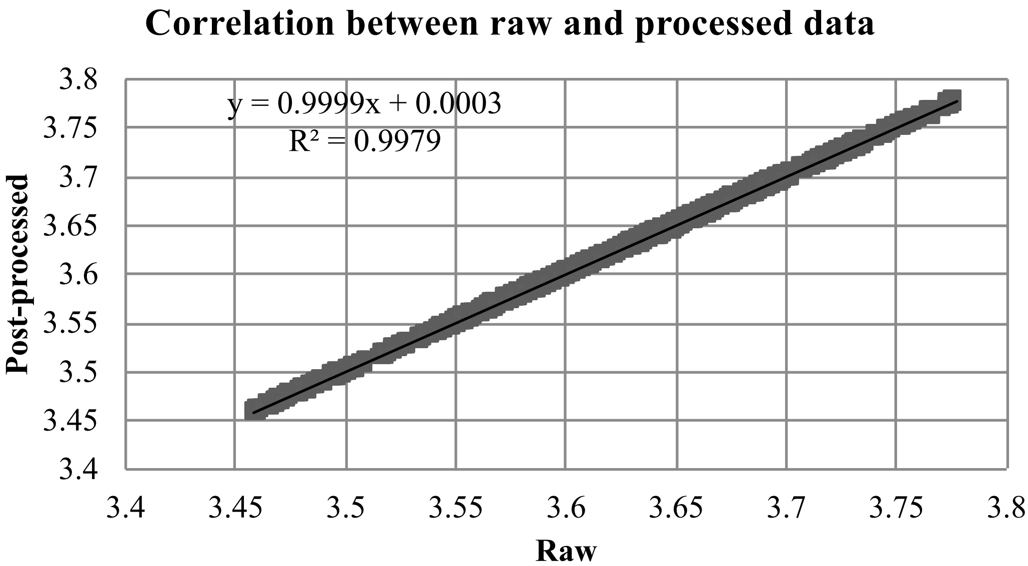
To further strengthen the validity of this claim, the worst case from Table 3:5, namely instance 25, is further analysed (Figure 3:36). This case had an R^2 value of 0.998 and corresponds to the dataset measurements for the Cylinder Input JCFW Pressure. It is possible that the nature of this dataset is responsible for the lower correlation.

As presented in Figure 3:36a, the dataset has several sudden changes at *11,935 min*, *25,858 min* and *27,847 min*. These could be due to data not being recorded by the DAQ system used, or due to other issues in data transmission and storage. These sudden changes are the only points in the graph were the two sets do not totally overlap. However, even during these changes the tertiary set closely follows the primary. Further examining the correlation analysis between the two sets in Figure 3:36b, it is evident from the curve that the two sets are very well correlated even in this worst-case scenario.

After the post-processing phase the tertiary datasets were inputted to the reliability analysis tool and DSS. The DSS reported no warning or failure for any of the measurements. The DSS output is valid as the input dataset was recorded on a new-built ship at optimum operating condition. Also, the DSS output is valid for the pressure measurements of the laboratory engine as it was also reported in good operating condition. In this case study the DSS did not raise any false positives/negatives, demonstrating its ability to successfully predict good operating condition. As no warnings or failures were identified by the DSS, no actions were suggested and resulting operating costs were not calculated. No instances of unexpected increasing predicted reliability were recorded.



(a)



(b)

Figure 3:36 – Worst case result of correlation analysis between initial data and post-process generated data (a) the two sets presented against the time for the duration of the case study (b) correlation analysis.

3.3.5 Third Case Study: Temperature, Vibration Measurements

This case study focused on identifying the validity of the data, measurements taken by the sensors, as well as verifying the processing of two different type streams. Furthermore, an additional goal of this case study is to demonstrate the validity of the DSS system. Thus, the study completes the evaluation of the system.

Two sources of input data were utilised during the experiment. The benchtop model was used to record the outlet temperature of the cooling water of the heat exchanger in the machine room. Moreover, a virtual sensor setup was used to generate input read from the IMS dataset from NASA's open repository (IMS, 2007). The virtual sensor setup is presented in detail in Section 3.3.4. Thus, two DAQ units were deployed within the engine room (Figure 3:16) similarly to the benchtop model deployment in the second case study (Figure 3:31). At this stage the wireless network performance was not evaluated.

The IMS dataset includes three run-to-failure experiments; in each case bearings failed either because of identified defects or due to mechanical failure. All the failures occurred after the expected life of the bearing was exhausted; according to manufacturer guidelines. The reported failures presented in Table 3:6 were used for cross-validation of the DSS output.

Table 3:6 – IMS dataset experiments and recorded failures.

Experiment	Duration	Failure
1st experiment	34.5 days	• *inner race defect in bearing 3* • *roller element defect in bearing 4.*
2nd experiment	7 days	• *outer race failure in bearing 1*
3rd experiment	44 days	• *outer race failure in bearing 3*

The first experiment recorded both x and y axis vibration for each of the four monitored bearings (8 readings from Table 3:7). However, for experiments 2 and 3 only the x axis vibration was recorded (readings 1 – 4 from Table 3:7). The original data is recorded in csv format and for the total of the 3 datasets the experiments span 86 days (approximately 2.8 months). The collective dataset is 6.55 GB. Transmission of the raw data would require approximately 76 MB of data to be wirelessly transmitted from one DAQ unit per day.

Table 3:7 - Measured parameters from IMS dataset on bearing vibration measurements.

No.	Measurement	No.	Measurement
1	Bearing 1 x axis	**5**	Bearing 1 y axis
2	Bearing 2 x axis	**6**	Bearing 2 y axis
3	Bearing 3 x axis	**7**	Bearing 3 y axis
4	Bearing 4 x axis	**8**	Bearing 4 y axis

For the configuration of the two DAQ units Table 3:8 presents the selected parameters. No thresholds were specified in this case as there was no available specification for the engine's pre-installed temperature sensor or the bearings. However, we have assumed that the bearings were in perfect condition at the beginning of every experiment according to the IMS dataset description file. Similarly, the engine is performing in good condition at the beginning of the experiment. Thus, reliability of 100% was assumed. The temperature was pre and post processed following the same format as the first case study (Section 3.3.3). The vibration data was pre and post processed according to the signal type data processing method (Section 3.2). Finally, the evaluation in this case study focused on DSS results.

Table 3:8 – Configuration settings for the second case study.

Parameter	Setting DAQ_1	Setting DAQ_2
Measurement	Temperature	Vibration
Type	Value	Signal
Encryption	Generated key	Generated key
Measurement site	CW Outlet Temp	See Table 3:7
Range maximum limit	-1	-1
Range minimum limit	0	0
Upper threshold	-1	-1
Lower threshold	-1	-1

The overall case study duration was approximately one day (8 hours). In this period the sleep state of the system was reduced to 0 seconds so that processing of the dataset would complete in a short time. The engine was periodically switched on and off. The reliability analysis tool used for the value type data could support two types of input. The first was the raw data stream, used in case studies detailed in Sections 3.3.3 and 3.3.4 and the temperature data of this case study. The second type of input was the current reliability value of a component which was used in this case study for the signal type data. The vibration analysis tool was used instead of the reliability analysis tool. The reliability analysis tool did not support sinusoidal signal inputs measured in the Time and Fourier domain. However, the reliability analysis tool supported reliability inputs. Hence, the calculated reliability from the vibration analysis tool was used as input to the reliability analysis tool to predict reliability degradation in a defined prediction period of 5 weeks. The predicted reliability output was used inputted to the DSS.

As the IMS dataset was 6.55 GB it was split. The data from the 1^{st} experiment was pre-processed and transmitted from one DAQ unit (8 signal type inputs). The data from the other two experiments were transmitted sequentially from the second DAQ unit (4 signal type inputs each time). The second DAQ unit was also physically connected to the temperature sensor of the engine thus recording a 5^{th} input signal of value type. The raw data recorded were 1.1 MB. Hence, collectively the raw data for this case study were 6.5511 GB. After pre-processing, 6.347 MB of data was transmitted over the wireless network; thus, 0.097% of the total data were transmitted after pre-processing.

For the temperature recorded from the main engine the correlation between raw and post-processed data had an R^2 value of 0.999 (evaluation as in the first case study). The reliability of the heat exchange system was predicted to drop from 100% to 99.3% in 5 months (Figure 3:37). Thus, no warning was generated by the DSS for this system. Also, no other component of this diesel engine was monitored. The engine was predicted to continue to operate in good condition for 5 months. The period of prediction was a user defined input of reliability analysis tool.

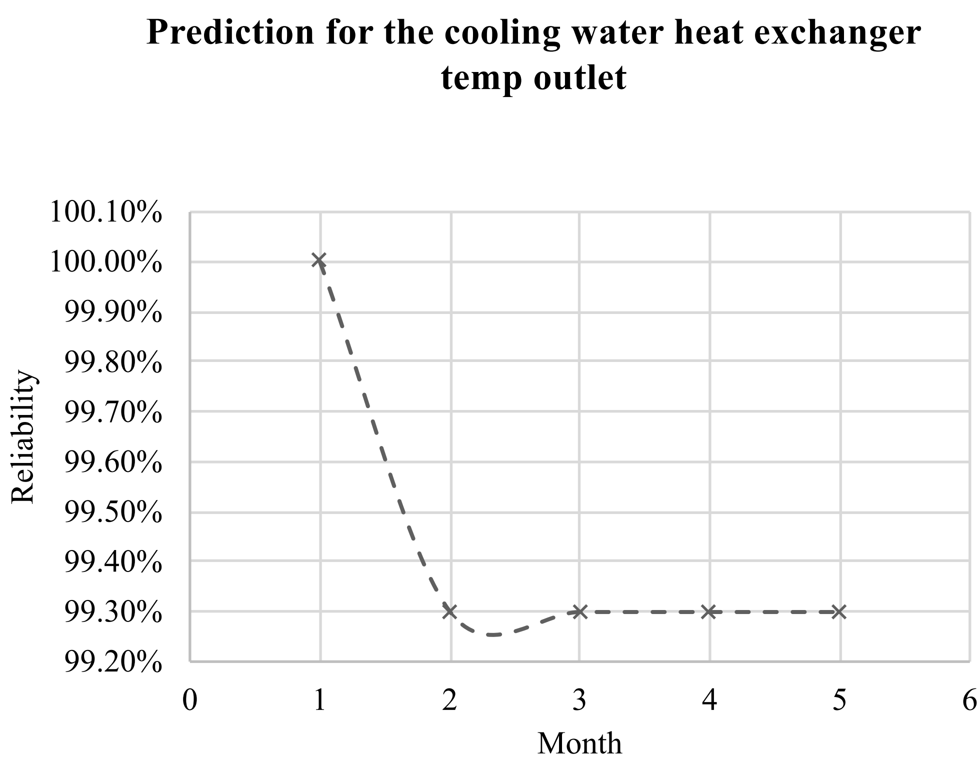


Figure 3:37 – Reliability analysis result for the recorded temperature sensor on the laboratory diesel engine.

The IMS dataset was examined for four different bearings that were unrelated. In that respect, the data was presented to the analysis tool and the DSS as independent components in independent systems. Thus, each of the bearings on each test was evaluated as an entity that was not affected by any other monitored component. This allowed the review the DSS and its capability to predict individual component warnings and/or failures.

The scatter plots presented in Figure 3:38 and Figure 3:39 map the pre-processing extracted features of the bearings in the first experiment of the IMS dataset to the corresponding calculated reliability output of the analysis tool. The extracted features were directly inputted to the vibration analysis tool sequentially as they were received; to comply with input requirements. Each point in the graph corresponds to the reliability calculated based on the synchronous measurement window. Each window corresponds to 10 minutes of vibration measurements. Thus, the horizontal axis presents the change of calculated reliability in time. The features extracted during pre-processing and presented in the graphs are: mean, standard deviation, variance, peak-to-peak and RMS.

Bearing 1 starts with 100% reliability and the last value reported is 91%. The reliability values for this bearing had a slight variation coinciding with the peaks of the standard deviation curve in plots (a) and (b) of Figure 3:38. It is evident that the information retrieved from the y-axis vibration did not provide additional information regarding the condition as the DSS results were identical for both x and y axis (no predicted warnings or failures). There was no reported failure or warning by the DSS for bearings 1 or 2 as expected according to the IMS dataset description (Table 3:6). The reliability of the second bearing deteriorated to 89% at the end of the experiment. Bearings 3 and 4 displayed a different behaviour and reliability degradation compared to the first two (Figure 3:39).

Bearing 3 displays a faster trend in degradation while the last value of reliability reported was 40%. Once again, the results between x and y axis vibration are very similar with the DSS identifying the same issues at the same points in time. In this case, the DSS predicted a warning (orange) and later a failure (red) which are both marked on the plot as vertical lines (Figure 3:39 a & b). The warning was detected 19 days before the end of the experiment while the failure predicted 8.6 days before the end of the experiment. A failure of Bearing 3 was recorded in the ISM dataset description (Table 3:6).

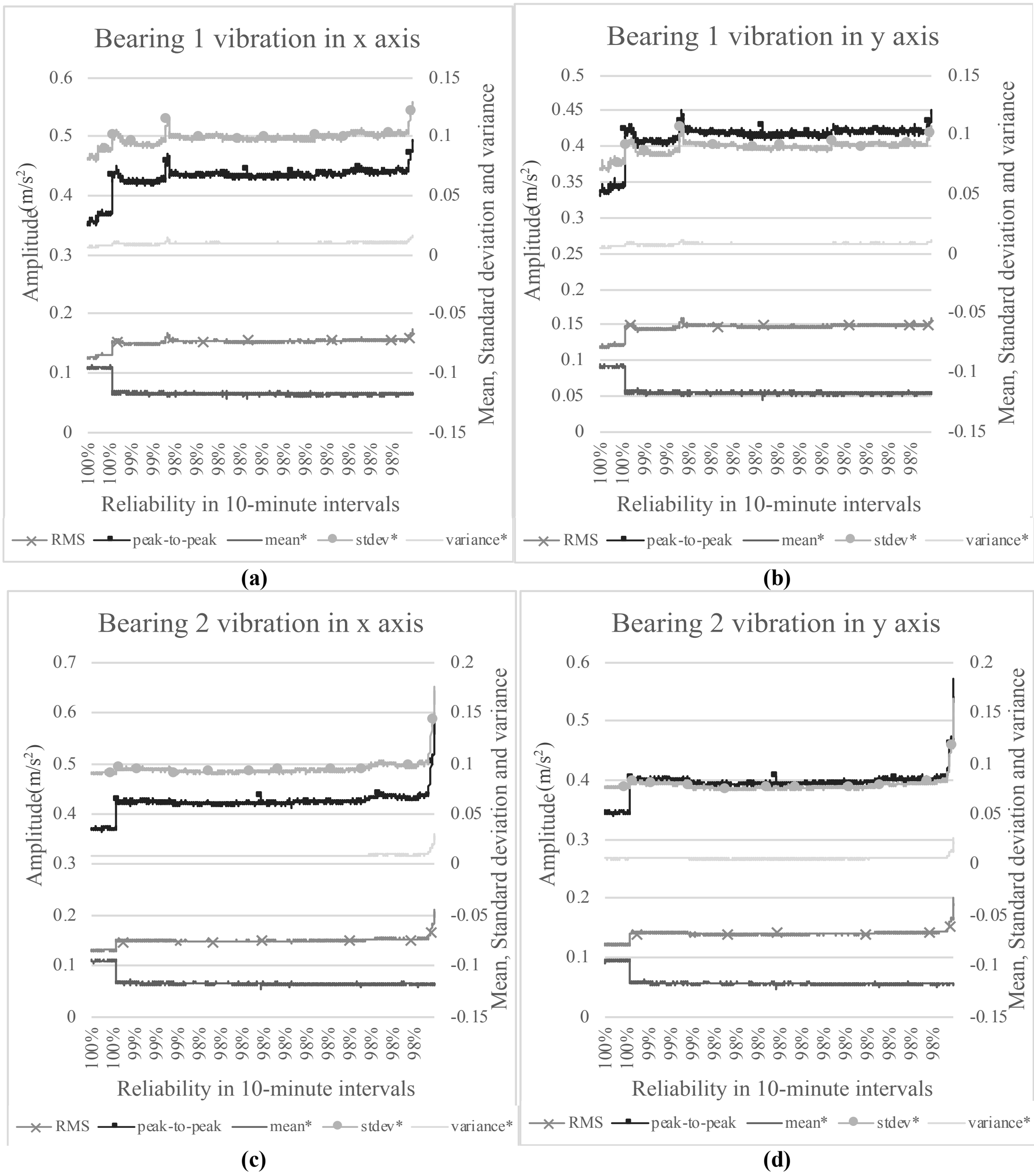
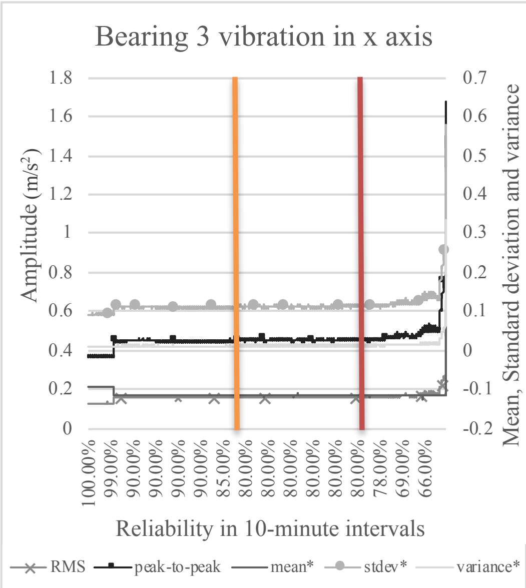


Figure 3:38 – Statistical properties results of pre-processing of bearings 1(a, b) and 2 (c, d) mapped to the reliability results of post-processing. Series marked with * in the legend are plotted on the secondary vertical axis (right side) while the remaining are plotted against the primary vertical axis (left side).

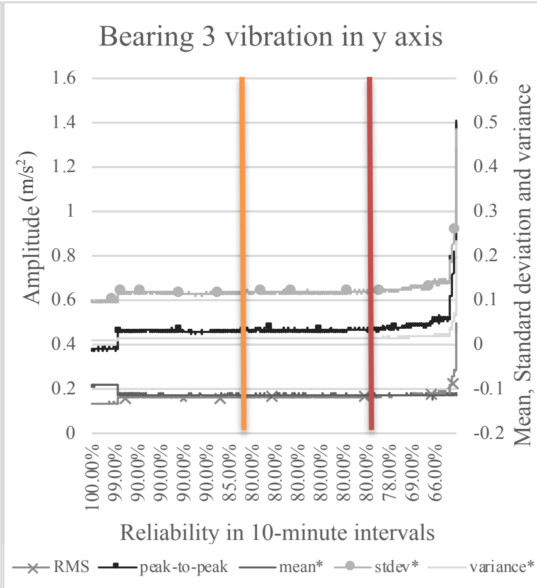
At the warning stage the DSS suggested the following actions in order of likelihood:

1) Check Bearing 3 for material wear and tear.
2) Check Bearing 3 for non-effective lubrication.
3) Check Bearing 3 for overheating.

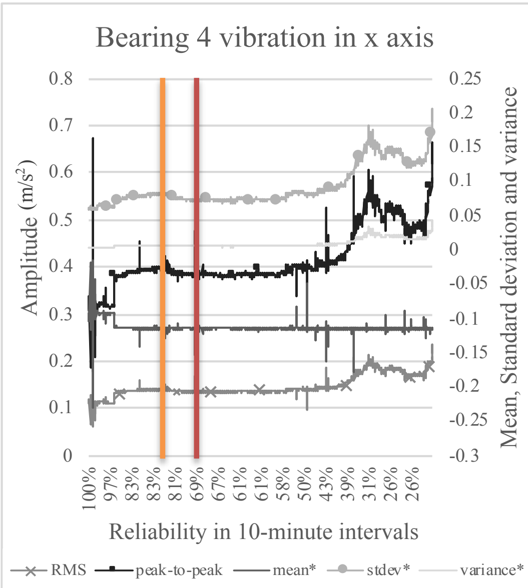
At the failure stage the DSS suggested that material wear and tear was the root cause for bearing 3 failing which was different to the actual cause reported in the ISM dataset. The cost associated with the warning stage was $2,000 for the asset, the cost of maintenance was $0[13] assuming engineers on the ship were trained to replace this component, and the cost of delay was $15,000 for one day assuming the main engine of the ship would need to stop operating for one day for the bearing to be replaced.



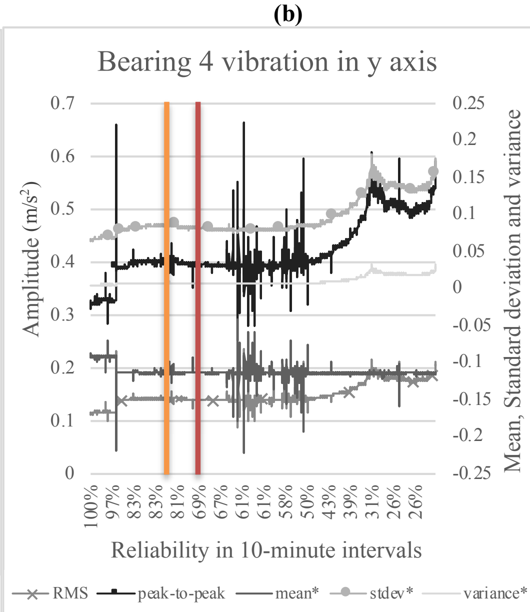
(a)



(b)



(c)



(d)

Figure 3:39 – Statistical properties results of pre-processing of bearings 3 (a, b) and 4 (c, d) mapped to the reliability results of post-processing. Series marked with * in the legend are plotted on the secondary vertical axis (right side) while the remaining are plotted against the primary vertical axis (left side). DSS warnings are vertical orange lines and DSS failures are vertical red lines.

There were no costs associated with environment, safety and performance. Hence,

---

[13] The cost of an engineer onboard performing a maintenance action is $0 as there is no added to cost to the ship operator. Thus, no expense to the maintenance budget. Assumption verified by ship engineers and operating companies during the development of the DSS (Michala et.al., 2015)

the identified condition of the bearing would result to a total cost $17,000 before the component could return to good operating condition.

Similarly to bearing 3, bearing 4 also displayed large variation in the reported statistical properties since the beginning of the experiment. This is the only bearing where the profile of the y axis is significantly different to the one on the x axis. There is significant difference in RMS, mean and peak-to-peak values reported during the experiment. In this case, the DSS predicted the warning 29 days before the end of the experiment and the failure 25 days before the end of the experiment for both x and y axis data. The costs in the warning stage were the same as those predicted for bearing 3. However, the actions suggested by the DSS were:

1) Check Bearing 4 for manufacturer defect
2) Check Bearing 4 for material wear and tear
3) Check Bearing 4 for non-effective lubrication

In both cases the DSS successfully identified that bearings 3 and 4 were not operating in good condition. Failure instead of defect was identified for bearing 3 as it demonstrated good operating condition at the beginning of the experiment. However, a defect was identified in the second case which was the expected outcome (Table 3:6).

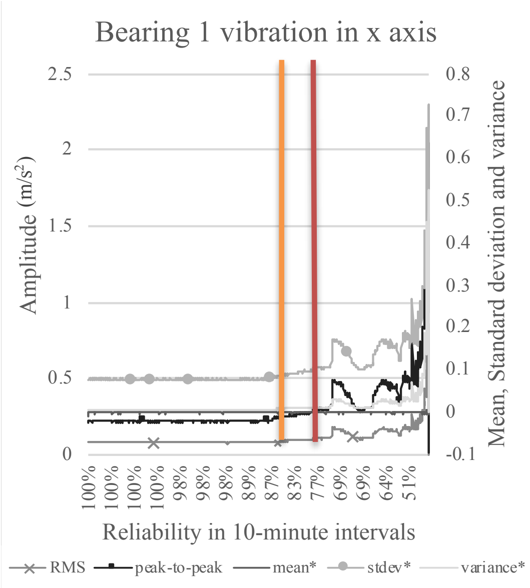
Additionally to the time domain extracted properties of the data, the frequency domain was analysed and frequencies with the highest amplitude reported. These were used to reconstruct the signal using the inverse FFT as injected points to the statistically reconstructed dataset. The statistical reconstruction followed the same process as in the previous case studies. Thus, the inverse FFT data points were added in the same manner as special events into the reconstructed stream. The correlation of the reconstructed data stream to the raw data stream is reported in Table 3:9. Evidently, there is greater loss of information in the case of vibration data compared to other case studies.

Table 3:9 – Correlation between raw and processed IMS dataset on bearing vibration measurements for experiment 1.

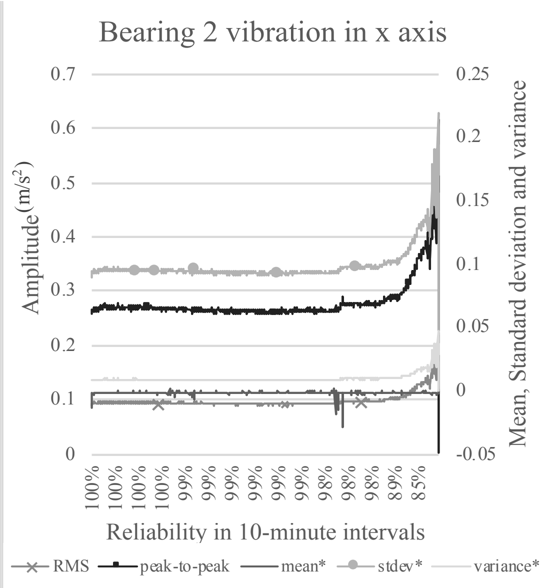
No.	Measurement	R^2
1	Bearing 1 x axis	0.899
2	Bearing 2 x axis	0.873
3	Bearing 3 x axis	0.799
4	Bearing 4 x axis	0.862

No.	Measurement	R^2
5	Bearing 1 y axis	0.901
6	Bearing 2 y axis	0.885
7	Bearing 3 y axis	0.907
8	Bearing 4 y axis	0.797

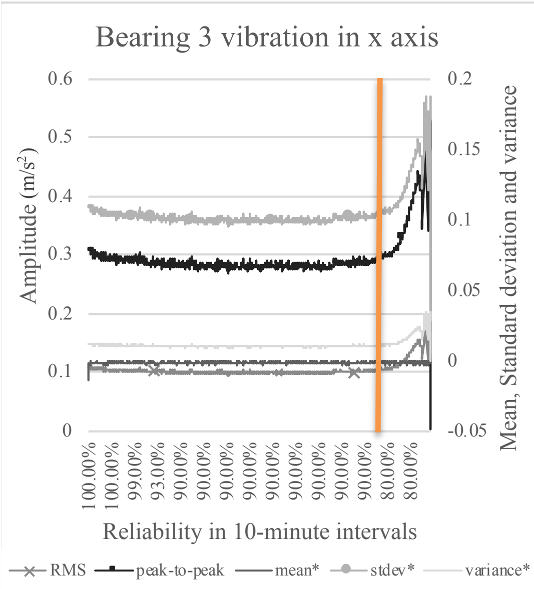
Extracted features for experiment 2 of the IMS dataset against the calculated reliability value are presented in Figure 3:40 and for the 3rd experiment in Figure 3:41.



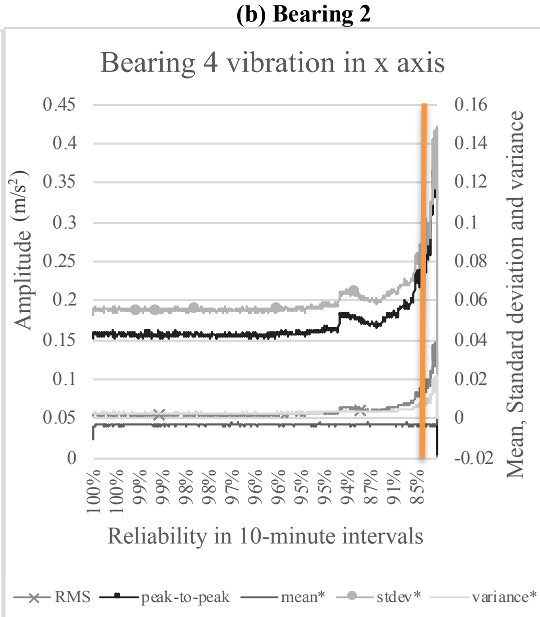
(a) Bearing 1



(b) Bearing 2



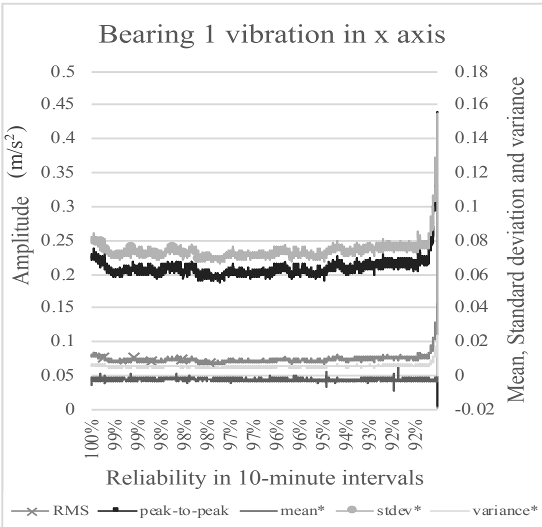
(c) Bearing 3



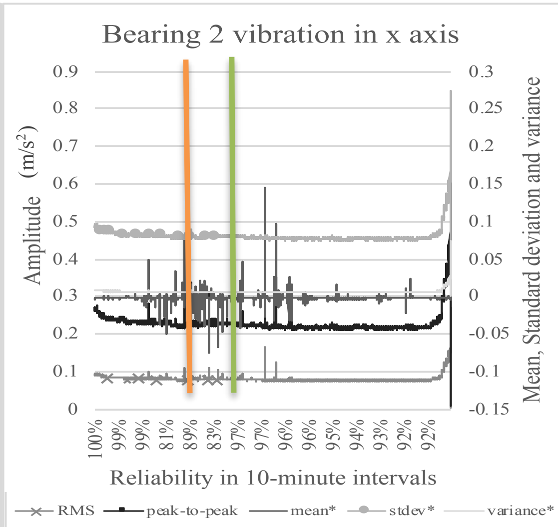
(d) Bearing 4

Figure 3:40 – Statistical properties results of pre-processing in experiment 2 mapped to the reliability results of post-processing. Series marked with * in the legend are plotted on the secondary vertical axis (right side) while the remaining are plotted against the primary vertical axis (left side). DSS warnings are vertical orange lines and DSS failures are vertical red lines.

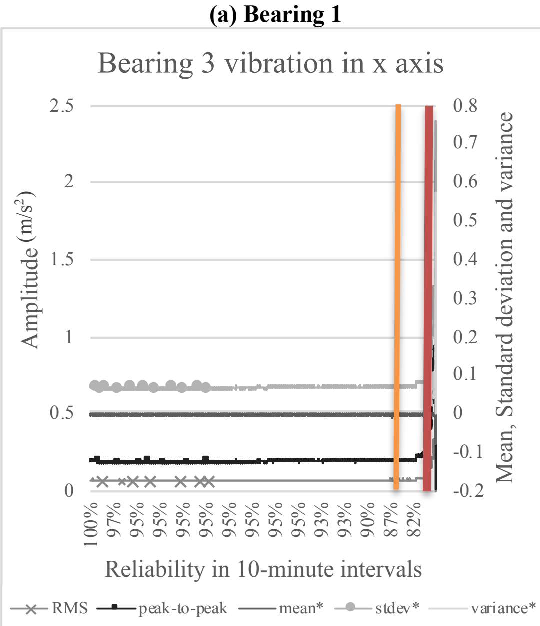
In the figures DSS outputs resulting from the predicted reliability are also presented. Warnings were predicted for Bearing 1, 3 and 4 of experiment 2. The suggested actions and cost presented by the DSS were the same as in the case of Bearing 3 in experiment 1 above. A failure was predicted for Bearing 1 which matched the expected in this experiment (Table 3:6). For bearings 3 and 4 a warning was raised towards the end of the experiment. No failures were raised for bearings 3 and 4 which is in line with the expected condition at the end of the IMS dataset. The warnings raised predict a potential failure of bearings 3 and 4 at the end of the 5 weeks prediction period. The experiment ends sooner than the 5 weeks prediction period. It is thus impossible to validate those two warnings against the actual condition of the bearing due to lack of data to cover the full prediction period after the warning was raised. Inspection of the data can indicate that the condition of the bearing is deteriorating as there is rising trend of the peak-to-peak amplitude and standard deviation for both bearings towards the end of the experiment.



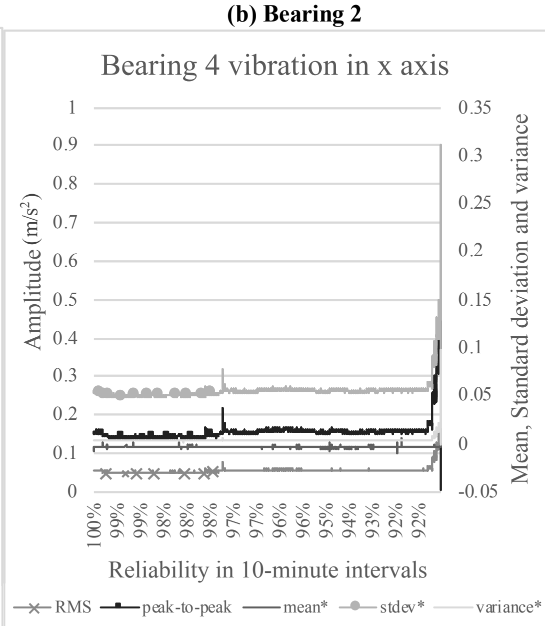
(a) Bearing 1



(b) Bearing 2



(c) Bearing 3



(d) Bearing 4

Figure 3:41 – Statistical properties results of pre-processing in experiment 3 mapped to the reliability results of post-processing. Series marked with * in the legend are plotted on the secondary vertical axis (right side) while the remaining are plotted against the primary vertical axis (left side). DSS warnings are vertical orange lines and DSS failures are vertical red lines. Vertical green lines signify lifted warning/failure state.

For the 3rd experiment a warning was produced for Bearing 2 which was however later removed as the reliability of the bearing increased. As the warning was removed, the bearing was predicted to be in good operating condition at the end of the experiment which is in line with the recorded ISM dataset condition. Bearings 1 and 4 were also predicted to be in good operating condition; as expected (Table 3:6). Bearing 3 raised a warning just 9 days before the end of the experiment which was raised to failure only 2 days before the end of the experiment. In that respect, the failure was correctly identified (Table 3:6) but there was no significant warning period ahead of the failure.

Overall all the failures reported in the ISM end of experiment condition were identified successfully for all three experiments. The experiment completed without the DSS raising failures for any of the bearings that were expected to be in good condition. This validates the DSS as false positives/negatives were not identified. A warning was raised and consecutively removed for a bearing that was expected to complete the experiment in good operating condition. Two additional warnings were raised that were not reported in the ISM results. These two warnings could not be validated as additional data would be required; for a failure to be raised or for the warning to be removed.

The correlation between raw and regenerated signals for the 2nd experiment of the IMS dataset is presented in Table 3:10. For the 3rd experiment, Table 3:11 presents the correlation analysis results.

Table 3:10 – Correlation between raw and processed IMS dataset on bearing vibration measurements for experiment 2.

No.	Measurement	R^2	No.	Measurement	R^2
1	Bearing 1 x axis	0.778	3	Bearing 3 x axis	0.941
2	Bearing 2 x axis	0.934	4	Bearing 4 x axis	0.905

Based on the reported R^2 values it is evident that method used for compression of the volume resulted in a higher error margin. In most cases the error is approximately 10% and, in a few occasions, rises to approximately 20%. Thus, the selected method cannot reconstruct the original vibration raw dataset with high fidelity. This renders the approach inappropriate for use with analysis tools that require a lower error margin such as ANNs. However, this error margin did not affect the decision-making process. As demonstrated above the DSS results matched the expected ISM end of experiment reported condition of all bearings regardless of the loss of information.

Table 3:11 – Correlation between raw and processed IMS dataset on bearing vibration measurements for experiment 3.

No.	Measurement	R^2	No.	Measurement	R^2
1	Bearing 1 x axis	0.892	3	Bearing 3 x axis	0.926
2	Bearing 2 x axis	0.797	4	Bearing 4 x axis	0.916

3.4 Business Case Evaluation

The maintenance of vessels is one of the largest operational costs (Section 1.1). The cost effectiveness of CM systems is well documented (DeMott, 1978a, 1978b). Holroyd (2015) support that deterioration to a gearbox was identified in advanced of the pre-scheduled maintenance period saving the operator an estimated $150,000. This cost would have accumulated through parts, replacement actions, unplanned stoppage and unexpected production disruption. The last two are the highest. Also, they present a second case study of an actual bearing failure of an anchor recovery system leading to a cost of $100,000. Other costs such as environmental damage fines can occur. For example, 35,224,000 litres of crude oil were spilled in the ocean in 2003 due to various incidents involving tanker ships (Devanney, 2010). The cost of repair is but a small contributor to the expenses associated with the event. The cost due to lost productivity, initiated through a failure of equipment, rises with criticality as presented in Figure 3:42 (SKF, 2016).

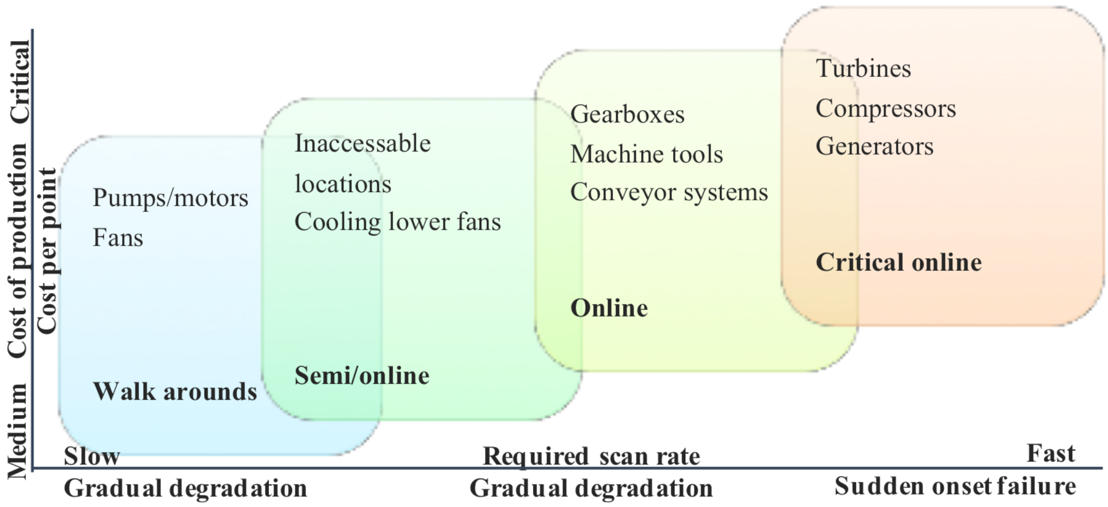


Figure 3:42 – Cost of loss of productivity against machinery/equipment criticality, adapted from SKF (2016).

Several authors have documented the cost benefit through avoidance of unnecessary maintenance and better scheduling (Shin and Jun, 2015, Schwabacher, 2005). According to Shin and Jun (2015), a wide spread use of CM can result in $35 billion savings for the industry. Other indirect cost savings, or benefits, can be drawn from improved productivity (Prajapati et al., 2012). However, the capital cost of implementation and staff training must be taken into account (SKF, 2012b). To perform a cost benefit analysis the benefits must be identified and categorised. As this thesis proposes a CM system the benefits of CM versus non-CM will be reviewed. Then as the proposed system is an advancement of the current state-of-the-art in ship CM applications, the benefits versus existing approaches will be presented in this section.

The benefits of CM to the shipping industry[14] have already been discussed (Chapter 1) and are:

- increase in business value and strategic positioning (DNV GL, 2014)
- reduction in risk and uncertanty, better management of tolerable risk, and overall increased employee satisfaction
- better compliance with health and safety regulations and adhere to environmental regulations (EMSA, 2017, 2015, Logan, 2015, Takata et al., 2004)
- better audit trails for maintenance and operation activities adhering to corporate standards.
- reduction of cost and maintenance budget (Moore Stephens LLP, 2015, Michala et al., 2015, Greiner, 2014)
- effective utilisation of maintenance personnel and assets (DNV GL, 2014)
- effective maintenance planning
- reduced working capital
- inventory requirements and spare part planning
- better supplier, procurement and warranty management
- energy efficiency (Michala et al., 2015, Kara et al., 2015, Logan, 2015, Panagakos et al., 2015) through Slow steaming, lower-cost fuel and improving operational efficiency (Psaraftis and Kontovas, 2015).

---

[14] MICHALA, A. L., LAZAKIS I. & THEOTOKATOS, G. 2015. ‘Predictive maintenance decision support system for enhanced energy efficiency of ship machinery’, *International Conference of Shipping in Changing Climates 2015 Conference proceedings, 24-26 November 2015*, Glasgow.

- support reductions in CO_2 emissions (Panagakos et al., 2015, ECSA, 2012, Webster, 2001)., EC (2011), (Diakaki et al., 2015, Kara et al., 2015).
- effective performance

Similar findings have been reported in several industries (De Giovanni and Esposito Vinzi, 2014, de Azevedo et al., 2016, Eker et al., 2015, Kara et al., 2015, Haque et al., 2015, The British Institute of Non-Destructive Testing, 2015, Lees, 2015). In the following paragraphs, two of the most important direct cost benefits will be further analysed. The benefits of appropriate CM implementation, as has been demonstrated in other industries (Tourvalis, 2007, DNV GL, 2014, DeMott, 1978a). However, for the successful implementation of CM the full business cycle needs to be adjusted to guarantee maximum benefits (DNV GL, 2014).

Wireless installations have been praised for their cost benefits by several authors (Feng et al., 2015, Ralston, 2007). Particularly, Colpo and Mols (2011) identify that the installation costs of wireless systems in industrial applications can be 50% – 90% lower than an equivalent wired installation. According to Katsikas (2013), a wireless commercial system in the same category as the one proposed in this thesis (LAROS), is reported to have 50% cost reduction from installation alone. The unit cost of the LAROS system is not publicly available, so a direct comparison was not possible. A further cost reduction is expected due to low maintenance costs such as automated firmware updates, available for commodity hardware such as the BBB (JaeHyuk et al., 2013). The benefits of using wireless networks for CM on ships are:

- *immediate savings on installation and wiring costs (Feng et al., 2015, Mehta and Reddy, 2015, Ralston, 2007), including acquiring the materials, the careful planning for cable lay, connection, setup, and infrastructure (such as junction boxes, termination panels, network connection documentation etc.).*
- *reduced dry-docking time and labour and ship availability is minimally perturbed.*
- *removing the need for installing power supply cables.*
- *short commissioning time before on-ship installation.*
- *installation and maintenance of the network is much more straightforward.*

- *more resilient to the effects of noise, path obstruction and technical failures due to dynamic routing (Mehta and Reddy, 2015).*
- *availability, and scalability, as no additional effort is required to introduce new nodes to the system at a later date, at no extra overhead for re-commissioning.*
- *installed in difficult to access areas, enhancing safety compliance (Myhre et al., 2014).*
- *increases the energy efficiency of the solution and reduces the carbon footprint for the business.*

The following analysis will take into account the work presented by Katsikas et al. (2014), JaeHyuk et al. (2013) and Ralston (2007) in combination with the benefits of CM and Wireless Transmission. Table 3:12 presents a summary of the benefits of wireless compared to wired systems.

Table 3:12 – Summary of wireless network benefits.

	Benefits		Benefits cont.
1	Savings on wiring costs	**7**	Reduced power need
2	Reduced dry-docking	**8**	No electrical installation requirement
3	Savings on installation and labour	**9**	Short commission time
4	Less training for installation	**10**	No additional infrastructure
5	Dynamic routing	**11**	High resilience to failures
6	Scalability	**12**	Can be installed in difficult to access areas

There are also other unquantifiable benefits that were not included in the following cost/benefit analysis for simplicity and to reduce the amount of assumptions made. Unexpected failures even though not often recorded, can have a disruptive effect on the business model and reduce or eliminate the profit margin of a company for a given ship at a specific journey (Rofle, 2015). Moreover, an unplanned failure often links to other maintenance costs as side-effects of the failure. A 10% – 15 % reduction of this "consequential loss" can be achieved through CM according to the same author. Reduced dependence on the onboard crew is another unquantifiable benefit as the shore-based personnel can have a thorough knowledge of the ship's condition at any point in time. In that respect, personnel retention rates have no effect on condition.

Another indirect benefit is in the ordering parts planning process. In the event of an unexpected failure, a certain part may require several days from the order being placed to it arriving at the ship. This process adds costs for the company and unnecessary delays (Wingrove, 2016).

Other benefits such as better compliance to health and safety regulations, better management of tolerable risk, better supply/procurement/warrantee management were not included in the CM versus non-CM analysis as it was difficult to assign monetary values to each. Long term benefits include better performance, better operating condition, business growth, strategic maintenance planning, spare part management, better compliance with health/safety requirements, and reduced incident/casualty records. Other costs such as penalties due to delays and contractual agreements, insurance, accident and emergency costs can be also significantly reduced, if not eliminated.

3.4.1 Cost Benefit Analysis

The following analysis was based on benefits and on prices available from literature reviewed in the earlier sections of this chapter. A total of 9 DAQ units were assumed to cover the most important systems and subsystems identified in Section 1.1.2. Moreover, the cost of sensors was not considered as most machinery have pre-installed sensors. Some of the estimates such as the cost of installation are based on assumptions which are worst-case-scenario. For example, the installation of the system could be performed while the ship is sailing with the engineer working at times that the ship is in port and thus, further reduce the cost in Table 3:13.

Table 3:13 – Costs associated with adoption of proposed CM method.

Description	Cost within 12 months
DAQ unit cost	£107
Collector point	£40
Software cost	£0
Sensor cost (assuming existing sensors)	£0
Internet usage on ship/vessel (Adamson, 2016a)	£14,800 (0.82£/$)
Cost of installation (assuming one day stoppage)	£50,000
Staff training (onboard short courses max 2 hours/engineer)	£0
Trainer fees (training videos & mooc courses)	£0
Software support (assumed commercial arrangement)	£5,000
Total cost (assuming 9 units)	**$86,100 (£70,803)**
Total cost of hardware/software/support (9 units)	**$7293 (£6003)**

In comparison to not using a CM method, the cost benefit analysis payback is calculated through dividing the total cost presented in Table 3:13 by the total benefit of adopting the proposed system or any other CM approach in Table 3:14. This payback is 0.59 rounded down years; equal to 7.13 months without the rounding error. Adopting the system for a ship that is currently not utilising any CM approach can provide a return on investment within 7.13 months of its installation.

Table 3:14 – Benefits of adopting the proposed CM method over non-CM methods.

Description	Benefit (12 months)
Reduced unexpected stoppage (one failure) (Holroyd, 2015)	$100,000
Reduced failures & maintenance (40%), fuel consumption (8%) (Katsikas et al., 2014)	$40,880
Reduced communication over telephone and email (approximation based on 10% reduction) (Adamson, 2016a, Katsikas et al., 2014)	$4000
Total	**$144,880**

Assuming that sensors would need to be purchased and installed would increase the total cost by $5,400 but still would provide a return on investment of 7.58 months. After this period, the cost would be significantly reduced to support and maintenance of the system alone and the benefit for the company would continue to rise annually.

This analysis has assumed one unexpected failure in one year. However, the current average failure rate per ship per year across all strategies is reported to be 1×10^{-4} for major failures that could result to stoppage (HSE, 2012). Even taking that into account, the cost of unexpected stoppage in the first 12 months would be $10 and the payback period 1 year and 11 months which is still a small period of time compared to the operational life-time of the vessel considering an annual $44,890 benefit throughout this period.

A secondary comparison is made here with other CM methods. In this analysis, the cost of adopting the system is presented in Table 3:13 ($7,293). The cost is divided by the total benefit over utilising any alternative wired CM method presented in Table 3:15 ($377,250). The overall payback period was calculated to be 0.23 months rounded down; 7.19 days without the rounding error.

Table 3:15 – Benefits of adopting the proposed CM method over other CM methods.

Description	Benefit (12 months)
Savings on installation and wiring costs (network and power) (50%)	$50,000
Savings on equipment cost and software support	$183,250
Reduced dry-docking/commission time (commission in advance)	$100,000
Reduced power consumption (this is negligible over the period)	$0
Reduced training (free of cost training)	$25,000
No additional infrastructure (cost for routers etc.)	$1000
High resilience to failures (healing)	$0(operational cost)
Scalability (only cost of additional DAQ unit – no other cost)	$18,000
Total	**$377,250**

No data was available for the cost of existing CM solutions for ships to the best of the author's knowledge. For that reason, an estimation of the cost was based on two existing CM systems, and capital and operational costs reported. The first is a CM system for an offshore wind farm estimated at an average of £306,500 (May et al., 2015) and the second is the cost of an online CM of electrical power transformers cost at £60,000 (Kim et al., 2005). These were selected as upper and lower limits. The upper limit was selected because it is retrofitted, applicable to large machinery comparable to those on a ship, and includes costs for transporting the equipment to a remote location installing under extreme conditions. The lower limit was selected as dictated by sensitivity analysis methods to mitigate any overestimation. The average translated to dollars is $183,250. Furthermore, some systems require the ship to be at dry-docking or at major refitting for installation of a full wired network. In that respect, the cost was estimated based on an average $50,000 cost of 1 day out of operation and a total of 2 days was assumed for this work to take place. Additionally, a half day as equivalent to employee man-hours was assumed for training. Finally, the cost of scalability is variable depending on the extent of work that is required and a 10% of the initial operation and capital investment cost was assumed to cover this amount.

Chapter 4: Discussion

This chapter presents the discussion of the findings of the previous chapters. The first section is the evaluation of the system based on the results of the previous chapter and the outcomes of the literature review and methodology chapters. In Section 4.2 the proposed system, its impact and its feasibility to address the research question are elaborated as well as the impact on sector business based on the findings of Chapter 3 in conjunction with Chapter 1. Section 4.3 compares the proposed approach to other commercial systems. Finally, Section 4.4 provides an overview of the transferability of the research to other domains, the limitations and threats to validity.

4.1 System Performance

The proposed system was developed to accommodate temperature, pressure and vibration sensors for CM onboard ships, utilising commercially available sensors. These measurements were identified as sufficient for CM on ships (Chapter 1). Critical equipment and machinery components, systems and sub-systems were identified as the ideal targets. Industrially rated RF communications were used as optical, and ultrasound were either too primitive or too unreliable for use within the engine room. Moreover, there is little Wi-Fi interference onboard which limits the obstructions to performance. The system can handle multiple sensor inputs simultaneously which differentiates it from other existing ship CM approaches. Processing at the edge of the network increases scalability, robustness and reliability of the system while addressing the need for reduced data transfer rates.

The DSS system utilises multiple sources of information to immediately suggest actions onboard the vessel, or actions that can be performed in the future. This depends on the length of prediction period. The GUI was developed based on feedback acquired during workshops, conferences and meetings. This feedback refined the GUI and supported the usability of the system[15].

In the first case study, several events were successfully generated, and there was a

---

[15] LAZAKIS, I., DIKIS, K., MICHALA, A.L. & THEOTOKATOS, G. 2017. 'Advanced Ship Systems Condition Monitoring for Enhanced Inspection, Maintenance and Decision Making in Ship Operations', *Transportation Research Procedia*, 14, 1679–1688.
DIKIS, K., LAZAKIS, I., MICHALA, A.L., RAPTODIMOS, Y. & THEOTOKATOS, G. 2016. 'Dynamic risk and reliability assessment for ship machinery decision making', *European Safety and Reliability Conference, 25-29 September 2016,* Glasgow.

LAZAKIS, I., DIKIS K. & MICHALA, A. L. 2016. 'Condition Monitoring for Enhanced Inspection, Maintenance and Decision Making in Ship Operations', *Proceedings of the 13th International Symposium on Practical Design of Ships and Other Floating Structures, 4-8 September 2016*, Copenhagen.

MICHALA, A. L., LAZAKIS, I., THEOTOKATOS, G. & VARELAS, T. 2016. 'Wireless condition monitoring for ship applications', *The Royal Institution of Naval Architects Smart Ship Technology proceedings, 26-27 January 2016*, London.

MICHALA, A. L., LAZAKIS I. & THEOTOKATOS, G. 2015. 'Predictive maintenance decision support system for enhanced energy efficiency of ship machinery', *International Conference of Shipping in Changing Climates 2015 Conference proceedings, 24-26 November 2015*, Glasgow.

DIKIS, K., LAZAKIS I. & MICHALA, A. L. 2015. 'D4.5 (WP4): Architecture, framework and development of Decision Support System', *Inspection Capabilities for Enhanced Ship Safety Consortium*, EC FP 7 (FP7/2007-2013). Grant Agreement No 605200.

significant variation in the raw input data. Utilising the events appropriately, the resulting dataset closely follows the raw dataset (correlation with $R^2 = 0.99998$). Hence, the validity of the processing feature and event extraction algorithms for time domain inputs and methodology is proven. Moreover, the reliability analysis tool produced similar results for both datasets (1% difference in the last point of the prediction curve). In that respect, the information provided to the reliability analysis tool can be considered identical as the difference is not statistically relevant (R^2 between the two reliability prediction curves was 0.989). In both cases, the predicted reliability followed the expected trend as deterioration occurs over time. However, when the events were not considered, depending on the particular input, the curve demonstrated a rising reliability trend which is against expectation. This was due to limitations on of the reliability analysis tool. Thus, events are of paramount importance, so that post-processing does not input false data to the reliability analysis and DSS tools. The appropriate use of events can eliminate such inputs and thus unreliable results. The algorithm that generates events is independent from the processing algorithm. As a result, the DAQ can support new algorithms for the generation of events on demand. Hence, the system has the added advantage of flexibility. Further, if the event was not generated to warn the DSS that this equipment is not operating, a failure would have been identified. Thus, the incorporation of events provides benefits not only to data management so that the processed data correlated well with the raw measurements, but also to the analysis and decision suggestion parts of the system. In this case study, it was demonstrated that reduction of the transmitted information does not result in any loss of information, particularly when events can be captured[16].

The second case study demonstrated the suitability of the volume reduction and the wireless transmission mechanism for operation within an engine room environment. The performance of the network was highly satisfactory under load. The QoS evaluation provides evidence for the appropriateness of the utilised method for transmitting CM information. Overall, 90.53% of data transmissions were successful in first attempt. Thus, bottlenecks due to repeated send attempts were avoided rendering dealy

---

[16] MICHALA, A. L. & LAZAKIS, I. 2016. 'Ship machinery and equipment wireless condition monitoring system', *Proceedings of the International Conference of Maritime Safety and Operations, 13-14 October 2016, University of Strathclyde, Glasgow*, ISBN No 978-1-909522-16-9, 63-69.

tollerant networking appropriate for the system. All packets were guaranteed to be received (Acknowledgement mechasnism), so any gaps in data stream could only be generated by a failure of the DAQ unit. In this case an event is also generated to mark the gap in the data stream. As a result, the information extraction tool can easily identify incomplete datasets and avoid issues affecting the predictive outcome. Additionally, the ability of the system to transmit such a large proportion of packets on the first attempt demonstrates that interference is not significantly affecting the DAQ units. As a result, the proposed approach is a valid alternative to networks of individual measurement acquisition units. These units serve a single sensor and as demonstrated in Figure 3:33 it would be impossible to support the amount of data generated by several sensors simultaneously in a WMNs network without generating network issues.

Further in the second case study the correlation of the raw dataset and the post-processed dataset was evaluated. In every case R^2 was either 1 or statistically insignificantly away from 1. The worst case was identified to have R^2=0.998 (Figure 3:36a), possibly due to the nature of this dataset, but it was still not statistically significant. Finally, there is an increase in correlation, compared to the first case study when events were not enabled. This increase was attributed to the use of events[17].

As no warnings or failures were identified by the DSS in this case study, no actions were suggested and resulting operating costs were not calculated. This was due to the data streams being sourced from a new ship under excellent operating condition. Thus, it was reasonable that no failures would be identified within the time limits of the prediction. However, this demonstrates the ability of the DSS to recognises highly reliable operating states of the monitored equipment/machinery and successfully predict that the system will continue to operate in good condition. Also, due to the presence of events, the data points near zero were not sent to the reliability analysis tool; preventing the system from raising false positives or negatives.

The third case study focused on proving the validity of data measurements through

---

[17] MICHALA, A. L. & VOURGANAS, I. 2017. 'A Smart Modular Wireless System for Condition Monitoring Data Acquisition', *Proceedings of the 16th International Conference on Computer and IT Applications in the Maritime Industries, Cardiff, 15-17 May 2017*, Technische Universität Hamburg, Harburg, ISBN 978-3-89220-701-6, 212-225.

recording the laboratory diesel engine cooling water temperature outlet of the heat exchanger. The recorded raw dataset was within the expected range for the engine as specified in the datasheet. Moreover, the data recorded was used for the validation of the processing method against the reconstructed signal which was verified by the correlation results ($R^2 = 0.999$).

Additionally, the third case study verified the capability of the system to process both data types simultaneously (time and time-frequency domain). This was achieved by processing both types on the same DAQ unit. No synchronisation or other issues were identified in this case study while executing both types of processing algorithms in parallel. Both signal types displayed good correlation between collected and processed datasets which verifies the operation of the system. However, the vibration measurements displayed larger correlation error making the proposed pre-processing algorithm an unsuitable back-end for some analysis tools. Finally, this case study verifies the vibration processing and validates the DSS methodology by comparing the results of the DSS to the original DSS version and the recorded (expected) failures of the IMS dataset.

According to the results presented in Section 3.5, the DSS successfully reported warnings and failures in advance of their occurrence for every expected failure. The DSS also successfully did not predict a failure where a failure was not expected. The root cause was not identified in experiment 1 bearing 3 (wear and tear was suggested instead of defect). But a warning and failure were correctly identified. All other failures were identified as expected based on the IMS dataset description.

In experiments 1 and 2, warnings of the expected failures were first identified approximately at the middle of the experiment or even earlier. This means that the issue was predicted before the bearing had gone through half of the revolutions expected by the manufacturer as useful life-time of the bearing. However, in experiment 3, bearing 3, a warning was raised just 9 days before end of experiment. So, not sufficient warning time-to-failure was given. In experiment 2, two more warnings were raised that did not match the IMS dataset reported failures but did not escalate to failure (as expected). Also, in experiment 1 one unexpected warning (not corresponding to an IMS reported failure) would have been raised if the experiment was allowed to run longer; based on the recorded data trend. These warnings could not have been verified due to lack of further data. The same warnings were raised by the original DSS. Also, they were all running in excess of their useful life-time so any failure at that stage would have been expected at any moment according to the manufacturer. Additionally, in experiment 3, bearing 2 produced a warning which was then removed as the data provided higher reliability values. No action was selected in the DSS as taken, so the order of future suggested actions was not affected. The final result was consistent with the expected condition of the bearing at the end of the experiment.

The DSS predicted a total cost of $17,000 for each bearing; this cost was calculated based on the effect of the predicted failure to the system, its maintenance, and the effect on operational costs. This is because all bearings were assumed to be in the same position in the system and no other components of the affected equipment were being monitored. Thus, the cost of this failure was not affected by predicted warnings on other parts of the monitored machinery/equipment. The actions suggested by the DSS were validated against the original list of actions for deterioration in bearings (as supplied by a shipping company maintenance department – Chapter 3). While the prioritisation is different due to the additional constraints, the suggested actions are still within those identified by the experts.

For this case study, 0.097% of data was transmitted over the communication network. Only the spectrum components that were within the top 1% margin from the component with the maximum amplitude were transmitted from the Fourier domain. Greater information loss was identified compared to value type with worst case R^2 in experiment 1 equal to 0.797, in experiment 2 equal to 0.778, and in experiment 3 equal to 0.797. Overall, the worst case of information loss had a correlation of 0.778 between the processed and raw datasets. Even with this low correlation value the DSS was able to correctly identify and predict the operational condition of the bearing. A final observation in this case study was that the y-axis vibration (i) gave no additional information in terms of DSS output in any case as the DSS output did not differ between x and y axis data for the same bearing and (ii) it provided different statistical properties in only one case.

The third case study further strengthens the validity of the data processing method. Moreover, it proves the ability of the system to handle two different data stream types simultaneously. Finally, the results of the comparative analysis for the two DSS systems support its validity and suitability.

Finally, through the case studies, it is demonstrated that the pre and post processing units cooperate to allow the user of the system to deploy alternative feature extraction tools according to the needs of the company. They cooperate to successfully eliminate compatibility issues between DAQ and any information extraction strategy, as proven through the case on the reliability analysis tool. Currently the system components have been developed to TRL6 according to the classification of the UK parliament[18].

The presented research achieves reduction of the transmitted data that is comparable to lossy compression. Transmitted data volume was reduced by 1 order of magnitude for value type data which is equal to CM data state-of-the-art compression algorithms (Kwan and Luk, 2018). For vibration data, volume reduction of 3 orders of magnitude was achieved which is higher than any reported compression algorithm. However, the proposed approach has one order of magnitude higher error margin compared to compression algorithms. The processing capacity at the edge was not exhausted during data compression while events were also generated through a single computation applied to each input measurement.

4.2 System Impact

The proposed approach advances ship CM within the identified constrains, does not compromise the decision-making process and advances edge processing research through demonstrating analytics at 0 hops from the data acquisition point using portable algorithms. The thesis addresses the identified gap in current literature. As applied research the work presented in this thesis advances the technical results reported in literature in the performance and suitability of wireless networks in shipping CM. The proposed system further advances the research in edge computing by extending the known work to processing directly on the data collecting device in the shipping domain.

Through the results presented in Chapter 3 and the system evaluation presented in Section 5.1 of this Chapter, it is apparent that the proposed system is suitable to edge

[18] https://publications.parliament.uk/pa/cm201011/cmselect/cmsctech/619/61913.htm

process and transmit equipment and machinery condition monitoring data wirelessly onboard a ship. Also, the minimum requirement for recording data was identified as the extracted features instead of the raw data, along with the generated events that characterise changes in the data patterns. As these can be combined to re-generate the raw data, there is no significant loss of information as there was no observed compromise of the decision-making process. Thus, the first aim of the thesis was addressed.

The system is based on an extension of the edge processing paradigm while utilising commodity hardware at the specific environment and constrained context. The distributed, scalable and adaptable nature of the feature extraction along with the capability of regenerating the information for further processing provides a unique system for managing big data generated through CM sensors. The system is suitable for the versatility of the application environment and can adapt to perform other computation on the edge of the network. Thus, providing a platform for further development. Finally, the multiple-parameter multiple-constrain approach for the DSS system contributes to the proposed methodology. As a result, the objectives of this thesis were addressed through the proposition of the system hardware-software co-design investigation, the methodology and algorithms developed, the suitability evaluation and the cost effectiveness analysis. The reliability and usability of the DSS system is evidence towards the minimisation of training requirements. The system's contribution to knowledge comes from the evaluation of this system for suitability and use within the harsh environment of the ship's engine room.

The system addresses the identified gap in literature providing wireless data transfer of extracted features with very low network overheads, minimising the amount of data transmitted. This enhances significantly the reliability and scalability of the system beyond the limitations of existing CM approaches in shipping. At the same time, it is proven to be cost effective and requires minimal initial training due to the DSS system. Additionally, the DSS system addresses the need of efficient maintenance action decision making software that was identified through the literature review.

The shipping industry is lagging behind developments in monitoring and analytics. Computerised systems are superior to human inspection in identifying failures very early. But current systems are not well adopted by the industry. As presented through the previous chapters as well as Section 5.1 the proposed system meets all of the requirements identified in Section 2.3 (Figure 2:2). The design considerations identified in Chapter 2 were addressing the industry needs and requirements as presented in Figure 2:4. As a result, this approach can increase the adoption of CM in the existing global fleet.

The impact to stakeholders was presented in Section 1.9 and the benefits of the developed system analysed in Chapter 3. In summary, the selected CM approach results in reduction of failures, business target management, reduction of human error, maintenance of higher quality, and reduction of maintenance cost. Even though exhaustive CM is not necessary, critical machinery/equipment monitoring is required for the successful application of the proposed method. The DAQ units can provide significant coverage of the critical system monitoring requirements of any ship; leading to less maintenance at sea, no need for permanent crew that has experience on the particular vessel, better performance and condition of ship, reduction of risk, better emission management, and increased availability of the ship.

According to the analysis presented in Chapter 3, using CM demonstrates returns on investment within approximately half a year from implementation (7.13 months). Even considering the low probability of major failures this period extends to just 1 year and 11 months. As a result, it provides a considerable benefit over the lifetime of the ship. Furthermore, the payback period of using DAQ instead of other CM methods was calculated to approximately 7 days. In that respect, the use of DAQ is by far the most cost-effective solution for to the shipping industry. It offers a significant competitive advantage over other wired CM methods and can demonstrate direct benefit in very short payback periods, maintaining a low capital investment and operational cost ceiling. Finally, it can increase trust in the technology through the use of encryption and regulated development.

4.3 Comparison to Commercial Systems

The LAROS system became commercially available in 2015. This system has some similarities to the system presented in this thesis. It utilises low cost wireless industrial ZigBee and a modular embedded system approach (LAROS, 2015). In that respect, a commercial interest in developing such a system further strengthens the selected approach as a viable solution to the identified gap and industry needs. Moreover, according to Katsikas (2013) it demonstrates "outstanding" performance sending packets from the engine room all the way to the bridge of the ship.

LAROS has a connection through satellite to shore sending the full raw dataset, which increases the operational cost. A DSS software implementation exists only on the shore-based computer for maintenance action suggestion. Thus, this is one of the first differences between this and the proposed methodology. Moreover, there is no reference of cost/impact analysis to demonstrate the direct benefit of using CM on any of the publications available at the time of writing this thesis (Koutsoubelias et al., 2016, LAROS, 2015, Katsikas et al., 2014, Katsikas, 2013).

However, there is a significant shortcoming in regard to the LAROS system that this thesis addresses. Firstly, the system does not support remote network management or self-healing according to the existing publications, which is one of the novelties of the proposed system for wireless ship CM. Additionally, the computation capabilities of the embedded system are low as well as the available memory. Hence, the system is not able to support demanding edge computation and delay tolerant networking which are all addressed in this thesis. In conclusion, data is not edge-processed and there is no record of reliability and robustness of transmission, loss of data, handling error readings and self-healing. All of these shortcomings were targeted by the work presented in this thesis, significantly differentiating the two systems.

Recently other companies have started working on smart sensor wireless installations for ship CM, such as KONGSBERG (2017). However, there is still very limited information available and these systems are expected to become more well used in the near future. At the moment the smart sensor presented by KONGSBERG (2017) is a minimal power consumption system that is only concerned with transmitting the raw data in close proximity so as to enable ease of installation. In that respect, this system is addressing a different need to the work presented in the thesis. Many companies have developed commercial wireless sensors that can be used for fault diagnosis (Feng et al., 2015). Utilising ZigBee as a protocol of communication it is possible that any number of this sensors could be interfaced directly to the proposed system. However, the issue of data output and data processing requirements of these added wireless sensors may become a significant restriction or even a hindering point.

Another system that is related to the presented work and was recently introduced to the market is PRUDAQ which was presented in August 2016 (GroupGets, 2016). It is a DAQ cape for BBB. This product emerged in the market following similar reasoning as in this thesis to meet a demand for low cost DAQ for the future IoT generation. The main differences between that system and the work presented here are that (a) this thesis presents an approach that supports industrial sensors which require external power supply and (b) this thesis presents a a hardware design that can support up to 8 sensors sampled at 100 Ksps instead of the limited option of 2 sensors supported by PRUDAQ (c) this thesis supports a full framework for capturing, processing and transmitting the data instead of just a library for DAQ. In this category, other simpler board designs have been published to support DAQ but offer an incomplete solution (KNJN, 2017, Nathan, 2017).

4.4 Transferability, Limitations & Threats to Validity

The research outcomes presented in this thesis can be transferred to any other domain where CM is applicable. The DAQ system can be deployed with different sensors. In that respect, any other application can be suitable as long as the edge processing algorithm is adapted to suit the purpose. Examples of applicable domains include the autonomous ships, robotics, factories, power generation systems, wind turbines, telephony infrastructure, Interment infrastructure and other machinery/equipment operating in remote locations where access to the Internet is not a given commodity. The DAQ units are transferable with minimal intervention. However, the DSS system and reliability analysis tools would need to be either altered or replaced to serve different industries. For example, constraints and optimisation goals of the DSS would need to be adjusted to the needs of another industry. Furthermore, other monitoring requirements can be served by the DAQ units that are not related to CM. Examples include building environmental monitoring, smart homes and smart hospital applications. In this case the reliability analysis tools and the DSS would not be applicable. Though, the post-processing unit can bridge the gap between the DAQ units and any tool.

The limitations of the proposed system are mostly defined by hardware considerations. Currently the maximum number of sensors supported are 8. However, this does not include the ability of the DAQ units to be expanded to support Bluetooth connectivity to ad-hoc sensors. A limitation would be the maximum number of edge processing algorithms that can be deployed before the DAQ is overloaded in CPU or Bandwidth. These considerations can be explored through simulation but currently exceed the potential of sensor network alternatives. Finally, if the device is battery power, additional computation will limit the lifetime of the battery. Two options would be available in this case. Either to increase the battery capacity or to change to mains supply. However, in both cases this will increase the initial investment and the payback period of the system.

Another limitation to be considered is the ability of the DSS to incorporate new constraints. It is possible that after a certain limit the addition of constraints would significantly affect the processing time of the DSS. This would result in significant delays and thus reduced usability of the system. Finally, the large margin of error identified in post-processing some of the vibration datasets limits the capacity of the system to interface to any analysis tool. This can be addressed through altering the pre-processing algorithm to send a larger portion of the Fourier domain in the expense of compression gain.

Threats to the validity of the proposed method, results and conclusions can be identified mostly in the assumptions made in this thesis. One of the fist assumptions taken was that the raw data stream was accurate. The sensorial input was not calibrated. Data is trusted as the sensors are commercial graded and comply with regulations and standards (Chapter 1). Moreover, the results of this thesis were independent on the accuracy of the measurements when comparing the raw and processed datasets. Inaccuracies of the measurements would mostly affect the results of the information extraction and DSS tools. However, this thesis does not examine the accuracy of the prediction of the reliability analysis tools which is mostly discussed in related literature. This thesis was focused on providing a system of data management and processing to support CM and DSS on ships. The results of the DSS were found to be within the expected reported failures and suggested actions. As a result, any inaccuracy of the recorded data stream did not significantly affect the performance of the DSS. Finally, as the system offers remote management, calibration factors could be added through remote updates of the software.

Another threat to validity was the case study environment. The measurements for the suitability of the wireless transmission method were taken under laboratory conditions. The laboratory used approximated an engine room. However, it cannot be disputed that the actual measurements within a ship might have provided a different profile. On the other hand, the existing commercial systems in Section 5.4 and other research measurements presented in Appendix B demonstrate that the operation of ZigBee within ships is both possible and effective; further supporting the findings of this thesis.

Finally, threats could arise from other assumptions made during the cost benefit analysis. There was no data available for the cost of CM solutions and estimations were used based on offshore and electrical power system monitoring solutions. This approximation considered both the remote and harsh environment of the offshore platforms as well as the low cost of the wired installations in an industry where CM is very well established. This approach attempted to estimate the cost of existing CM using the two most extreme cases according to sensitivity analysis methods. It is possible that this cost was either under or over estimated. However, it is still orders of magnitude larger than the cost of the system. Hence, there is confidence in the outcome. In terms of assumptions, the difference between cost and benefit are vast, so any minor assumptions would not have significantly affected the payback time. Moreover, several other benefits were not calculated as there was no obvious way to predict a monetary equivalent. However, these could easily be contributing to the estimated benefit more than any overestimation of the calculated benefit.

Chapter 5: Conclusions

This chapter summarises the content of the thesis, emphasises the impact of the proposed system as well as limitations and weaknesses identified in the previous chapter. Then it suggests possible extensions to the work presented in this thesis. There are several directions of development which were not explored during the course of this PhD and could significantly add to the development of better CM in the shipping industry.

5.1 Conclusions

The system presented in this thesis decentralised data analytics, effectively edge-processed and wirelessly transmitted equipment and machinery condition monitoring data and is a pillar for future low cost CM for the maritime industry; based on the findings of the literature review and the excellent validation and verification results presented in Chapter 3.

The minimum data transmission required is (i) a subset of the frequency spectrum, (ii) the statistical properties of the recorded signal, and (iii) a set of events that describe those signals. This information was extracted with a single computation over the input measurement. Using this information, the presented methodology can successfully reconstruct signals that carry the required information without compromising the decision-making process; successfully demonstrated through the DSS evaluation.

The developed system is suitable for gradual integration of CM in a vessel or vessels through a modular, wireless, remotely controlled and managed approach. It reduces the traffic of data from the data acquisition point to the final presentation point both onboard and on shore. The system has very low capital cost and training overheads, so it supports enhanced utility and applicability providing several benefits to industry stakeholders.

The system can support several input sensors and process them in parallel. The wireless communication is delay tolerant and no information was lost over the transmission network without causing delays. The noise profile in engine rooms is not expected to be an inhibiting factor. Sensor signals are categorised in value or signal type inputs. In value type inputs, the reconstructed signal is identical to the originally recorded signal. The worst case R^2 for this type of input was 0.998 in 1 of the 40 cases analysed (2.5%). In the signal type inputs, there is some loss of information. The worst case R^2 recorded was 0.778 in 2 of the 16 cases analysed (12.5%). In all other cases there was no statistically significant difference between the original and reconstructed signal making the system reliably open-ended for any further processing. Nevertheless, even in the worst-case scenarios with the lowest R^2 value there was no effect on the decision-making process as the DSS successfully identified the expected results (failure or non-failure of the system).

The benefits provided to the industry include reduction in failure rates, maintenance cost and dependency on ship specific expertise. The system extends ship CM state-of-the-art through decentralised wireless onboard decision assistance, low cost and direct benefit association, data encryption and development according to Class standards, impacting on increase industry adoption. Return on investment of 1 year and 11 months compared to not using any CM system and 7.19 days compared to any other commercial system was identified.

The system is transferable to other domains when the DSS tool is removed. DAQ units have a capacity ceiling in the number of sensors that can be connected and in the amount of processes that can run in parallel without affecting performance. The DSS has a limitation on how many constraints can be considered before effects on performance are noticeable as well.

In conclusion, the overall system addresses the current industry needs but also contributes to existing research in processing data away from central servers within the ship CM domain and a constrained context. Thus, it can become a pillar for future CM systems where Big Data introduce limitations to business adoption.

5.2 Future Work

The most important extension to the current work would be the further case studies to increase the amount of Fourier domain data that are transmitted over the wireless network. Increasing the percentage of frequency spectrum peaks that is sent, could increase the amount of information that is successfully transmitted. Experiments, could identify an optimum number of peaks to transmit (e.g. 10% of the highest peaks, or 20 first harmonics etc.) to have better R^2 with optimum amount of data transmission. However, these were not conducted as the decision-making process was not affected in the original case study's worst-case correlation scenarios.

An addition to the current thesis would be the comparison of ZigBee with other alternatives in terms of performance. Other RF technologies for industrial deployment could be used such as WirelessHART and ISA100-11a to identify if a benefit exists in using these technologies for better QoS.

The limitations of the DSS could be explored. The DSS tool can be further expanded to incorporate other optional constraints or optimisation targets such as allocation of maintenance actions to specific geographical locations such as the port of preference etc. The performance of the software would need to be measured to establish an ideal balance between expectation and applicability.

Another addition to the DSS is the IFTTT approach of generating mobile phone alerts, emails or text messages when the DSS identifies a new warning or failure.

Other measurements could be added to the system for completeness. For example, speed is an important parameter for monitoring.

To deploy the system in a ship, several practical considerations would need to be addressed. It will require the installation of various sensors by experts and the installation of predefined cable lengths to locations that are not difficult to access for maintenance but will have to be carefully chosen so that they do not obstruct day-to-day operations in the engine room. Additional hardware might need to be installed in the form of RF repeater nodes to increase signal strength and reliability of the overall system. The post-processing unit will need wire access to the control room. Software will need to be installed in the appropriate PC in the control room. If this deployment is possible Appendix G presents a method for evaluating the suitability of the system for wireless transmission within the ship's engine room. However, this method was not used in this thesis.

One of the directions that was not explored in this thesis was the utilisation of optical or ultrasound wireless data transfer. In this case data mules would be required. Using mulling is faster and less energy expensive than wireless routing (Vasilescu et al., 2005). The post-processing unit instead of being stationary, it could be a mobile unit that moves through the engine room either independently (possibly using a track) or by being carried through the engine room by the engineer who inspects the room every so many hours. Then, the unit would return to a docking station in the control room to both re-charge and send the data to the PC. These two possibilities would need to be explored based on both cost and availability of space in the engine room as well as other parameters such as noise interference etc. Moreover, a data mule could be used even in the current system as a backup option. It could allow for access to the locally stored raw data on the DAQ units, as well as troubleshooting when wireless communications fail.

Moreover, two additional avenues could be explored to make the system more robust, autonomous and less expensive. Those were:

- *Incorporating MEMs sensors for vibration measurements.*

- *Incorporating a nine-axis MEMs sensor for ship motion tracking.*

Micro-Electro-Mechanical Systems (MEMs) sensors were initially introduced in 2007 on iPhone, providing 6-axis inertial motion tracking. That corresponds to 3-axis acceleration and 3-axis rotation sensing. Such SoC solutions have become more widely available since 2013 (Acar, 2016, Judd, 2008). Also MEMs sensors have progressively expanded into vibration sensing for CM in recent years (Uhlmann et al., 2015). However, such sensors for applications on ships rated in the particular conditions of humidity and temperature ranges experienced on the main engine are not yet available. Some sensors are appearing in the market but at the moment are priced much higher than the main stream MEMs products available for general applications.

On the other hand, MEMs sensors could be used for ship motion tracking. This sensor would need to be installed on the central hub and away from operating machinery. In that respect, this sensor would not need to be rated for high temperature ranges. Incorporation of this sensor will provide higher autonomy to the system as traveling conditions of the ship could be directly inferred from the recorded motion sensing algorithm. As a result, the voyage and weather data needed for the DSS system could be possibly identified or predicted through the MEMs sensor readings. This addition to the system would reduce user input dependency.

To further enhance the hardware and software interface of the device further remote-control options would be required. Replacing the manually set variable resistors with digitally controlled equivalents would make this setup process remotely controllable.

The system uses a battery (Appendix H). Actual consumption of power of the system was not implemented. Data processing is expected to have a lower impact on power than transmission. However, processing may need to be adjusted, to make the system more power efficient. Additionally, powering up the ZigBee chip is expensive in power, and a potential reason for not using it. However, the most important contributor to power consumption are the sensors.

References

ABSOLUTE ELECTRICS. 2016. *Thermographic Survey as part of a Predictive Maintenance Program* [Online]. Available at: http://www.absoluteelectrics.com.au/industrial-thermographic-survey.html [Accessed 09/06/2016].

ACAR, C. 2016. High-performance 6-Axis MEMS inertial sensor based on Through-Silicon Via technology. *IEEE International Symposium on Inertial Sensors and Systems*, *22-25 Feb. 2016*, IEEE, 62-65.

ADAMSON, K. D. 2015a. Big Data & the new IT. *In: 2015 Roundtable Series.* London: Mayfair.

ADAMSON, K. D. 2015b. Crew Connectivity Survey Report. *In: 2015 Roundtable Series.* London: Mayfair.

ADAMSON, K. D. 2016a. Maritime Satellite Communications & Applications. *In: 2016 Research White Pape*. London: Mayfair.

ADAMSON, K. D. 2016b. Bits & Pieces. *Future Nautics The Maritime Future,* 10**,** 20-23.

AHUJA, S. I. P. 2009. Total Productive Maintenance. *In:* BEN-DAYA, M., DUFFUAA, O. S., RAOUF, A., KNEZEVIC, J. & AIT-KADI, D. (eds.) *Handbook of Maintenance Management and Engineering.* London: Springer.

AI, Y., PENG, M. & ZHANG, K. 2017. Edge cloud computing technologies for internet of things: A primer. *Digital Communications and Networks*, 4(2),77-86.

AL-BUGHARBEE, H. & TRENDAFILOVA, I. 2015. Autoregressive modelling for rolling element bearing fault diagnosis. *Journal of Physics: Conference Series,* 628 (1)**,** 012088. IOP Publishing.

AL-DOURI, Y. K., TRETTEN, P. & KARIM, R. 2016. Improvement of railway performance: a study of Swedish railway infrastructure. *Journal of Modern Transportation,* 24 (1)**,** 22-37.

AL-NAJJAR, B. 1996. Total quality maintenance: An approach for continuous reduction in costs of quality products. *Journal of Quality in Maintenance Engineering,* 2 (3)**,** 4-20.

AL-NOWAIHI, A. & DHAMI, S. 2010. *Probability Weighting Functions, Working Paper No. 10/10,* Leicester: University of Leicester.

ALLEN, T. M. 2001. US Navy Analysis of Submarine Maintenance Data and the Development of Age and Reliability Profiles. *In*: Department Of The Navy (ed.)*, S. M. E., Planning And Procurement (Submepp)*.

ANDERSON, P. 2007. *The ISM Code - Instructions for the Guidance of Surveyors* [Online], International Maritime Organization, ConsultISM Ltd (eds). Available at: http://www.ismcode.net/auditing_procedures/mca_instructions_for_the_guidance_of_surveyors.pdf [Accessed: 20/12/2016]

API 670 2000. *Machinery Protection Systems*. USA: American Petroleum Institute.

API 678 1981. *Accelerometer-Based Vibration Monitoring System*. USA: American Petroleum Institute.

AROKIA MARY, A. & AMSALEKHA, K. 2014. Interference Reduction in Wireless Networks Using Graph Colouring Methods. *International Journal of Computing Algorithm,* 3**,** 845-848.

AVL. 2013. *Pressure Sensors For Combustion Analysis Product Catalog Combustion Measurement Technology From AVL* [Online]. Available at: https://www.avl.com/documents/10138/885965/AVL+Pressure+Sensors+for+Combustion+Analysis/6c844a54-7a84-429d-8e57-4f34e948f95d [Accessed 06/08/2016].

BAB, S., KHADEM, S. E., SHAHGHOLI, M. & ABBASI, A. 2017. Vibration attenuation of a continuous rotor-blisk-journal bearing system employing smooth nonlinear energy sinks. *Mechanical Systems and Signal Processing,* 84, Part A**,** 128-157.

BABICZ, J. 2015. *Ship Systems and Machinery. Introduction to Marine Engineering.* Gdansk: Baobab Naval Consultancy.

BADIS, H. 2007. An efficient bandwidth guaranteed routing for ad hoc networks using ieee 802.11 with interference consideration. *Proceedings of the 10th ACM Symposium on Modeling, analysis, and simulation of wireless and mobile systems.* Chania: ACM.

BADIS, H. & RACHEDI, A. 2015. Chapter 23 - Modeling tools to evaluate the performance of wireless multi-hop networks. *Modeling and Simulation of Computer Networks and Systems.* Boston: Morgan Kaufmann.

BAGAVATHIAPPAN, S., LAHIRI, B. B., SARAVANAN, T., PHILIP, J. & JAYAKUMAR, T. 2013. Infrared thermography for condition monitoring – A review. *Infrared Physics & Technology,* 60**,** 35-55.

BAKER, P. C. 2010. *Enhancing substation condition monitoring through integrated diagnostics, wireless sensor networks and multi-agent systems.* PhD thesis, University of Strathclyde: Glasgow.

BARLOW, R. E. & PROSCHAN, F. 1981. *Statistical theory of reliability and life testing : probability models*, To Begin With: Silver Spring.

BASILI, V. R. & WEISS, D. M. 1984. A Methodology for Collecting Valid Software Engineering Data. *IEEE Transactions on Software Engineering,* SE-10 (6)**,** 728-738.

BELAK, S. 2004. Terotechnology. *OCEANS '04. MTTS/IEEE TECHNO-OCEAN '04, 9-12 Nov, 1,* 201-204.

BERTOLA, A., STADLER, J., WALTER, T., WOLFER, P., GOSSWEILER, C., ROTHE, M. & SPICHER, U. 2006. *Pressure Sensors, Pressure Indication During Knocking Conditions,* Winterthur, Switzerland: Kistler Instrumente AG.

BHUIYAN, M. S. H., CHOUDHURY, I. A., DAHARI, M., NUKMAN, Y. & DAWAL, S. Z. 2016. Application of acoustic emission sensor to investigate the frequency of tool wear and plastic deformation in tool condition monitoring. *Measurement,* 92**,** 208-217.

BINSFELD ENGINEERING INC. 2015. *TorqueTrak 10K* [Online]. Available at: http://www.binsfeld.com/torquetrak/torquetrak-10k/specifications.html [Accessed 12/06/2016].

BJELADINOVIC, S. 2018. A fresh approach for hybrid SQL/NoSQL database design based on data structuredness. *Enterprise Information Systems***,** 1-19.

BMT. 2015. *BMT SMART: Fleet and Vessel Performance Monitoring* [Online]. Availableat at: http://www.bmtsmart.com/ [Accessed 05/11/2015].

BONALDI, E. L., OLIVEIRA, L. E. D. L. D., SILVA, J. G. B. D., LAMBERT-TORRES, G. & SILVA, L. E. B. D. 2012. *Predictive Maintenance by Electrical Signature Analysis to Induction Motors,* Brazil: InTech open science, open minds.

BONGJAE, K., YOOKUN, C. & JIMAN, H. 2014. AWNIS: Energy-Efficient Adaptive Wireless Network Interface Selection for Industrial Mobile Devices. *Industrial Informatics, IEEE Transactions on,* 10 (1)**,** 714-729.

BROOKS, R. R. & IYENGAR, S. S. 1996. Robust distributed computing and sensing algorithm. *Computer,* 29**,** 53-60.

BRÜEL & KJÆR 2016. *DeltaTron Accelerometers. Brüel & Kjær* [Online]. Available at: http://www.bksv.com/doc/bp1849.pdf.

BSI 1998a. *BS EN 50082-1:1998 Electromagnetic compatibility. Generic immunity standard. Residential, commercial and light industry*. U.K.: British Standards Institution.

BSI 1998b. *BS EN 50082-2:1998 Electromagnetic compatibility. Generic immunity standard. Industrial environment*. U.K.: British Standards Institution.

BSI 2004a. *BS EN 50081-1:1992 Electromagnetic compatibility. Generic emission standard. Residential, commercial and light industry*. U.K.: British Standards Institution.

BSI 2004b. *BS EN 50081-2:1994 Electromagnetic compatibility. Generic emission standard. Industrial environment*. U.K.: British Standards Institution.

BSI 2008. B*ritish Standards Institution, PAS55:2008-1:2008. Specification for the optimized management of physical assets*. U.K: British Standards Institution.

BSI 2014. *British Standards Institution, BS ISO 55002:2014, Asset management. Management systems. Guidelines for the application of ISO 55001*. AMS/1, U.K.: British Standards Institution.

BU. 2016. *Big Data is 21st-Century Gold, Bentley University* [Online]. Available at: http://www.bentley.edu/newsroom/featured/big-data-21st-century-gold [Accessed 28/09/2016].

BV 2014. BV Rules for the Classification of Steelships Part A Chapter 2 Appendix 1 Article 6. Bureau Veritas.

BYRNE, G., DORNFELD, D., INASAKI, I., KETTELER, G., KÖNIG, W. & TETI, R. 1995. Tool Condition Monitoring (TCM) — The Status of Research and Industrial Application. *CIRP Annals - Manufacturing Technology,* 44 (2)**,** 541-567.

CAESAR, L. D., CAHOON, S. & FEI, J. 2015. Exploring the range of retention issues for seafarers in global shipping: opportunities for further research. *WMU Journal of Maritime Affairs,* 14 (1)**,** 141-157.

CAESARENDRA, W., KOSASIH, B., TIEU, A. K., ZHU, H., MOODIE, C. A. S. & ZHU, Q. 2016. Acoustic emission-based condition monitoring methods: Review and application for low speed slew bearing. *Mechanical Systems and Signal Processing,* 72–73**,** 134-159.

CALIXTO, E. 2016. *Gas and Oil Reliability Engineering, 2nd Edition. Modeling and Analysis,* USA, Gulf Professional Publishing.

CAO, W., DONG, G., CHEN, W., WU, J. & XIE, Y.-B. 2015. Multisensor information integration for online wear condition monitoring of diesel engines. *Tribology International,* 82, Part A**,** 68-77.

CARRETERO, J., PÉREZ, J. M., GARCíA-CARBALLEIRA, F., CALDERÓN, A., FERNÁNDEZ, J., GARCíA, J. D., LOZANO, A., CARDONA, L., COTAINA, N. & PRETE, P. 2003. Applying RCM in large scale systems: a case study with railway networks. *Reliability Engineering & System Safety,* 82 (3)**,** 257-273.

CENELEC 2006. *EN 55022 Information Technology Equipment - Radio Disturbace Characteristics - Limits and Methods of Measurement (CISPR 22:2005, modified)*. Brussels: European Committee for Electrotechnical Standardization.

CHANG, H.-C., JHENG, Y.-M., KUO, C.-C. & HUANG, L.-B. 2016. On-line motor condition monitoring system for abnormality detection. *Computers & Electrical Engineering*, 51, 255-269.

CHEN, J., RANDALL, R., PEETERS, B., DESMET, W. & VAN DER AUWERAER, H. 2012. Neural network based diagnosis of mechanical faults in IC engines. *10th International Conference on Vibrations in Rotating Machinery.* Woodhead Publishing.

CHENG, J., ZHU, J. & XU, T. 2013. Intelligent Nodes for the Industrial Wireless Measurement and Control Network. *Jisuanji Xitong Yingyong - Computer Systems and Applications,* 22 (12)**,** 206-209.

CHO, D. I. & PARLAR, M. 1991. A survey of maintenance models for multi-unit systems. *European Journal of Operational Research,* 51**,** 1-23.

CHRISTER, A., WANG, W. & SHARP, J. 1997. A state space condition monitoring model for furnace erosion prediction and replacement. *European Journal of Operational Research,* 101**,** 1-14.

CHUNG, H., KANG, M. AND CHO, H.D., 2012. Heterogeneous Multi-Processing Solution of Exynos 5 Octa with ARM® big. LITTLE™ Technology. *Samsung White Paper*.

CLARKE, K., HARDSTONE, G., ROUNCEFIELD, M. & SOMMERVILLE, I. 2006. *Trust in Technology: A Socio-Technical Perspective,* Dordrecht, The Netherlands: Springer.

COLPO, J. & MOLS, D. 2011. No strings attached: Industrial Wireless for Safety Applications. *Hydrocarbon Engineering,* November**,** 47-52.

CONACHEY, R. M. 2004. ABS TECHNICAL PAPERS. Development of RCM Requirements for the Marine Industry. *In: 2nd International ASRANet Colloquium,* Barcelona, Spain: American Bureau of Shipping.

CORONADO, D. & FISCHER, K. 2015. Condition monitoring of wind turbines: State of the art, user experience and recommendations. VGB Research Foundation (ed.). Bremerhaven: Fraunhofer Institute for Wind Energy and Energy System Technology (IWES).

COSTILLO, J. 2015. *Using sensors effectively in your Android-based embedded design* [Online]. Available at: http://www.embedded.com/design/system-integration/4438629/Using-sensors-in-your-Android-based-embedded-design [Accessed 07/08/2016].

DANAOS 2009. FLAGSHIP SP A2 Key performance indicators for technical operation. *Impact of new technology on shipping operations.*Piraeus: Danaos.

DAVIS, M. 2015. *When Do Exhaust Gas Temperatures Become A Cause For Concern? Hot Rod* [Online]. Available at: http://www.hotrod.com/how-to/additional-how-to/1504-when-do-gas-exhaust-temperatures-become-cause-for-concern/ [Accessed 09/06/2016].

DE AZEVEDO, H. D. M., ARAÚJO, A. M. & BOUCHONNEAU, N. 2016. A review of wind turbine bearing condition monitoring: State of the art and challenges. *Renewable and Sustainable Energy Reviews,* 56**,** 368-379.

DE GIOVANNI, P. & ESPOSITO VINZI, V. 2014. The benefits of a monitoring strategy for firms subject to the Emissions Trading System. *Transportation Research Part D: Transport and Environment,* 33**,** 220-233.

DE SOUZA, J.C.S., ASSIS, T.M.L. & PAL, B.C. 2017. Data compression in smart distribution systems via singular value decomposition. *IEEE Transactions on Smart Grid*, 8(1), 275-284.

DELVECCHIO, S. 2012. On the Use of Wavelet Tranform for Practical Condition Monitoring Issues. *In:* Baleanu, D. (ed.) *Advances in Wavelet Theory and Their Applications in Engineering, Physics and Technology.* Italy: InTech.

DEMOTT, L. R. 1978a. *TF41-A-2/A7E inflight engine condition monitoring system /IECMS.* Technology Research Database: 23217157; 200212-12-016947 (MT); A78-47918 (AH)

DEMOTT, L. R. 1978b. *TF 41 condition monitoring system effectiveness study.* Technology Research Database: 23214032; 200212-12-017406 (MT); A79-16440 (AH)

DEVANNEY, J. 2010. *Tankship tromedy.* 2nd edn. Florida: Tavernier.

DHILLON, B. S. 1986. *Human Reliability with Human Factors,* New York: Pergamon.

DHILLON, B. S. & LIU, Y. 2006. Human error in maintenance: a review. *Journal of Quality in Maintenance Engineering,* 12 (1)**,** 21-36.

DHUKARAM, A. V. 2016. *CISDA Development Process for Decision Aids to Support Self-care Decision Making.* PhD thesis, University of Birmingham.

DIAKAKI, C., PANAGIOTIDOU, N., POULIEZOS, A., KONTES, G. D., STAVRAKAKIS, G. S., BELIBASSAKIS, K., GEROSTATHIS, T. P., LIVANOS, G., PAGONIS, D.-N. & THEOTOKATOS, G. 2015. A decision support system for the development of voyage and maintenance plans for ships. *International Journal of Decision Support Systems,* 1 (1)**,** 42-71.

DIKIS, K., LAZAKIS, I., MICHALA, A. L., RAPTODIMOS, Y. & THEOTOKATOS, G. 2016. Dynamic risk and reliability assessment for ship machinery decision making. *In: European Safety and Reliability Conference.* Glasgow, 685-692.

DIKIS, K., LAZAKIS, I., TAHERI, A. & THEOTOKATOS, G. 2015. Risk and Reliability Analysis Tool Development for Ship Machinery Maintenance. *In: International Symposium on Ship Operations, Management and Economics, 28-29 May*, Athens.

DNV GL 1995. *Classification Notes Electromagnetic Compatibility.* Høvik: Det Norske Veritas 45 (1).

DNV GL 2006. *Standard For Certification No. 2.4 Environmental Test Specification For Instrumentation And Automation Equipment,* Høvik: Det Norske Veritas.

DNV GL. 2014. Beyond condition monitoring in the maritime industry. *DNV GL Strategic Research & Innovation.*

DOD. 2005. *DOD guide for achieving reliability, availability, and maintainability.* USA: Department of Defence.

DOD 2008. *Condition Based Maintenance Plus DoD Guidebook*. USA: Department of Defence.

DOT 2015. *Maritime Growth Study: keeping the UK competitive in a global market*. London: Department of Transport.

DUNN, A. 2006. Assuring Quality in Maintenance. *In:* MATHEW, J., KENNEDY, J., MA, L., TAN, A. & ANDERSON, D. (eds.) *Engineering Asset Management: Proceedings of the 1st World Congress on Engineering Asset Management (WCEAM) 11 – 14 July 2006.* London: Springer London.

EC 2009. Regulation (EC) No 391/2009 of the European Parliament and of the Council of 23 April 2009 – (Common Rules and Standards for Ship Inspection and Survey Organisations). *Official Journal of the European Union.*

EC 2011. Staying ahead of the wave: Towards Greener, Safer and More Competitive Waterborne Transportation. *In:* REPORTS, S. A. (ed.). *European Comission, Directoreate-General for Research and Innovation, Directorate H - Transport, Unit H.2 - Surface transports.*

EC 2014a. Directive 2014/30/EU Of The European Parliament And Of The Council of 26 February 2014 on the harmonisation of the laws of the Member States relating to electromagnetic compatibility (recast). *Official Journal of the European Union,* L 96/79.

EC 2014b. Directive 2014/35/EU Of The European Parliament And Of The Council of 26 February 2014 on the harmonisation of the laws of the Member States relating to the making available on the market of electrical equipment designed for use within certain voltage limits (recast). *Official Journal of the European Union,* L 96/357.

EC 2015. Study on the Analysis and Evolution of International and EU Shipping Zoetermeer: European Commission, University of Antwerp, maritime-insight, Panteia, Significance, PWC.

ECSA 2010. *Annual report 2009-2010*. Brussels: European community ship owners' association.

ECSA 2012. *Annual report 2011-2012*. Brussels: European community ship owners' association.

ECSA 2013. *Annual report 2012-2013*. Brussels: European community ship owners' association.

ECSA 2016. *Setting sail for 2017: a new boost for European shipping policy*. Brussels: European community of ship owners' association.

EE. 1998. Capacitively Decoupled BNC Connector Shunts EMI On Cable Shield To Ground. *Electronic Design* [Online]. Available at: http://electronicdesign.com/products/capacitively-decoupled-bnc-connector-shunts-emi-cable-shield-ground [Accessed 06/08/2016].

EGREENSHIP 2012a. Deliverable 1.3 Acquisition of ship's operational available parameters, meteorological data – Definition of necessary and not available parameters. *In:* EGREENSHIP (ed.).

EGREENSHIP 2012b. Deliverable 4.1 Definition of parameters recorded on board the ship and technical requirements of necessary equipment *In:* EGREENSHIP (ed.).

EGREENSHIP 2013. Deliverable 4.2 Results of initial experiments in laboratory environment *In:* EGREENSHIP (ed.).

EGS. 2015. *IPMS (EGSIS)* [Online]. İstanbul, Turkey Available at: http://www.egselektrik.com.tr/urunler/ipms-egsis [Accessed 21/06/2016].

EKER, F., KHAN, F., SKAF, Z., CAMCI, F. & JENNIONS, I. 2015. Collection of a benchmark dataset for prognostic modelling. *Condition Monitor,* December (345)**,** 5-8.

EL-HAWARY, M. E. 2008. *Introduction to Electrical Power Systems.* Hoboken: New Jersey John Wiley & Sons, Inc.

EMOVON, I., NORMAN, R. A. & MURPHY, A. J. 2015. Hybrid MCDM based methodology for selecting the optimum maintenance strategy for ship machinery systems. *Journal of Intelligent Manufacturing***,** 1-13.

EMSA 2015. *Annual Overview of Marine Casulaties and Incidents 2015*. Lisboa: European Maritime Safety Agency.

EMSA 2017. *Annual Overview of Marine Casulaties and Incidents 2017*. Lisboa: European Maritime Safety Agency.

EP & EC 2015. Regulation (EU) 2015/757, of the European Parliament and of the Council on the monitoring, reporting and verification of carbon dioxide emissions from maritime transport, and amending Directive 2009/16/EC, the European Parliament and the Council of the European Union. *Official Journal of the European Union.,* L 123**,** 55-76.

EU 1993. *COUNCIL DIRECTIVE 93/68/EEC of 22 July 1993.* European Union: The Council Of The European Communities.

FAN, C.-C., SYU, J.-W., PAN, M.-C. & TSAO, W.-C. 2011. Study of start-up vibration response for oil whirl, oil whip and dry whip. *Mechanical Systems and Signal Processing,* 25 (8)**,** 3102-3115.

FANG, I., CHENG, F., INCECIK, A. & CARNIE, P. 2013. *Global Marine Trends 2030,* London: QinetiQ, Lloyd's Regsiter Group Limitied & University of Strathclyde.

FCC 1993. Understanding The Fcc Regulations For Low-Power, Non-Licensed Transmitters. *Office of Engineering and Technology.* USA: Federal Communications Commission.

FENG, G.-J., GU, J., ZHEN, D., ALIWAN, M., GU, F.-S. & BALL, A. 2015. Implementation of envelope analysis on a wireless condition monitoring system for bearing fault diagnosis. *International Journal of Automation and Computing,* 12 (1)**,** 14-24.

FENG, Q., BI, X., ZHAO, X., CHEN, Y. & SUN, B. 2017. Heuristic hybrid game approach for fleet condition-based maintenance planning. *Reliability Engineering & System Safety,* 157**,** 166-176.

FERNANDO, N., LOKE, S. W. & RAHAYU, W. 2013. Mobile cloud computing: A survey. *Future Generation Computer Systems,* 29**,** 84-106.

FISHER, J. 2017. An avoidable steering pump failure *James Fisher and Sons PLC, Marine Services Worldwide* [Online]. Available at: http://www.jfmimic.co.uk /files/8313/7821/5774/Steeringpump.pdf [Accessed 10/03/2017].

FORD, G., IGBA, J., MCMAHON, C., ALEMZADEH, K., ROWLEY, C. & HENNINGSEN, K. 2014. Knowledge Management: A Cross Sectorial Comparison of Wind Generation and Naval Engineering. *In:* FUKUDA, S., BERNARD, A., GURUMOORTHY, B. & BOURAS, A. (eds.) *Product Lifecycle Management for a Global Market: 11th IFIP WG 5.1 International*

Conference, PLM 2014, Yokohama, Japan, July 7-9, 2014, Revised Selected Papers. Berlin: Springer Berlin Heidelberg.

FREY, D., LAKHLEF, H. & RAYNAL, M. 2016. Optimal Collision/Conflict-Free Distance-2 Coloring in Wireless Synchronous Broadcast/Receive Tree Networks. *45th International Conference on Parallel Processing (ICPP), 16-19 Aug*. 350-359.

FRIGO, M. & JOHNSON, S. G. 2005. The Design and Implementation of FFTW3. *Proceedings of the IEEE Special issue on Program Generation, Optimization, and Platform Adaptation,* 93 (2)**,** 216-231.

FRÖHLICH, P. 2012. WiFi technology for industrial environments. *Control Engineering* [Online]. Available at: http://www.controleng.com/single-article/wifi-technology-for-industrial-environments/b052b06edadf338d61e3db4848c8b69c.html [Accessed 20/09/2016].

FURUSETH, A. 1914. Safety of life at sea :analysis and explanatory notes of the London Convention on Safety of Life at Sea in relation to the American Merchant Marine. *Senate 63d Congress 2d Session Document No. 476.* Washington: G. P. O.

GANGADHARAN, V. 2013. *Automated multi-parameter monitoring of neo-nates.* PhD thesis, University College London.

GARCÍA, D. C., AL-BUGHARBEE, H. & TRENDAFILOVA, I. 2014. Vibration-Based Health Monitoring Approach for Composite Structures Using Multivariate Statistical Analysis. *14th European Workshop on Structural Health Monitoring* At Nantes, France.

GARDNER, B. 2012. Implementing wireless solutions for industrial communication applications. *Control Engineering*, 59(6).

GLOWACZ, A. & GLOWACZ, Z. 2016. Diagnostics of stator faults of the single-phase induction motor using thermal images, MoASoS and selected classifiers. *Measurement,* 93**,** 86-93.

GOODMAN, D. 2015 . Expanding the boundaries of test and diagnostics: Prognostics and Health Management (PHM) for complex systems. *20th IEEE European Test Symposium (ETS), 25-29 May*, 1-1.

GRAMI, A. 2016. Chapter 12 - Wireless Communications. *Introduction to Digital Communications.* Boston: Academic Press.

GRAY, W. D. & SALZMAN, M. C. 1998. Damaged Merchandise? A Review of Experiments That Compare Usability Evaluation Methods. *Human–Computer Interaction,* 13**,** 203-261.

GREENE, W. C. 2006. Evaluation of non-intrusive monitoring for condition based maintenance applications on US navy propulsion plants. *STAR,* 44 (14).

GREINER, R. 2014. *Ship operating costs: Current and future trends*. U.K.: Moore Stephens LLP.

GRIFFIN, D. 2011. *Attitudes in maintenance towards excellence: PAS55-1 2008.* Brazil: Pragma Academy. Available at: www.pragmaworld.net

GROUPGETS 2016. *PRUDAQ by GetLab* [Online]. 08/2016 ed.: GetLab. Available at: https://groupgets.com/manufacturers/getlab/products/prudaq [Accessed 10/02/2017].

GROVER, M., MALASKA, T., SEIDMAN, J. & SHAPIRA, G. 2015. *Hadoop Application Architectures,* Sebastopol, USA, O'Reilly Media, Inc.

GUNAWAN, I. 2014. *Fundamentals of Reliability Engineering: Applications in Multistage Interconnection Networks,* Beverly, MA: Scrivener Publishing, Wiley.

GUO, J., LI, Z. & WOLF, J. 2016. Reliability centered preventive maintenance optimization for aircraft indicators. *Annual Reliability and Maintainability Symposium (RAMS), 25-28 Jan*. 1-6.

GUPTA, L. A. & PEROULIS, D. 2013. Wireless Temperature Sensor for Condition Monitoring of Bearings Operating Through Thick Metal Plates. *Sensors Journal, IEEE,* 13 (6)**,** 2292-2298.

GUPTA, R., MUSACCHIO, J. & WALRAND, J. 2007. Sufficient rate constraints for QoS flows in ad-hoc networks. *Ad Hoc Networks,* 5 (4)**,** 429-443.

HAQUE, M. E., ZAIN, M. F. M. & JAMIL, M. 2015. Performance Assessment of tree topology sensor network based on scheduling algorithm for overseeing high-rise building structural health information. *Optik - International Journal for Light and Electron Optics,* 126 (18)**,** 1676-1682.

HARTH, N., ANAGNOSTOPOULOS, C. & PEZAROS, D. 2017. Predictive intelligence to the edge: impact on edge analytics. *Evolving Systems*.

HASHEMIAN, H. M. & BEAN, W. C. 2011. State-of-the-Art Predictive Maintenance Techniques. *In: IEEE Transactions on Instrumentation and Measurement,* 60 (10)**,** 3480-3492.

HASSLER, B. 2016. Oil Spills from Shipping: A Case Study of the Governance of Accidental Hazards and Intentional Pollution in the Baltic Sea. *In:* GILEK, M., KARLSSON, M., LINKE, S. & SMOLARZ, K. (eds.) *Environmental Governance of the Baltic Sea.* Cham: Springer International Publishing.

HENTSCHEL, K., JACOB, D., SINGER, J. & CHALMERS, M. 2016. Supersensors: Raspberry Pi Devices for Smart Campus Infrastructure. *In: IEEE 4th International Conference on Future Internet of Things and Cloud (FiCloud), 22-24 Aug*, 58-62.

HIEKATA, K. & MOSER, B. 2014. A Requirements Evaluation Method for Ships to Maximize Operational Value under Uncertainty. *In:* FUKUDA, S., BERNARD, A., GURUMOORTHY, B. & BOURAS, A. (eds.) *Product Lifecycle Management for a Global Market: 11th IFIP WG 5.1 International Conference, PLM 2014, Yokohama, Japan, July 7-9, Revised Selected Papers.* Berlin, Heidelberg: Springer Berlin Heidelberg.

HOLROYD 2015. *Holroyd acoustic innovation, Marine Industry - A Safe Harbour for Your CM Requirements*. Derbyshire, UK: Kittiwake Holroyd Ltd,.

HOU, L. & BERGMANN, N. W. 2012. Novel Industrial Wireless Sensor Networks for Machine Condition Monitoring and Fault Diagnosis. *IEEE Transactions on Instrumentation and Measurement,* 61 (10)**,** 2787-2798.

HOUNTALAS, D. T. & KOUREMENOS, A. D. 1999. Development and application of a fully automatic troubleshooting method for large marine diesel engines. *Applied Thermal Engineering,* 19 (3)**,** 299-324.

HSE 2012. *Health and Safety Executive, Faiulre Rate and Event Data for use within Risk Assessments, PCAG chapter 6, Version 12*. UK: HSE.

HUMPHREYS, I., EISENBLÄTTER, G. & O'DONNELL, G. E. 2014. FPGA based Monitoring Platform for Condition Monitoring in Cylindrical Grinding. *Procedia CIRP,* 14**,** 448-453.

IACS 2004. *Procedural Requirements for Thickness Measurements.* UK: IACS.

IACS. 2014. *IACS UR Z-20, Planned Maintenance Scheme (PMS) for Machinery* [Online]. Available at: http://www.iacs.org.uk/document/public/Publications/URallocation.pdf [Accessed 27/06/2016].

IBISWORLD. 2016. *Global Ship & Boat Building: Market Research Report* [Online]. Available at: http://www.ibisworld.com/industry/global/global-ship-boat-building.html [Accessed 10/06/2016].

IBRAHIM, M. E. 2016. Nondestructive testing and structural health monitoring of marine composite structures. *In:* SUMMERSCALES, J. (ed.) *Marine Applications of Advanced Fibre-Reinforced Composites.* Woodhead Publishing, 147-183.

ICS. 2017. Shipping and World Trade - Global Supply and Demand for Seafarers. *International Chamber of Shipping* [Online]. Available at: http://www.ics-shipping.org/shipping-facts/shipping-and-world-trade/global-supply-and-demand-for-seafarers [Accessed 05/01/2017].

IEC 2001. *International Standard IEC 61010-1 Safety requirements for electrical equipment for measurement, control, and laboratory use – Part 1: General requirements.* Switzerland: International Electrotechnical Commission.

IEC 2005. *International Special Committee On Radio Interference (CISPR) 22.* Switzerland: International Electrotechnical Commission.

IEC 2007a. *IEC 60068-2-1 Environmental testing – Part 2-1: Tests – Test A: Cold International Standard.* Switzerland: International Electrotechnical Commission.

IEC 2007b. *IEC 60068-2-2 Basic environmental testing procedures – Part 2: Tests Tests B: Dry heat. International Standard.* Switzerland: International Electrotechnical Commission.

IEC 2012. *IEC 60068-2-78 RLV Environmental testing – Part 2-78: Tests – Test Cab: Damp heat, steady state. International Standard.* Switzerland: International Electrotechnical Commission.

IEEE COMPUTER SOCIETY 2003. Standard for Information technology— Telecommunications and information exchange between systems— Local and metropolitan area networks Specific requirements—. *802.15.4™ Part 15.4: Wireless Medium Access Control (MAC) and Physical Layer (PHY) Specifications for Low-Rate Wireless Personal Area Networks (LR-WPANs).* New York: IEEE.

IFTT 2017. *Knowledge Base - General API requirements.* [Online] Available at: https://ifttt.com/ [Accessed 05/01/2017].

IGBA, J., ALEMZADEH, K., DURUGBO, C. & EIRIKSSON, E. T. 2016. Analysing RMS and peak values of vibration signals for condition monitoring of wind turbine gearboxes. *Renewable Energy,* 91**,** 90-106.

IMO. 1993a. *The International Safety Management Code, International Maritime Organisation Assembly Resolution A.741(18)* [Online]. Available at: http://www.admiraltylawguide.com/conven/ismcode1993.html [Accessed 25/07/2016].

IMO 1993b. *Resolution A.744(18) adopted on 4 November 1993, Guidelines on the enhanced programme of inspections during surveys of bulk carriers and oil tankers.* Washington: International Maritime Organization.

IMO 2013. *World Maritime Day A Concept Of A Sustainable Maritime Transportation System.* SEKIMIZU, K. (eds). London: International Maritime Organisation.

IMO. 2015. *Energy management plans and systems, energy efficient ship operation* [Online]. Available at: http://www.imo.org/en/OurWork/Environment/PollutionPrevention/AirPollution/Documents/Air%20pollution/M6%20TTT%20course%20Posters%20final1.pdf [Accessed 28/7/2016].

IMS 2007. *NASA Ames Prognostics Data Repository: The Center for Intelligent Maintenance Systems (IMS), University of Cincinnati "Bearing Data Set"* [Online]. Available at: http://ti.arc.nasa.gov/project/prognostic-data-repository. Moffett Field, CA: Nasa Ames Research Center.

INCASS 2014a. *Deliverable D4.1 Machinery and equipment requirement specification. Inspection Capabilities for Enhanced Ship Safety. EC FP7 Project* [Online]. Available at:. http://www.incass.eu/download/outcomes/ [Accessed 17/03/2018].

INCASS 2014b. *Deliverable D4.2 Stakeholders' data requirements. INCASS - Inspection Capabilities for Enhanced Ship Safety. EC FP7 Project* [Online]. Available at: http://www.incass.eu/download/outcomes/ [Accessed 17/03/2018].

INCOSE. 2016. *What is Systems Engineering?* [Online]. Available at: http://www.incose.org/AboutSE/WhatIsSE [Accessed 03/01/2016].

INFO MARINE SP. 2015. *Case study 1 - Wear of main Engine bearing* [Online]. Available at: http://www.info-marine.com/case-study-1.html [Accessed 9/6/2016].

INMARSAT PLC. 2013. *Inmarsat Global Xpress* [Online]. Available at: http://www.igx.com [Accessed 04/11/2015].

IUNG, B., LEVRAT, E., MARQUEZ, A. C. & ERBE, H. 2009. Conceptual framework for e-Maintenance: Illustration by e-Maintenance technologies and platforms. *Annual Reviews in Control,* 33 (2)**,** 220-229.

JAEHYUK, J., BERDY, D. F., JANGJOON, L., PEROULIS, D. & BYUNGHOO, J. 2013. A Wireless Condition Monitoring System Powered by a Sub-100 /spl mu/W Vibration Energy Harvester. *Circuits and Systems I: Regular Papers, IEEE Transactions on,* 60 (4)**,** 1082-1093.

JARDINE, A. K. S., 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)**,** 109-119.

JARDINE, A. K. S., LIN, D. & BANJEVIC, D. 2006. A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical Systems and Signal Processing,* 20 (7)**,** 1483-1510.

JATZECK, B. M. & ROBINSON, A. M. 1996. WATSUN-PV 4.0 modifications to include wind turbine generator, AC load shedding, and operation with zero-capacity diesel generator. *In: Canadian Conference on Electrical and Computer Engineering*, *26-29 May*, 2, 655-658.

JAUREGUI, J. C. 2014. Application of signal processing to mechanical systems. *Parameter Identification and Monitoring of Mechanical Systems Under Nonlinear Vibration.* Woodhead Publishing.

JEE, G., BRINDA, V., LALITHAMBIKA, V. R. & DHEKANE, M. V. 2014. Influence of accelerometer location on autopilot stability of reusable launch vehicle attitude control system. *IFAC Proceedings Volumes,* 47 (1)**,** 205-210.

JEGADEN, D. 2013. Noise. *In:* SCHREINER, A. (ed.) *Textbook of Maritime Medicine.* 2nd edn. Bergen: Norwegian Centre for Maritime Medicine.

JIANG, R. & YAN, X. 2008. Condition Monitoring of Diesel Engines. *Complex System Maintenance Handbook.* London: Springer.

JIZE, N. 2015. *Proactive Maintenance Saves NIF Shot Time and Money* [Online]. Available at: http://reliabilityweb.com/articles/entry/proactive-maintenance-saves-nif-shot-time-and-money [Accessed 9/6/2016].

JONES, K. & COLLIS, S. 1996. Computerized maintenance management systems. *Property Management,* 14 (4)**,** 33-37.

JUDD, B. 2008. *United Electronic Industries App Notes: Using Accelerometers in a Data Acquisition System* [Online]. Available at: http://www.ueidaq.com/media/static/apps/appnote-029_accel.pdf [Accesed: 20/12/2016].

JUDD, B. 2016. *White Paper: Everything You Ever Wanted to Know about Data Acquisition, Version 2.1.* USA: United Electronic Industries, Inc.

KAMEL, T., BILETSKIY, Y. & CHANG, L. 2015. Fault diagnosis and on-line monitoring for grid-connected single-phase inverters. *Electric Power Systems Research,* 126**,** 68-77.

KAMILA, N. K. 2016. *Handbook of Research on Wireless Sensor Network Trends, Technologies, and Applications,* Hershey: IGI Global.

KARA, S., ABELE, E., PANTEN, N. & MENZ, B. 2015. The 22nd CIRP Conference on Life Cycle EngineeringData Collection for Energy Monitoring Purposes and Energy Control of Production Machines. *Procedia CIRP,* 29**,** 299-304.

KATSIKAS, S. 2013. An innovative system for vessels monitoring, diagnosis and prognosis and the challenges to be faced. *In:* SPITAS, C., SPITAS, V. & RAJABALINEJAB, M. (eds.) *Case Studies in Advanced Engineering Design: Proceedings of the 1st International Conference.* The Netherlands: IOS Press.

KATSIKAS, S., DIMAS, D., DEFIGOS, A., ROUTZOMANIS, A. & MERMIKL, K. 2014. Wireless Modular System for Vessel Engines Monitoring, Condition Based Maintenance and Vessel's Performance Analysis. *In: Procedings of 2nd European Conference of the Prognostics and Health Management Society, (PHME'14),* Nantes, France, 1-10.

KELLY, A. 1997. Business Centered Maintenance. *In:* BUTTERWORTH-HEINEMANN (ed.) *Maintenance Strategy.* Oxford: Elsevier.

KENDALL, L. C. 1986. Procurement of Vessel Stores and Supplies. *The Business of Shipping.* Dordrecht: Springer Netherlands.

KHAC TUAN, H., TORRES CASTRO, I., BARROS, A. & BERENGUER, C. 2014. On the Use of Mean Residual Life as a Condition Index for Condition-Based Maintenance Decision-Making. *Systems, Man, and Cybernetics: Systems, IEEE Transactions on,* 44 (7)**,** 877-893.

KHALILI-DAMGHANI, K., ABTAHI, A.-R. & TAVANA, M. 2014. A Decision Support System for Solving Multi-Objective Redundancy Allocation Problems. *Quality and Reliability Engineering International,* 30 (8)**,** 1249-1262.

KHAN, A., KHAN, A., KHAN, M. & UZAIR, M., 2017. Lossless image compression: application of Bi-level Burrows Wheeler Compression Algorithm (BBWCA) to 2-D data. *Multimedia Tools and Applications,* 76(10), 12391-12416.

KIM, J. & LEE, M. 2009. Real-time diagnostic system using acoustic emission for a cylinder liner in a large two-stroke diesel engine. *International Journal of Precision Engineering and Manufacturing,* 10 (3)**,** 51-58.

KIM, Y. J., HWANG, D. H. & KANG, D. S. 2005. Technologies and Cost Evaluation of Condition Monitoring and Diagnosis System under Distributed Power Generation System. *CIGRE-EPFL Colloquium on Large Electrical Machines.* International Council of Large Electric Systems.

KISTLER 2016. *Product catalogue, Sensors and Solutions for Cutting Force Measurement*. Winterthur: Kistler Group.

KIYANG, S. T. & VAN ZYL, R. 2014. Empirical investigation of wireless sensor network performance in noisy environments. *Journal of Engineering, Design and Technology,* 12 (1)**,** 29-38.

KLEMPOUS, R., NIKODEM, J., RADOSZ, L. & RAUS, N. Byzantine Algorithms in Wireless Sensors Network. 2006 International Conference on Information and Automation, 15-17 Dec. 2006 2006. 319-324.

KNJN. 2017. *Flash analog acquisition board* [Online]. Available at: http://knjn.com/ShopFlashy.html [Accessed 10/02/2017].

KONGSBERG. 2017. *Wireless temperature monitoring for compressors* [Online]. Available at: https://www.km.kongsberg.com/ks/web/nokbg0240.nsf/AllWeb/6B5FEFE64164D3FBC12577CB003EFDDA?OpenDocument [Accessed 01/02/2017].

KOUTSOUBELIAS, M., GRIGOROPOULOS, N., LALIS, S., LAMPSAS, P., KATSIKAS, S. & DIMAS, D. 2016. System Support for the In Situ Testing of Wireless Sensor Networks via Programmable Virtual Onboard Sensors. *IEEE Transactions On Instrumentation And Measurement,* 65 (4)**,** 744-753.

KRENZEL, A. 1992. *Computer-aided data collection system for assisting in analyzing critical situations, US Patent* [Online]. Available at: https://www.google.com/patents/US5124915.

KRITZINGER, D. 2017. 5 - Failure Modes and Effects Analysis. *Aircraft System Safety.* Woodhead Publishing.

KWAN, C. & LUK, Y. 2018. Hybrid sensor network data compression with error resiliency. *In Data Compression Conference,* Snowbird, Utah.

LAIRD, W. C. 1989. *U.S. Navy Testing/Diagnostic RDT&E Program Plan, Technical Document 1646*. San Diego: Naval Ocean Systems Center, 92152-5000: NOSC.

LAROS. 2015. *LAROS System* [Online]. Available at: http://www.laros.gr/index.php/laros-system [Accessed 05/11/2015].

LATARCHE, M. 2015. The Connected Ship. *ShipInsight* [Online]. Available at: https://www.shipinsight.com/the-connected-ship-dnv-gl/ [Accessed 25/07/2016].

LAZAKIS, I. 2011. *Establishing an innovative and integrated reliability and criticality based maintenance strategy for the maritime industry.* PhD Thesis, University of Strathclyde.

LAZAKIS, I., DIKIS, K. & MICHALA, A. L. 2016a. Condition Monitoring for Enhanced Inspection, Maintenance and Decision Making in Ship Operations. *Proceedings of the 13th International Symposium on Practical Design of Ships and Other Floating Structures.* Copenhagen, Denmark.

LAZAKIS, I., DIKIS, K., MICHALA, A. L. & THEOTOKATOS, G. 2016b. Advanced Ship Systems Condition Monitoring for Enhanced Inspection, Maintenance and Decision Making in Ship Operations. *6th Transport Research Arena.* Warsaw, Poland

LAZAKIS, I., DIKIS, K., MICHALA, A. L. & THEOTOKATOS, G. 2017. Advanced Ship Systems Condition Monitoring for Enhanced Inspection, Maintenance and Decision Making in Ship Operations. *Transportation Research Procedia,* 14**,** 1679-1688.

LAZAKIS, I., MICHALA, A. L. & TURAN, O. 2016c. The European Commission's role in marine materials, equipment and components mutual recognition certification,. *Journal of European Contemporary Research,* 12 (3)**,** 615-633.

LAZAKIS, I., TURAN, O. & MICHALA, A. L. 2015. *Final Report on the level reached in the process of harmonising the rules and procedures and on Mutual Recognition (MR) of certificates for materials, equipment and components, pursuant to Article 10.2 of Regulation (EC) 391/2009*. European Commission

LEDUC, M. 2001. *The marine Diesel engine. Part one: The two stroke* [Online]. Available at: http://www.dieselduck.info/machine/01%20prime%20movers/diesel_engine/diesel_engine.01.htm [Accessed 28/09/2016].

LEE, G. 2014. *Goldman Sachs, The Big Data Phenomenon* [Online]. Available at: http://www.goldmansachs.com/our-thinking/pages/big-data.html [Accessed 28/09/2016].

LEES, A. W. 2015. Recent Advances and Prospects in Condition Monitoring. *In:* SINHA, K. J. (ed.) *Vibration Engineering and Technology of Machinery: Proceedings of VETOMAC X 2014, held at the University of Manchester, UK, September 9-11.* Cham: Springer International Publishing.

LEES 2012. Reliability Engineering. *Lees' Loss Prevention in the Process Industries.* 4th edn. Oxford: Butterworth-Heinemann.

LENNVALL, T., SVENSSON, S. & HEKLAND, F. 2008. A comparison of WirelessHART and ZigBee for industrial applications. *IEEE International Workshop on Factory Communication Systems* (WFCS), 21-23 May, 85-88.

LEVINZON, F. 2015. *Piezoelectric Accelerometers with Integral Electronics.* Switzerland: Springer International Publishing.

LEWIS, B. 2015. 10 sensors, 3 protocols, 3 minutes, 1 dev kit for cloud-connected IoT apps. *OpenSystems Media* [Online]. Available at: http://embedded-computing.com/articles/10-sensors-3-protocols-3-minutes-1-dev-kit-for-cloud-connected-iot-apps/# [Accessed 07/08/2016].

LI, P., CHENG, L., HE, Y., JIAO, S., DU, J., DING, H. & GAO, J. 2016a. Sensitivity boost of rosette eddy current array sensor for quantitative monitoring crack. *Sensors and Actuators A: Physical,* 246**,** 129-139.

LI, X., OUELHADJ, D., SONG, X., JONES, D., WALL, G., HOWELL, K. E., IGWE, P., MARTIN, S., SONG, D. & PERTIN, E. 2016b. A decision support system for strategic maintenance planning in offshore wind farms. *Renewable Energy,* 99**,** 784-799.

LI, Z., YAN, X., YUAN, C. & PENG, Z. 2012. Intelligent fault diagnosis method for marine diesel engines using instantaneous angular speed. *Journal of Mechanical Science and Technology,* 26 (8)**,** 2413-2423.

LILAS, G. 2009. *Telemetry of model ship.* Bachelor Ordinary thesis, TEI of Athens.

LIU, J., SERAOUI, R., VITELLI, V. & ZIO, E. 2013. Nuclear power plant components condition monitoring by probabilistic support vector machine. *Annals of Nuclear Energy,* 56**,** 23-33.

LIU, J. W. S. 2000. *Real-Time Systems,* Upper Saddle River, N.J. : Prentice Hall ; London Pearson Education

LLOYD'S LIST. 2014. *Exclusive Lloyd's List sulphur survey reveals growing trust in technology* [Online]. Available at: https://www.lloydslist.com/ll/sector/ship-operations/article439066.ece [Accessed 25/07/2016].

LOGAN, K. 2015. Integrating data with CBM. How predictive analytics can ensure propulsion system health. *Marine Technology,* January, 56-62.

LOGIMATIC. 2009. *Søværnet - Bemærk: Engelsksproget version. Integrated Platform Management System - for navy vessels* [Online]. Available at: http://www.logimatic.dk/vores-kunder/soevaernet [Accessed 21/06/2016].

LOISELLE, R., XU, Z. & VOLOH, I. 2015. Essential motor health monitoring. *IEEE Petroleum and Chemical Industry Committee Conference (PCIC), 5-7 Oct*, 1-5.

LR. 2013. *Lloyd's Register, ShipRight Design and construction. Machinery Planned Maintenance and Condition Monitoring*. London: Lloyd's Register.

LR. 2015. *Lloyd's Register Marine Type Approval System Test Specification, Number 1.* Global Marine Technical Services.

LR. 2016. *Cyber-enabled ships. Deploying information and communciations technology in shipping - Lloyd's Register's apporach to assurance*. 5th edn, UK: Lloyds' Register.

LR, QINETIQ & SOUTHAMPTOM, U. O. 2015. *Global Marine Technology Trends 2030*. UK: Lloyd's Register Group Limited.

LYNCH, J. P. 2007. An overview of wireless structural health monitoring for civil structures. *Philosophical Transactions of the Royal Society of London A: Mathematical, Physical and Engineering Sciences,* 365 (1851)**,** 345-372.

LYRIDIS, D. V., VENTIKOS, N. P., ZACHARIOUDAKIS, P. G., DILZAS, K. & PSARAFTIS, H. N. 2005. Introduction to an innovative crew composition approach based on safety/operational and financial requirements. *WMU Journal of Maritime Affairs,* 4 (1)**,** 33-55.

MACIÁN, V., PAYRI, R., TORMOS, B. & MONTORO, L. 2006. Applying analytical ferrography as a technique to detect failures in Diesel engine fuel injection systems. *Wear,* 260 (4–5)**,** 562-566.

MAGGARD, B. N., BAILEY, C. L. & MOSS, D. 1989. Total productive maintenance; TPM that works. *In: Proceedings of the Seventh IEEE/CHMT International Electronic Manufacturing Technology Symposium*, *25-27 Sep*,13-17.

MAI. 2016. *Wear Particle Analysis* [Online]. Metallurgical Associates Inc. Available at: http://metassoc.com/site/services/wear-particle-analysis/ [Accessed 9/6/2016].

MAKOWSKI, M. 2011. Multi-objective decision support including sensitivity analysis. *Encyclopedia Of Life Support System*. UNESCO.

MARINTEK. 2010. *The Shipping KPI Standard V2.0* [Online]. Available at: https://www.shipping-kpi.org/downloads [Accessed 21/7/2016].

MARSAGLIA & TSANG. 2013. *Ziggurat Random Number Generator* [Online]. Available at: https://people.sc.fsu.edu/~jburkardt/cpp_src/ziggurat/ziggurat.html [Accessed 17/02/2017].

MARWALA, T. 2012. *Condition Monitoring Using Computational Intelligence Methods, Applications in Mechanical and Electrical Systems*. London: Springer.

MAY, A., MCMILLAN, D. & THÖNS, S. 2015. Economic analysis of condition monitoring systems for offshore wind turbine sub-systems. *IET Renewable Power Generation,* 9**,** 900-907.

MCFADYEN, J. & ADAMSON, K. D. 2016. Buying the Cow. *Furturenautics,* 10**,** 8-13.

MCGEORGE, H. D. 1999. Tanker and gas carrier cargo pumps and systems. *Marine Auxiliary Machinery*. 7th edn. Oxford: Butterworth-Heinemann.

MCMENAMIN, E. 2015. Remote Visual Inspection: Video Borescopesto NDT Standards. Today's video borescopes can help quickly view parts and flaws. *Quality Magazine* [Online]. Available at: https://www.qualitymag.com/articles/92794-remote-visual-inspection-video-borescopesto-ndt-standards [Accessed 9/6/2016].

MEASUREMENT COMPUTING 2012. *Data Acquisition Handbook, A Reference For DAQ And Analog & Digital Signal Conditioning.* 3rd edn. USA: Measurement Computing Corporation.

MECHEFSKE, C. K. 2005. *Machine Condition Monitoring and Fault Diagnosis,* Boca Raton: CRC Press, Taylor & Francis Group.

MEHTA, B. R. & REDDY, Y. J. 2015. Wireless communication. *Industrial Process Automation Systems.* Oxford: Butterworth-Heinemann.

MEI, H. & YIN, Y. 2009. Studies on marine oil spills and their ecological damage. *Journal of Ocean University of China,* 8 (3)**,** 312-316.

MENDES, A. A. & RIBEIRO, J. L. D. 2015. A study of the quantitative methods that support RCM operation. *Reliability and Maintainability Symposium (RAMS).* Palm Harbor.

MENEGHETTI, A. & DE ZAN, E. 2016. Technicians and Interventions Scheduling for the Maintenance Service of Container Ships. *Procedia CIRP,* 47**,** 216-221.

MEPC 2011. *The Marine Environment Protection Committee, RESOLUTION MEPC.203(62), 62/24/Add.1, Amendments to the Annex of the protocol of 1997 to amend the international convention for the prevention of pollution from ships, 1973, as modified by the protocol of 1978 relating thereto (Inclusion of regulations on energy efficiency for ships in MARPOL Annex VI).* IMO.

MICHALA, A. L., BARLTROP, N., AMIRAFSHARI, P., LAZAKIS, I. & THEOTOKATOS, G. 2016a. An intelligent system for vessels structural reliability evaluation. *Proceedings of the International Conference of Maritime Safety and Operations.* Glasgow: The University of Strathclyde.

MICHALA, A. L., LAZAKIS, I. & THEOTOKATOS, G. 2015. Predictive maintenance decision support system for enhanced energy efficiency of ship machinery. *International Conference of Shipping in Changing Climates.* Glasgow.

MICHALA, A. L., LAZAKIS, I., THEOTOKATOS, G. & VARELAS, T. 2016b. Wireless condition monitoring for ship applications. *Smart Ship Technology* London: The Royal Institution of Naval Architects

MICRO-EPSILON. 2016. *Sensors & measurement systems* [Online]. Available at: http://www.micro-epsilon.co.uk/index.html?gclid=CNW02sbyx80CFdUy0wod2IoAuQ [Accessed 06/07/2016].

MING-TUO, Z., VINH DIEN, H., HARADA, H., PATHMASUNTHARAM, J. S., HAIGUANG, W., PENG-YONG, K., CHEE-WEI, A., YU, G. & SU, W. 2013. TRITON: high-speed maritime wireless mesh network. *IEEE Wireless Communications,* 20 (5)**,** 134-142.

MING, S., YAOQUN, X., XUEFENG, D. & YUAN, G. 2012. Noise-Tuning-Based Hysteretic Noisy Chaotic Neural Network for Broadcast Scheduling Problem in Wireless Multihop Networks. *IEEE Transactions on Neural Networks and Learning Systems,* 23 (12)**,** 1905-1918.

MIP. 2000. *APPLICATION NOTE 34 Low-Power Op-Amp Reduces Cable Costs for pH Probe, Maxim Integrated Products Inc.* [Online]. Available at: https://www.maximintegrated.com/en/app-notes/index.mvp/id/34 [Accessed 29/08/2016].

MIRHADIZADEH, S. A. & MBA, D. 2009. Observations of acoustic emission in a hydrodynamic bearing. *Journal of Quality in Maintenance Engineering,* 15 (2)**,** 193-201.

MITROUSSI, K. & NOTTEBOOM, T. 2015. Getting the work done: motivation needs and processes for seafarers and dock workers. *WMU Journal of Maritime Affairs,* 14 (2)**,** 247-265.

MOBLEY, R. K. 2001a. Vibration Fundamentals. *Plant Engineer's Handbook.* Woburn: Butterworth-Heinemann.

MOBLEY, R. K. 2001b. Vibration Monitoring and Analysis. *Plant Engineer's Handbook.* Woburn: Butterworth-Heinemann.

MOBLEY, R. K. 2001c. Predictive Maintenance. *Plant Engineer's Handbook.* Woburn: Butterworth-Heinemann.

MOBLEY, R. K. 2001d. Regulatory Compliance Issues in the US. *Plant Engineer's Handbook.* Woburn: Butterworth-Heinemann.

MOD 2006a. *Defence Standard 00-45: Using Reliability Centred Maintenance to Manage Engineering Failures. Part 1 - Requirements for the Application of Reliability Centred Maintenance.* USA: Ministry Of Defence.

MOD 2006b. *Defence Standard 00-45: Using Reliability Centred Maintenance to Manage Engineering Failures. Part 2 - Developing an RCM Project Plan.* USA: Ministry Of Defence.

MOD 2006c. *Defence Standard 00-45: Using Reliability Centred Maintenance to Manage Engineering Failures. Part 3 - Guidance on the Application of Reliability Centred Maintenance.* USA: Ministry Of Defence.

MOGHADDAM, K. S. & USHER, J. S. 2011. A new multi-objective optimization model for preventive maintenance and replacement scheduling of multi-component systems. *Engineering Optimization,* 43 (7)**,** 701–719.

MOLLOY, D. 2015a. BeagleBone Basics. *Exploring BeagleBone.* Inidianapolis: John Wiley & Sons, Inc.

MOLLOY, D. 2015b. *Exploring BeagleBone, Tools and Technologies for Building with Embedded Linux,* Inidianapolis: Wiley.

MOLLOY, D. 2015c. Front Matter. *Exploring BeagleBone.* Inidianapolis: John Wiley & Sons, Inc.

MONITION LTD. 2014. *Monition Vibration Analysis for Everyone* [Online]. Nottinghamshire. Available at: http://www.vibrationanalysis.co.uk/index.html [Accessed 26/01/ 2014].

MOORE STEPHENS LLP 2015. Future Operating Costs Report 2015. *OpCost.* London.

MORGAN, L. 2014. *How Sensors are Changing Software Design* [Online]. Available at: http://blog.smartbear.com/apis/how-sensors-are-changing-software-design/ [Accessed 07/08/2016].

MOUBRAY, J. 1996. Maintenance management: a new paradigm. *Maintenance,* 11 (1).

MOUBRAY, J. 1997. *Reliability centered maintenance RCM II,* Oxford: Butterwoth/Heinnemann.

MOZINA, C. 2007. Undervoltage load shedding. *In: Power Systems Conference: Advanced Metering, Protection, Control, Communication, and Distributed Resources (PSC 2007), 13-16 March*, 39-54.

MRO, M. A. E. 2015. New lubricant and oil analysis laboratory for Edmonton. *News.* PEM Magazine. [Online] Available at: http://www.mromagazine.com/2015/06/23/new-lubricant-and-oil-analysis-laboratory-for-edmonton/ [Accessed 09/06/2016].

MS. 2016. *How a Four-stroke cycle diesel engine works. Marine diesel engine guideline* [Online]. Available at: http://www.machineryspaces.com/Four-stroke-cycle-diesel-engines.html [Accessed 28/09/2016].

MSG 1980. *Maintenance Steering Group - 3 TaskForce, Maintenance program development document*. Washington: Air Transport Association of America.

MYHRE, B., PETERSEN, S. & UGARELLI, R. 2014. Using Wireless Vibration Monitoring to Enable Condition-based Maintenance of Rotating Machinery in the Water and Wastewater Industries. *Procedia Engineering,* 89**,** 1397-1403.

NACHMAN, L., HUANG, J., SHAHABDEEN, J., ADLER, R. & KLING, R. 2008. IMOTE2: Serious Computation at the Edge. *In: International Wireless Communications and Mobile Computing Conference, 6-8 Aug*, 1118-1123.

NANDI, M., DEWANJI, A., ROY, B. & SARKAR, S. 2014. Model Selection Approach for Distributed Fault Detection in Wireless Sensor Networks. *International Journal of Distributed Sensor Networks,* 2014**,** 12.

NATHAN, S. 2017. Predicting maintenance needs with wireless motor monitors. *Industrial Strength* [Online]. Available at: https://e2e.ti.com/blogs_/b/industrial_strength/archive/2017/09/21/predicting-maintenance-needs-with-wireless-motor-monitors?hootPostID=f13ac0e83bdb6ea0451a7c82480cfeb6 [Accessed 05/01/2018].

NEMARICH, C. P., BOBLITT, W. W. & HARRELL, D. W. 1990. Condition based maintenance monitoring system for naval shipboard machinery. *REP. DAVID TAYLOR RES. CENT***,** 17.

NENNI, M. E. 2013. COST ASSESSMENT FOR INTEGRATED LOGISTIC SUPPORT ACTIVITIES. *International Journal of Industrial Engineering,* 20 (5/6)**,** 412-418.

NI. 2016a. *NI 9217 Measurement System* [Online]. Available at: http://sine.ni.com/nips/cds/view/p/lang/en/nid/209890 [Accessed 09/08/2016].

NI. 2016b. *NI 9234 Module with 1-slot NI CompactDAQ Chassis* [Online]. Available at: http://sine.ni.com/nips/cds/view/p/lang/en/nid/209893 [Accessed 07/08/2016].

NOURI, M., FUSSELL, B. K., ZINITI, B. L. & LINDER, E. 2015. Real-time tool wear monitoring in milling using a cutting condition independent method. *International Journal of Machine Tools and Manufacture,* 89**,** 1-13.

NOWLAN, F. S. & HEAP, H. F. 1978. Reliability-centered maintenance. Technical report AD/A066-579. *National Technical Information Service US Department of Commerce.* Springfield, Virginia.

NTRC. 2016. Nondestructive Testing Resource Center, Conductivity Measurements. Available: https://www.nde-ed.org/EducationResources/CommunityCollege/EddyCurrents/Applications/conductivitymeasurements.htm [Accessed 9/6/2016].

ONO SOKKI CO LTD 2016. *Vibration Application, Monitoring abnormal movement of machinery [Vibration from equipment], Endurance test for transmission* *(gear)*. [Online] Available at: https://www.onosokki.co.jp/English/hp_e/products/application/vc/vib_a_2_3.htm [Accessed 09/06/2016]

OREDA. 2016. *Offsore and onshore reliability data* [Online]. Available at: http://www.oreda.com/ [Accessed 12/06/2016].

OSWALD, C. & SIVASELVAN, B. 2018. An optimal text compression algorithm based on frequent pattern mining. *Journal of Ambient Intelligence and Humanized Computing,* 9(3), 803-822.

OXFORD ECONOMICS 2015. *The economic value of the EU shipping industry – update*. UK: European Community Shipowners' Associations.

PAIK, B.-G., CHO, S.-R., PARK, B.-J., LEE, D., BAE, B.-D. & YUN, J.-H. 2009. Characteristics of wireless sensor network for full-scale ship application. *Journal of Marine Science and Technology,* 14 (1)**,** 115-126.

PAIK, B.-G., CHO, S.-R., PARK, B.-J., LEE, D., YUN, J.-H. & BAE, B.-D. 2007. Employment of Wireless Sensor Networks for Full-Scale Ship Application. *In:* KUO, T.-W., SHA, E., GUO, M., YANG, L. T. & SHAO, Z. (eds.) *Proceedings of Embedded and Ubiquitous Computing: International Conference, Taipei, Taiwan, December 17-20.* Heidelberg: Springer.

PALCZYNSKA, B., SPIRALSKI, L. & WYSZKOWSKI, J. 2006. Assessement of low frequency electromagnetic field intensities on board of ships. *XVIII IMEKO world congress.* Rio de Janeiro.

PANAGAKOS, G., PSARAFTIS, N. H. & HOLTE, A. E. 2015. Green Corridors and Their Possible Impact on the European Supply Chain. *In:* LEE, C.-Y. & MENG, Q. (eds.) *Handbook of Ocean Container Transport Logistics: Making Global Supply Chains Effective.* Cham: Springer International Publishing.

PAYNE, B. S., HUSBAND, S. M. & BALL, A. D. 2002. Development of condition monitoring techniques for a transverse flux motor. *In: International Conference on Power Electronics, Machines and Drives (Conf. Publ. No. 487)*. IET, 139-144.

PETERS, R. W. 2015. Defining Maintenance Strategies for Critical Equipment With Reliability-Centered Maintenance (RCM). *In:* PETERS, R. W. (ed.) *Reliable Maintenance Planning, Estimating, and Scheduling.* Boston: Gulf Professional Publishing.

PINTELON, L. M. & GELDERS, L. G. 1992. Maintenance management decision making. *European Journal of Operational Research,* 58**,** 301-317.

PITBLADO, G. 2001. Maintenance Management in UK. *Plant Engineer's Handbook.* Woburn: Butterworth-Heinemann.

PRAJAPATI, A., BECHTEL, J. & GANESAN, S. 2012. Condition based maintenance: a survey. *Journal of Quality in Maintenance Engineering,* 18 (4)**,** 384-400.

PSARAFTIS, N. H. & KONTOVAS, A. C. 2015. Slow Steaming in Maritime Transportation: Fundamentals, Trade-offs, and Decision Models. *In:* LEE, C.-Y. & MENG, Q. (eds.) *Handbook of Ocean Container Transport Logistics: Making Global Supply Chains Effective.* Cham: Springer International Publishing.

QIAO, B., ZHAO, T., CHEN, X. & LIU, J. 2016. The assessment of active vibration isolation performance of rotating machinery using power flow and vibrational energy: Experimental investigation. *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science,* 230 (2)**,** 159-173.

QUEZADA, A. 2017. *Open Source FFT Spectrum Analyzer* [Online]. Available at: https://hackaday.io/project/ [Accessed 03/03/2017].

RAHMAN, W. U., ALI, M., ULLAH, A., RAHMAN, H. U., IQBAL, M., AHMAD, H., ZEB, A., ALI, Z., SHAHZAD, M. A. & TAJ, B. 2012. Advancement in Wide Area Monitoring Protection and Control Using PMU's Model in MATLAB/SIMULINK. *Smart Grid and Renewable Energy,* Vol.03No.04**,** 14.

RALSTON, J. 2007. Wireless condition monitoring. *Control Engineering,* 54 (4)**,** 16.

REASON, J. 1997. *Managing the Risks of Organizational Accidents,* Aldershot: Ashgate Publishing.

RIGATOS, G. & SIANO, P. 2016. Power transformers' condition monitoring using neural modeling and the local statistical approach to fault diagnosis. *International Journal of Electrical Power & Energy Systems,* 80**,** 150-159.

RINA 2012a. *Rules for the Classification of Ships. Effective from 1 January 2012. Part C - Machinery, Systems and Fire Protection*. Genova, Italy: Registro Italiano Navale.

RINA 2012b. *Rules for the Classification of Ships Effective from 1 January 2012, Part F Additional Class Notations.* Genova, Italy: Registro Italiano Navale.

ROFLE, G. 2015. Condition Based Maintenance to optimize Asset efficiency. *GREEN4SEA Forum.* Athens: SQE4SEA.

ROLLS-ROYCE 2011. *Acon - marine automation. Ship control and monitoring. Fact sheet.* . [Online]. Available at: http://pdf.nauticexpo.com/pdf/rolls-royce/acon-marine-automation/39194-75397.html [Accessed 06/08/2016].

ROLLS-ROYCE. 2015. *Equipment Health Management* [Online]. Available at: http://www.rolls-royce.com/customers/marine/services/equipmetn-health-management.aspx [Accessed 05/11/2015].

ROSENBUSH, S. & TOTTY, M. 2013. How Big Data Is Changing the Whole Equation for Business, *Wall Street Journal* [Online]. Available at: http://www.wsj.com/articles/SB10001424127887324178904578340071261396666.

ROSENKRANZ, A., HEIB, T., GACHOT, C. & MÜCKLICH, F. 2015. Oil film lifetime and wear particle analysis of laser-patterned stainless steel surfaces. *Wear,* 334–335**,** 1-12.

SAECKER, M. & MARKL, V., 2012. Big data analytics on modern hardware architectures: A technology survey. *In: European Business Intelligence Summer School*. Springer, Berlin, Heidelberg, 125-149.

SATBEAMS. 2015. *Satbeams - Satellite Details -Thor 7* [Online]. Available at: http://www.satbeams.com/satellites?id=2571 [Accessed 04/11/2015].

SAYOOD, K. 2017. *Introduction to data compression*. Morgan Kaufmann.

SCHULTZ, S. 2007. The use of wireless technology in hazardous areas. *Ex-Magazine,* 19-25.

SCHWABACHER, M. 2005. A survey of data-driven prognostics. *In: AIAA Infotech@Aerospace Conference*, Virginia.

SDT INTERNATIONAL - BD. 2016. *Ultrasonic applications in predictive maintenance (PdM), Contribution of ultrasound in machine monitoring* [Online]. Available at: http://www.sdt.eu/index.php?page=applications-uaipm-machine_parts_acoustic_vibration_monitoring_by_means_of_ultrasonic_signals [Accessed 09/06/2016].

SEASTEMA SPA. 2016. *Seastema - Integrated Platform Management Systems* [Online]. Available: http://www.naval-technology.com/contractors/consoles/sea stema/ [Accessed 21/06/2016 2016].

SEAWORTHY ENGINE SYSTEMS, I., ADMINISTRATION, U. S. M., RESEARCH, U. S. M. A. O. O. & DEVELOPMENT 1982. *An Assessment of*

Performance and Condition Monitoring Requirements of Foreign Marine Diesel Propulsion Systems: Final Report, The Office.

SERRIDGE, M. & LICHT, T. R. 1987. *Piezoelectric Accelerometers and Vibration Preamplifier*. Briiel & Kjaer.

SHADAB FAR, M. & WANG, Y. 2016. Approximation of the Monte Carlo Sampling Method for Reliability Analysis of Structures. *Mathematical Problems in Engineering*, 9.

SHELBY, Z. & BORMANN, C. 2009a. *6LoWPAN*. John Wiley & Sons Ltd.

SHELBY, Z. & BORMANN, C. 2009b. B: IEEE 802.15.4 Reference. *6LoWPAN*. John Wiley & Sons Ltd.

SHERWIN, D. 2000. A review of overall models for maintenance management. *Journal of Quality in Maintenance Engineering,* 6 (3)**,** 138-164.

SHIN, J.-H. & JUN, H.-B. 2015. On condition based maintenance policy. *Journal of Computational Design and Engineering,* 2 (2)**,** 119-127.

SHORTEN, D. C. 2012. *Marine Machinery Condition Monitoring. Why has the shipping industry been slow to adopt?*. UK: Technical Investigations Department Lloyd's Register EMEA

SI, H., NG, B.L., RAHMAN, M.S. & ZHANG, J. 2017. A novel and efficient vector quantization based CPRI compression algorithm. *IEEE Transactions on vehicular technology,* 66(8), 7061-7071.

SIKA 2010. Measuring Instruments for Marine Applications. *Technical Information Manual*. SIKA.

SIMUNEK, M. & PELIKAN, E. 2008. Temperatures data preprocessing for short-term gas consumption forecast. I*n: IEEE International Symposium on Industrial Electronics, June 30-July 2*, 1192-1196.

SKF. 2008. *Cut maintenance costs and safety risks with turbocharger condition monitoring, Sweden, SKF Group, 6703 EN* [Online]. Available at: http://www.skf.com/binary/tcm:12-63762/index.html [Accessed 14/3/2016].

SKF. 2011. *Monitoring critical applications at sea* [Online]. Available at: http://evolution.skf.com/monitoring-critical-applications-at-sea/ [Accessed 8/5/2016].

SKF. 2012a. *Extend warning time and reduce the risk of bearing failure using SKF Acoustic Emission Enveloping* [Online]. Available at: www.skf.com [Accessed 21/7/2016].

SKF 2012b. Condition-based maintenance must be set up correctly. *Marine Propulsion - Ship lifecyle management.* SKF.

SKF 2016. *SKF Integrated Condition Monitoring Industry-leading tools and technologies for optimized machine maintenance and reliability*. SKF.

SMITH, A. 1992. *Reliability Centered Maintenance.* Boston: McGraw Hill.

SMITH, R. 2001. Effective Maintenance Management. *Plant Engineer's Handbook.* Woburn: Butterworth-Heinemann.

SOLAS 1914. *Text of the Convention for the Safety of Life at Sea. Signed at London, January 20, 1914*. London: H.M. Stationery Off., Harrison and Sons, Printers.

SOLAS 1929. *Treaty Series No. 34 (1932) International Convention for the Safety of Life at Sea, Signed at London, May 31, 1929*. London: His Majesty's Stationery Office.

SOLAS 1948. *Treaty Series No.1 (1953) International Convention for the Safety of Life at Sea, London 10th June, 1948*. London: Her Majesty's Stationary Office.

SOLAS 1960. *Treaty Series No. 65 (1965) International Convention for the Safety of Life at Sea, London, 17 June 1960*. London: Her Majesty's Stationary Office.

SOLAS 1974. *Inter-Governmental Maritime Consultative Organization (IMCO) International Conference on Safety of Life at Sea, SOLAS/CONF/INF. 7, 17 February 1975*. London: IMCO.

SPECTRO SCIENTIFIC 2016. Revolutionize wear particle analysis for predictive maintenance [Online]. Available at: http://www.spectrosci.com/blog/revolutionize-wear-particle-analysis-for-predictive-maintenance/ [Accessed 09/06/2016].

SSE. 2016. *Sub-Committee on Ship Systems and Equipment (SSE), 3rd session, 14-18 March 2016* [Online]. Available at: http://www.imo.org/en/MediaCentre/MeetingSummaries/SSE/Pages/SSE-3rd-session.aspx [Accessed 26/7/2016].

STEPHENS, R. I., FATEMI, A., STEPHENS, R. R. & FUCHS, H. O. 2000. *Metal Fatigue in Engineering*. 2nd edn. New York:Wiley Interscience Publication.

STOPFORD, M. 2009. *Maritime economics*. 3rd edn. London: Routledge.

SUJATHA, M. S. & VIJAY KUMAR, M. 2013. Energy Management by Adaptive Neuro-Fuzzy For UnderFrequency Load Shedding/Case Study. *Int. Conf. on Control, Communication and Power Engineering.*

SUJATHA, M. S. & VIJAY KUMAR, M. 2014. *Chapter-6 Adaptive neuro fuzzy for under frequency load shedding.* PhD thesis, SVEC.

SUTTON, I. 2010. *Process Risk and Reliability Management*. 1st edn. Oxford: Elsevier.

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. *Shipping in Changing Climates.* Glasgow: University of Strathclyde Publishing.

TAKATA, S., KIRNURA, F., VAN HOUTEN, F. J. A. M., WESTKAMPER, E., SHPITALNI, M., CEGLAREK, D. & LEE, J. 2004. Maintenance: Changing Role in Life Cycle Management. *CIRP Annals - Manufacturing Technology,* 53 (2)**,** 643-655.

TAYLOR, D. A. 1996. Chapter 1 - Ships and machinery. *Introduction to Marine Engineering*. 2nd edn. Oxford: Butterworth-Heinemann.

THE BRITISH INSTITUTE OF NON-DESTRUCTIVE TESTING 2015. University collaboration improves condition monitoring. *Condition Monitor,* 345 (December)**,** 1.

THE MOTORSHIP. 2015. First low-pressure EGR for bulk carrier. *The Motor Ship* [Online]. Available at: http://www.motorship.com/news101/ships-equipment/first-low-pressure-egr-for-bulk-carrier?SQ_DESIGN_NAME=print&.

THE NORWEGIAN ELECTRICAL SAFETY DIRECTORATE 1993. Guidelines for earthing in maritime installations.

THURNHEER, T. & SOLTIC, P. 2012. The polytropic volume method to detect engine events based on the measured cylinder pressure. *Control Engineering Practice,* 20 (3)**,** 293-299.

TI. 2015. High Accuracy, Logarithmic RMS Power Detector for WLAN Applications. *TI Designs* [Online]. Available at: http://www.ti.com/lit/ug/tidub96/tidub96.pdf [Accessed 04/08/2016].

TI. 2016. *Texas Instruments 16-bit and 32-bit microcontrollers* [Online]. Available at: http://www.ti.com/lsds/ti/microcontrollers_16-bit_32-bit/overview.page [Accessed 10/08/2016].

TOMOTSUGU, A. 2013. *Novel Condition Monitoring Techniques Applied To Improve The Dependability Of Railway Point Machines.* PhD thesis, University of Birmingham.

TOURET, T., CHANGENET, C., VILLE, F., LALMI, M. & BECQUERELLE, S. 2018. On the use of temperature for online condition monitoring of geared systems – A review. *Mechanical Systems and Signal Processing,* 101**,** 197-210.

TOURVALIS, E. 2007. Application of neural networks to predict UH-60l electrical generator condition using (IMD-HUMS) data. *STAR,* 45 (6).

TSANAKAS, J. A., HA, L. & BUERHOP, C. 2016. Faults and infrared thermographic diagnosis in operating c-Si photovoltaic modules: A review of research and future challenges. *Renewable and Sustainable Energy Reviews,* 62**,** 695-709.

TSANG, A. H. C. 1995. Condition-based maintenance: tools and decision making. *Journal of Quality in Maintenance Engineering,* 1 (3)**,** 3-17.

TSUJIMOTO, M. & ORIHARA, H. 2018. Performance prediction of full-scale ship and analysis by means of on-board monitoring (Part 1 ship performance prediction in actual seas). *Journal of Marine Science and Technology*, 1-18.

TUSHIR, B., DHURANDHER, S. K., WOUNGANG, I., OBAIDAT, M. S. & TEOTIA, V. 2016. Graph colouring technique for efficient channel allocation in cognitive radio networks. *IEEE International Conference on Communications (ICC), 22-27 May*, 1-5.

TWI 2016. *Condition Monitoring*. Cambridge: The Welding Institue.

TYCO ELECTRONICS. 2016. *RF Coax Connectors, BNC Connectors* [Online]. Available at: http://www.te.com/commerce/DocumentDelivery/DDEController?Action=showdoc&DocId=Catalog+Section%7F1307191_BNC_Connectors%7F0307%7Fpdf%7FEnglish%7FENG_CS_1307191_BNC_Connectors_0307.pdf%7F5227161-1 [Accessed 06/08/2016].

UHLMANN, E., LAGHMOUCHI, A., HOHWIELER, E. & GEISERT, C. 2015. Condition Monitoring in the Cloud. *Procedia CIRP,* 38**,** 53-57.

UL 2001. *UL 3111-1 Standard For Safety Electrical Measuring And Test Equipment Part 1: General Requirements*. Illinois: Underwriters Laboratories.

UNCTAD 2015. Chapter 1: Developments in international seaborne trade. *Review of Maritime Transport.* New York and Geneva: United Nations Conference On Trade And Development.

UNCTAD 2016. Executive Summary. *Review of Marine Transport.* New York and Geneva: United Nations Conference On Trade And Development.

UNCTAD 2017. *Review of Marine Transport.* New York and Geneva: United Nations Conference on Trade and Development.

UNITED NATIONS 2016. *Review Of Maritime Transport.* Geneva: United Nations Publication.

US DOT. 2015. Research and Innovative Technology Administration. *US Department of Transportation Airlines and Airports, Data and Statistics* [Online]. Available at: http://www.rita.dot.gov/bts/sites/rita.dot.gov.bts/files/subject_areas/airline_information/index.html [Accessed 12/6/2016].

VALDEZ-FLORES, C. & FELDMAN, R. M. 1989. A survey of preventive maintenance models for stochastically deteriorating single-unit systems. *Naval Research Logistics Quarterly,* 36**,** 419-446.

VALLERIO, M., HUFKENS, J., IMPE, J. V. & LOGIST, F. 2015. An interactive decision-support system for multi-objective optimization of nonlinear dynamic processes with uncertainty. *Expert Syst. Appl.,* 42 (21)**,** 7710-7731.

VAN DONGEN, L. A. 2016. Asset management: A maintenance engineer's view. *Asset Management & Maintenance Journal,* 29 (1)**,** 20-27.

VARGHESE, B., WANG, N., LI, J. & NIKOLOPOULOS, D. S. 2017. Edge-as-a-Service: Towards Distributed Cloud Architectures. *ArXiv e-prints, presented at the EdgeComp Symposium 2017; will appear in Proceedings of the International Conference on Parallel Computing* [Online].

VARONE, M. 2017. *What is Machine Learning? A definition* [Online]. Expert Systems S.p.A. Available at: http://www.expertsystem.com/machine-learning-definition/ [Accessed 10/03/2018].

VASILESCU, I., KOTAY, K., RUS, D., DUNBABIN, M. & CORKE, P. 2005. Data collection, storage, and retrieval with an underwater sensor network. *Proceedings of the 3rd international conference on Embedded networked sensor systems.* San Diego: ACM.

VERAYIAH, R., MOHAMED, A., SHAREEF, H. & ZAINAL ABIDIN, I. 2014. Review of under-voltage load shedding schemes in power system operation. *Przegląd Elektrotechniczny,* 90 (7)**,** 99-103.

VERMA, A. K., AJIT, S. & KARANKI, D. R. 2016. Maintenance of Large Engineering Systems. *Reliability and Safety Engineering.* London: Springer.

WAEYENBERGH, G. & PINTELON, L. 2002. A framework for maintenance concept development. *International Journal of Production Economics,* 77 (3)**,** 299-313.

WAGNER, R. S. & BARTON, R. J. 2012. Performance comparison of wireless sensor network standard protocols in an aerospace environment: ISA100.11a and ZigBee Pro. *IEEE Aerospace Conference*, 3-10 March, 1-14.

WAN, S., TIEU, A. K., XIA, Y., ZHU, H., TRAN, B. H. & CUI, S. 2016. An overview of inorganic polymer as potential lubricant additive for high temperature tribology. *Tribology International,* 102**,** 620-635.

WANG, J., WANG, F., CHEN, S., WANG, J., HU, L., YIN, Y. & WU, Y. 2016. Fault-tree-based instantaneous risk computing core in nuclear power plant risk monitor. *Annals of Nuclear Energy,* 95**,** 35-41.

WANG, L. & GAO, R. X. 2006. *Condition Monitoring and Control for Intelligent Manufacturing.* Germany: Pringer-Verlag London Limited.

WANG, X.-J., CAI, Y.-P. & LIN, X.-Z. 2014. Diesel Engine PT Pump Fault Diagnosis based on the Characteristics of its Fuel Pressure. *IERI Procedia,* 7**,** 84-89.

WANKHEDE, A. 2016. Why 2-stroke Engines are Used More commonly than 4-stroke on Ships? *Marine Insight* [Online]. Available at: https://www.marineinsight.com/main-engine/why-2-stroke-engines-are-used-more-commonly-than-4-stroke-on-ships/ [Accessed 28/09/2016].

WÄRTSILÄ. 2012. *Propulsion Condition Monitoring Service* [Online]. Available at: www.wartsila.com [Accessed 30/2/2016].

WÄRTSILÄ. 2014. *Wärtsilä's Propulsion Condition Monitoring Service recognised by three major classification societies* [Online]. Available at: http://www.wartsila.com/media/news/07-04-2014-wartsila's-propulsion-condition-monitoring-service-recognised-by-three-major-classification-societies [Accessed 9/6/2016].

WEBER, M. 2002. *Operator's Manual Charge Preamplifiers ICP100 / 110 / 120* [Online]. Available at: http://www.mmf.de/manual/icp1x0mane.pdf [Accessed 28/08/2016].

WEBSTER, R. C. 2001. 45 - Air Pollution. *Plant Engineer's Handbook.* Woburn: Butterworth-Heinemann.

WEISMAN, D. 2016. *Silicon Labs to Showcase IoT Connectivity Innovations at Embedded World. A More Connected World Starts at Booth 4A-128 with Mesh Networks, Wireless SoCs, Energy-Friendly MCUs and Advanced Sensing Solutions* [Online]. Available at: http://news.silabs.com/blog/silicon-labs-showcase-iot-connectivity-innovations-embedded-world-0 [Accessed 7/8/2016].

WHITE, G. 2014. *Marine Photography Portfolio, Version 4 Scavenge Port Inspection* [Online]. Available at: http://www.gwlocphoto.com/scavenge-port-inspection-on-a-container-ship-engine-4/ [Accessed 9/6/2016].

WHITE, J., BROWN, J., RAMASWAMY, S., GEOGHAN, S. & ITMI, M. 2010. Securing P2P Wireless Communications by Deploying Honeytokens in a Cooperative Maritime Network. *In:* ELLEITHY, K., SOBH, T., ISKANDER, M., KAPILA, V., KARIM, M. A. & MAHMOOD, A. (eds.) *Technological Developments in Networking, Education and Automation.* Dordrecht: Springer Netherlands.

WINGROVE, M. 2016. CBM: The next step in smart ship maintenance. *Marine Electronics & Communications* [Online]. Available at: http://www.marinemec.com/news/view,cbm-the-next-step-in-smart-ship-maintenance_41431.htm [Accessed 10/03/2017].

WU, J.-D. & HUANG, C.-K. 2011. An engine fault diagnosis system using intake manifold pressure signal and Wigner–Ville distribution technique. *Expert Systems with Applications,* 38 (1)**,** 536-544.

WU, W., LIN, T. R. & TAN, A. C. C. 2015. Normalization and source separation of acoustic emission signals for condition monitoring and fault detection of multi-cylinder diesel engines. *Mechanical Systems and Signal Processing,* 64**,** 479-497.

XIA, M., LI, T., ZHANG, Y. & DE SILVA, C. W. 2016. Closed-loop design evolution of engineering system using condition monitoring through internet of things and cloud computing. *Computer Networks,* 101**,** 5-18.

XU, B.-G. & LIU, G.-Y. 2012. Robust distributed estimation in wireless sensor networks. *Journal of South China University of Technology,* 40 (10)**,** 198-202.

YANG, D., LI, H., HU, Y., ZHAO, J., XIAO, H. & LAN, Y. 2016. Vibration condition monitoring system for wind turbine bearings based on noise suppression with multi-point data fusion. *Renewable Energy,* 92**,** 104-116.

YANG, H., FONG, S., SUN, G. & WONG, R. 2012. A Very Fast Decision Tree Algorithm for Real-Time Data Mining of Imperfect Data Streams in a Distributed Wireless Sensor Network. *International Journal of Distributed Sensor Networks,* 8(12)**,** 16, 863545.

YANG, Z., ZHENG, X., SU, W., FEI, M. & FU, J. 2013. Design and Implementation of OPC Data Server of Industrial Wireless Network Measurement and Control System. *Computer Measurement & Control,* 21 (4)**,** 865-870.

ZHANG, B., GU, J., CHEN, C., HAN, J., SU, X., CAO, X. & LIU, J. 2018. One-two-one networks for compression artifacts reduction in remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing.*

ZHAO, J., QIN, Y., YANG, D. & DUAN, J. 2013. Reliable Graph Routing in Industrial Wireless Sensor Networks. *International Journal of Distributed Sensor Networks,* 9(12)**,** 758217.

ZHAO, J., YAN, X. & SHENG, C. 2014. Networked live lab for marine machinery. *Prognostics and System Health Management Conference (PHM-2014 Hunan)*, 24-27 Aug. 2014 2014. 364-367.

ZIGBEE ALLIANCE. 2016. *ZigBee PRO with Green Power. Technical Summary* [Online]. Available at: http://www.zigbee.org/zigbee-for-developers/network-specifications/zigbeepro/ [Accessed 28/09/2016].

ZIO, E. 2013. System Reliability and Risk Analysis by Monte Carlo Simulation. *In: The Monte Carlo Simulation Method for System Reliability and Risk Analysis*. London: Springer London.

ZIRAN, P.E.N.G., GUOJUN, W.A.N.G., JIANG, H. & SHUANGWU, M.E.N.G., 2017. Research and improvement of ECG compression algorithm based on EZW. *Computer methods and programs in biomedicine*, 145, 157-166.

Appendix A – Development Standards

This appendix is based on Cyber Systems Guidance from LR in regards to software development for any type of system from embedded to GUI in regards to survey related equipment and impact on safety and security (LR, 2016). These standards were followed in the development process of the proposed system in this thesis.

So as to comply with the guidelines any development must strive to follow the standards presented in the following table. The means through which these standards are applied in this particular case are further discussed below. Development based on methodical approaches such as Agile development further ensures that the final software is of high quality (Basili and Weiss, 1984).

Standards governing the development of the proposed methodology according to guidance by LR (2016).

Standard	Description
ISO/IEC/IEEE 15288	Systems and Software Engineering – System Lifecycle Processes; Framework for describing system lifecycles and lifecycle processes
ISO/IEC/IEEE 12207	Systems and Software Engineering – Software Life Cycle Processes; implementation of software systems
NIST SP 800-64	Security Considerations in the System Development Life Cycle
IEC/ISO 31000	Risk Management Principles and Guidelines
ISO/IEC 31010	Risk Management – Risk Assessment Techniques
BS EN 61508	Functional Safety of Electrical/Electronic Programmable Electronic Safety – Related Systems
ISO 9241-210	Human-Centred Design for interactive systems
IEC 61508	Software production and maintenance
LR Provisional Software Rules	Provisional Rules and Regulations for Software to be Used in Naval Ships
ISO 9001 / IEC 61508 / IEC 12207	Planning and Delivery of software production
ISO 10007	Configuration management and Software Maintenance
ISO/IEC 27001, ISO/IEC 15408	Cyber security

In order to comply with guidance on cyber system development the system components are initially defined. For the proposed development two systems are identified

1) the end device and the software for data acquisition and
2) the main coordinator device collecting the data in a central point.

Then for each of the devices the relevant subsystems had to be identified. The first is comprised of the main subsystems:

1) ZigBee communications
2) Embedded processing unit
3) Software
4) Connection to sensor and
5) Sensor.

The second is also comprised of the ZigBee communications subsystem and a software component. The failure modes associated with these subsystems were then identified. These are presented in the table below along with the effect, mitigation and avoidance actions addressing the requirements of the first six standards in the previous table. As the onshore system is not included in the development the remote connection is not an additional risk to be managed.

Moreover, as demonstrated through the mitigation and avoidance actions the developed system demands minimum training for failure mode identification and recovery. Also, in many cases it attempts to self-recover from the failure mode. Also, as development took into account the minimum requirements from all stakeholders, and the proposed software[19] leads to engineer centred suggested actions. The design was human-centred thus following the requirements of ISO 9241-210. Finally, software maintenance and updates are not accessible remotely and can only be performed during inspection or survey by dedicated staff.

In order to assure data, considerations were made towards the data integrity, availability authentication, confidentiality, authorisation, non-repudiation and data properties that preserve safety. In terms of cyber security, the marine environment is unique due to limitations in connectivity (LR, 2016). Most ships do not have the ability to download large files that could be infected. The common case is that the onboard PC is already setup with all necessary software and is never updated online. Moreover, the systems installed on ships do not usually have operating system discs or proprietary software which is the target of the great majority of infections and viral threat programs such as malware.

[19] Number of lines of developed code 77,070. Based on the C gearing factor* this takes 389 useful-code-average-developer months [i.e. 32.4 person years], or 51.7 highly-efficient-developer months [i.e. 4.3 person years]. The development was implemented in less than 2.5 years.
*http://www.qsm.com/resources/function-point-languages-table

Proposed system identified failure modes.

Failure Mode	Effect	Action to reduce risk	Failure mitigation	Avoidance trials/testing
Sensor damage	Do input data	Correct installation, Hardware protection of the rest of the hardware	Replace sensor	Ensure sensor is not damaged prior to installation
Sensor installation misalignment	Input data not matching real readings	Installation of sensors only by experts, test sensor readings at installation	Re-install sensor	Verification of installation
Sensor connection failure	Input data not matching real readings	Hardware identification, Hardware protection of the rest of the hardware	Hardware identification	Verification of installation
Embedded processing unit damage	System inaccessible but responding to network ping	Protective hardware and enclosure	Replacement of hardware	Verification of system operation at commission
Power failure	System not responsive to network ping	Batteries to be replaced at designated intervals	Replace batteries	Provide battery replacement schedule
Embedded processing unit infinite loop	System not responsive	Hardware watchdog	Watchdog instigated reset	Software development/testing of the highest standard
Pre-processing software failure	Data off limits, wrong data	Software based on established algorithms	Reset unit, Remote re-flashing of the software	Vigorous software testing, Agile development
Software undesired behaviour	Data off limits, wrong data, system unresponsive	Hardware watchdog	Watchdog instigated reset, Remote re-flashing of the software	Vigorous software testing, Agile development

Another, important parameter in system design is the ability of the system to utilise valid and verified input sources. Thus, several standards and regulations exist. As the proposed system needs to support input from sensors, the selected sensors need to comply with certification and regulation so that the data can be trusted. The table below presents a list of the standards regulating sensors and measurements.

As evident from the table, sensors that operate within the harsh environment of the ship's engine room need to comply with a variety of standards and must have passed relevant testing. For that reason, only sensors which are specifically graded for industrial applications, combustion engine monitoring and high humidity conditions are suitable for the proposed system.

Standards and regulations governing sensors and measurements in industrial applications.

Standard	Description
BS EN 61010–1, IEC 61010–1 (2001)	Safety requirements for electrical equipment for measurement, control and laboratory use.
UL 3111–1 (2001)	Standard for Safety – Electrical measuring and test equipment
BS EN 50081–1 (2004a)	Generic emission standard. Part 1: Residential, commercial and light industry.
BS EN 50081–2 (2004b)	Generic emission standard. Part 2: Industrial environment.
IEC CISPR 22 (2005), EN 55022 (2006)	Radio disturbance characteristics of information technology equipment. Class B Limits.
FCC Rules, Part 15 (FCC, 1993)	Complies with the limits for a Class B digital device
BS EN 50082–1 (1998a)	Generic immunity standard. Part 1: Residential, commercial and light industry.
BS EN 50082–2 (1998b)	Generic immunity standard. Part 2: Industrial environment.
IEC 60068–2–1 (2007a), IEC 60068–2–2 (2007b)	Environmental Testing. Cold and Dry Heat
IEC 68–2–78 (2012)	Damp Heat: 90% RH

These sensors are commodity in such systems and often are pre-installed by the manufacturers of machinery and equipment which is the current state-of-the-art for new-build ships. However, it may not be the case in older vessels.

Through using sensors that are available commercially, there are additional benefits to the development process. First and foremost, the sensors are guaranteed to collect the required data reliably. Secondly, and of equal importance for a shipping environment, the commercial sensors are CE marked [**C**onformité **E**uropéene Marked (EU, 1993)] and have passed Safety, Electromagnetic Compatibility (EMC), Emission and

Immunity (EMI) testing. Also, commercially available sensors for industrial applications comply with the international EMC Directive (EC, 2014a) and Low Voltage Directive (EC, 2014b). In that respect, sensorial input needs to be provided from commercially available sensors certified for operation in the desired environment. However, it is broadly acknowledged that acting upon the recorded data is the most important aspect of the CBM implementation process (Fisher, 2017).

Appendix B – Ship Noise Profile and Wireless Application in Hazardous Conditions

As this section discusses the proposed answer to the first research question, it provides an in-depth analysis of the applicability of wireless communication protocols in the shipping environment. It aims to discuss the noise profile of the ship engine room and the general conditions. This includes identifying if explosive atmosphere is formed within the engine room and if other hazardous conditions exist and could be affected by RF signal transmission.

In an engine room, apart from the ship's main engine, other devices also exist that can create electromagnetic noise. The main noise generators are the engine and systems in engine room such as electricity generators, reducers and ancillary machinery (e.g. winches, hydraulic motors) (Jegaden, 2013). This noise changes dynamically and is affected by several parameters such as the speed of the engine etc. (Bongjae et al., 2014). Furthermore, reflection and scattering can occur especially due to the metal enclosure that surrounds the engine room. On the other hand, the special isolated nature of the ship ensures that Wi-Fi and other ISM band cross-interference is minimal (Zhao et al., 2013).

Another important consideration is the transmission synchronisation of the network. When several nodes transmit simultaneously the interference increases and is linearly analogous to the number of nodes transmitting (Badis and Rachedi, 2015). However, this condition can be avoided through the correct geographical distribution of the network. By minimising the number of nodes covering the same geographical area and through the MAC layer, the Signal to Interference to Noise Ratio (SINR) can be minimised.

In that environment noise can exist between few Hz and the lower end of GHz. According to guidelines, radio installations are achievable between 150kHz and 300MHz for standard equipment operating outside the ISM band (The Norwegian Electrical Safety Directorate, 1993). Based on testing for radio devices on board vessels, scrutinised for certification by Lloyd's Register, it is necessary to prove that the system is not affected by noise in the region of 8MHz to 2GHz (LR, 2016, 2015). Also, the regulatory limit frequency range from 200MHz to 1GHz exists to protect machinery and equipment from other spectral emissions (DNV GL, 1995). Moreover, according to other research the EM noise reduces after 400kHz (Palczynska et al., 2006). Also for radiated emissions from equipment installed in any space on the ship, 2GHz is the maximum frequency permitted and it must be rated below 54 dBμV/m (DNV GL, 2006). In that respect, the operating frequency of ZigBee is ideally suited outside the frequencies most adversely affected. According to Baker (2010), the reliability of such networks in adverse conditions – and in particular the ZigBee technology – is reported as appropriate. Moreover, the LAROS commercial system currently installed on ships is operating successfully in this frequency range (Koutsoubelias et al., 2016, Katsikas, 2013). Moreover, other academic studies suggest that ZigBee is successfully transmitting across decks on actual ship trials (Paik et al., 2009, Paik et al., 2007).

The geography and topology of the wireless sensor network can significantly affect the performance and reliability. In that respect, carefully selected installation topology can reduce the effect of reflection and scattering (Xu and Liu, 2012). Further, according to Kiyang and Van Zyl (2014), wireless sensor networks based on the available standards are resilient to industrial noise as long as the separation between nodes is maintained under a threshold. For example, in noise characterised by 52dB Signal to Noise Ratio (SNR) a 6m separation is the maximum to guaranty QoS.

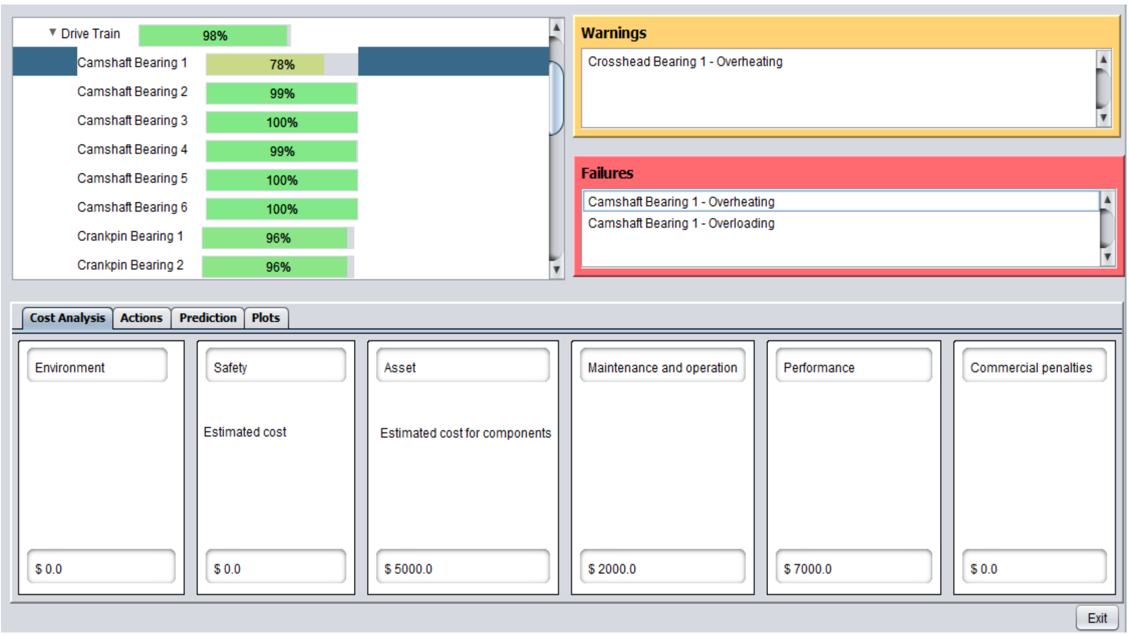
The industrial wireless systems such as ZigBee Pro, WirelessHART and ISA 100-11a are most often, by nature of application, battery operated; so intrinsically safe. Many systems developed with such technology have met regulatory needs in regards to environment, explosive classified areas and safety compliance in applications such as LPG pressure monitoring, safety relief valve monitoring, safety shower monitoring and rupture disc monitoring (Colpo and Mols, 2011). These are often installed in gas and crude oil processing plants which are some of the most hazardous industrial applications.

As discussed by Kamila (2016), for a wireless network to become an ignition source, other installed devices in the vicinity would have failed their safety requirements. In that respect, a wireless installation alone is not an ignition hazard as it is very unlikely that it can spark an explosion on its own (Schultz, 2007). Power of the RF signal larger than several hundred Watts is necessary, which is impossible in battery operated systems with ZigBee operating in 10mW. However, if the maintenance condition of other inductive machinery and equipment is low, then it could lead to ignition under certain circumstances. On the other hand, these are standard requirements for any installation onboard a ship. Thus, a wireless network is no more prone to creating ignition than any other machinery or equipment capable of conducting current as long as it has passed the appropriate testing and acquired certification. For example, ZigBee applications exist for underground mining conditions and coal mines. Moreover, explosion protected antennas would have to be used in some of these applications. Recent radios and antennas already implement protection for over current and over voltage to reduce the potential of explosion due to the antenna (Fröhlich, 2012).

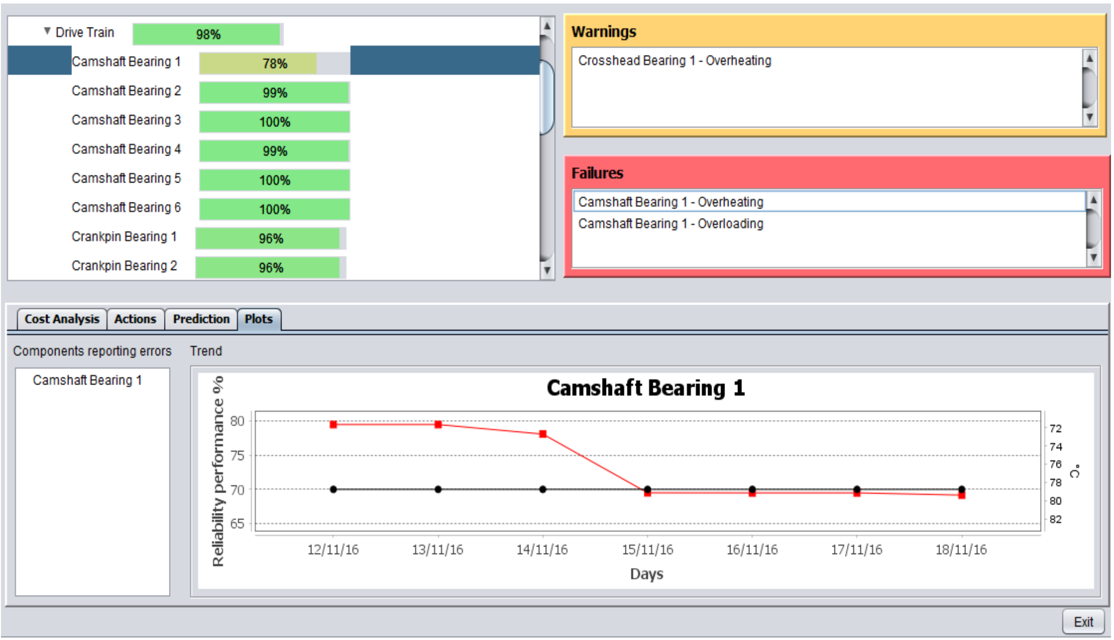
According to regulations, when new electronic equipment is introduced in an industrial installation, it must be tested for Electromagnetic Interference (EMI) (Schultz, 2007). This is to avoid induction of current on metallic objects. In that respect, the proposed system would need to be EMI certified before installation in ships and Explosion Certified. This could be achieved through selecting appropriate certified housing for the device. The housing can isolate the device and as a result remove the requirement for each part to be put through testing. However, as the initial prototype development was tested in laboratory conditions this was not a consideration in this thesis.

Appendix C – User Manual

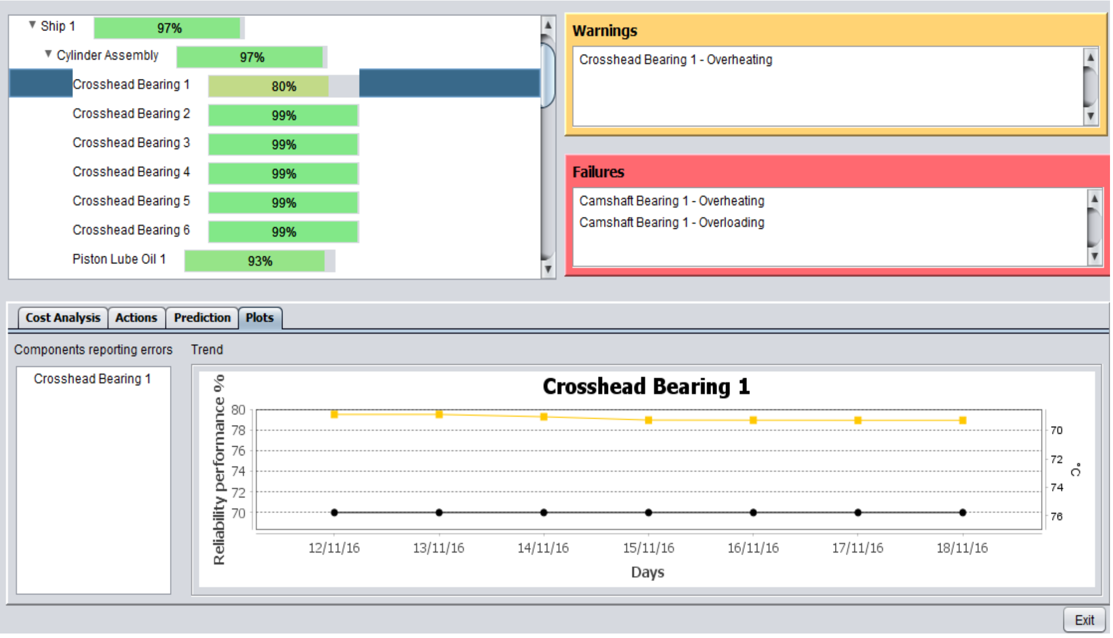
The DSS user manual follows the previously published work in (Michala et al., 2015). The only other difference from the previously discussed GUI is the addition of graph handling capabilities in the Plots area. The user can zoom in and out of a graph to inspect the plot in detail and can also hover over data points to see the exact reading. There are also two axes in this version to demonstrate the degradation in relative percentage an in actual expected temperature rise or pressure drop.



Camshaft bearing overheating cost prediction based on optimal DSS action prediction not being followed.



Camshaft bearing failure based on temperature readings.



Crosshead bearing warning based on temperature readings.

Appendix D – Technical Datasheets

Engine datasheet

Automotive Diesel Engine

The CM12 is a self contained diesel/biodiesel engine test rig, ideal for investigating typical performance parameters. The unit can be linked to a PC and is supplied with both educational software and the manufacturer's own diagnostic software.

CM12

INTERNAL COMBUSTION ENGINES
CM12 Automotive Diesel Engine – Issue 3

The Armfield CM 12 is a self-contained diesel engine test rig, which enables students to investigate typical engine performance parameters. The unit is designed to be linked to a computer and is supplied both with educational data acquisition and control software, as well as the engine manufacturers diagnostic software for monitoring the status of the Engine Control Unit (ECU).

Ordering Specification

- A four-cylinder, water-cooled, biodiesel compatible, 1.9-litre Volkswagen diesel engine, complete with services and ancillaries required to run the engine in a laboratory environment
- Variable load eddy current dynamometer, which acts as a brake, enabling direct measurement of engine torque
- Supported on strong steel framework via flexible mounts. The frame also houses the fuel tank, battery and electrical enclosures
- Protected by guards around the moving parts. Safety interlocks and emergency stops are provided
- Supplied with educational software for data logging and control
- Supplied with the engine manufacturer's diagnostic software
- Starter, throttle and dynamometer can be controlled from a computer
- Standard instrumentation includes sensors for:
  - Engine speed
  - Torque
  - Air flow
  - Cooling water temperature (inlet and outlet of heat exchanger)
  - Cooling water flow

- Optional engine indicator set for measuring cylinder pressure through the cycle

Features

- Four-cylinder automotive engine
- Biodiesel compatible
- Eddy current dynamometer to vary engine load
- Plotting of characteristic torque and power curves against engine speed
- Full software control of system, including load and throttle settings
- Closed-loop software control of brake loading to maintain constant engine speed during measurements
- Secondary water cooling by heat exchanger, with measurement of temperature change and flow rate
- Engine manufacturer's diagnostic software (displays fuel injection characteristics)
- Remote emergency stop, and facility for safety interlocks
- Optional measurement of cylinder pressure, and displaying this on a p-V diagram

Description

CM12 is a self-contained integrated multi-cylinder engine, dynamometer and instrumentation system. It is based on a 1.9-litre, four-cylinder automotive diesel engine as used in Volkswagen cars.

This engine is a modern design, with electronic engine management of fuel injection settings.

The Armfield CM12 can be run on a wide variety of biodiesel fuels and can be used for fuel testing and comparison exercises. After each run on nonstandard fuel, the engine should be run for a short time on a standard diesel fuel approved to EN590.

An eddy current dynamometer provides a variable load on the engine, enabling the characteristic power and torque curves to be reproduced in the laboratory. The system comes complete with extensive instrumentation, including rpm measurement, torque (from which power can be calculated), plus various temperatures, pressures and flows (see Technical Specification).

The whole system is designed to be linked to a computer using the software provided. This provides real-time monitoring of the various sensors, with a wide range of data logging and graphical display options.

The dynamometer and throttle can both be controlled electronically from the software, which makes installation into a closed test cell very straightforward, and enables remote computer operation.

A safety "watchdog" facility ensures the system shuts down safely in the event of computer failure or software lock-up. The interfaces are compatible with packages such as LabVIEW™ and Matlab for users who wish to provide their own control and monitoring software.

A further advantage of the computer control is that stable rpm readings can be easily achieved using the closed-loop control function on the dynamometer drive.

A closed-loop primary water-cooling system is incorporated, complete with a heat exchanger for connecting into a secondary cold water supply.

Technical Specification

Engine Data

CM12 - Software Mimic diagram

enlarge

Engine model:	Volkswagen SDI
Displacement:	1,896cc
Bore:	79.5mm
Stroke:	95.5mm
Cylinders:	4
Nominal power:	44kW @ 3,600rpm
Nominal torque:	130Nm @ 2,200rpm

Dynamometer Data

Dynamometer type:	Eddy current
Cooling:	Air cooled
Max power:	55kW for 20min

Instrumentation and Sensors:

- Engine speed counter
- Load cell to measure torque
- Inlet air flow measured by orifice plate
- Inlet air temperature
- Secondary cooling water flow and temperatures (inlet and outlet)

The VW diagnostic software can also be used to monitor a wide range of engine functions. In particular the injection characteristics can be used to establish the fuel consumption rate.

Options

CM12-12 Engine Indicator Set

The engine indicator set comprises a high temperature pressure sensor installed into one of the cylinders in place of the glow plug. A separate charge amplifier provides signal conditioning to generate a voltage which can be logged on the computer. A special routine in the Armfield software allows for the high-speed data acquisition of this signal, and automatically plots the results on a p-V diagram.

Essential Equipment

CM12 - Software graphical display

The user must have access to one or two PCs (according to preference). Two free USB ports are required, one to run the Armfield data logging and control software, and one to run the VW diagnostic software. The operating system requirements are Windows XP or later.

enlarge

Requirements

Installation and Services

The CM12 should be installed in a well-ventilated area with exhaust gas extraction facilities. The unit is supplied on wheels for ease of movement, but it is recommended that the wheels are removed and the unit bolted to the floor for permanent installation.

Apart from the master on/off switch, and the cooling water, everything can be controlled by computer, allowing the engine to be installed in a dedicated test cell, and operated from outside the cell. It is supplied with a 5-metre USB lead, giving a maximum distance between the unit and the controlling computer of approx 4 metres.

Electricity:

220-240V, single phase, 10 amp

Cooling Water:

6 l/min at 3 bar pressure, <20°C

Shipping Specification

Volume:	$3.2m^3$
Gross weight:	550kg (approx

Overall Dimensions

Height:	1.20m (without castors)
Width:	1.50m
Depth:	0.92m

Sensor datasheets – Pressure sensor

Extracts relevant to the work presented in this thesis.

Description

KISTLER
measure. analyze. innovate.

2. Description

2.1 Introduction

Modern multivalve engines and combustion engines with small volume often provide only inadequate space for fitting conventional pressure sensors.

Kistler has developed the miniature pressure sensor Type 6052B... and the miniature measuring probe Type 6053BB.../Type 6055BB... especially for such applications.

> **Attention:**
> The Types 6052B..., 6053BB... and 6055BB... are superseded by the Types 6052A..., 6053C... and 6055B... . They are 100 % mounting compatible since they have the same geometrical dimensions.

1:1
6052B1

6053BBsp30-60
6053BB60
6053BBsp60-120

6055BBsp40-80
6055BB80
6055BBsp80-140

Fig. 1: M5-Miniature pressure sensors

Both of them have an M5 x 0,5 mounting thread. As they use the same measuring element, their technical data are largely identical.

002-017e-02.03 (B03.6052e)

Seite 5

2.2 Principle of Operation

The pressure to be measured acts on the diaphragm, which converts it into a proportional force. This force is transmitted onto the quartz, which under loading yields an electrostatic charge. An electrode picks up this (negative) charge and takes it to the plug, after which the connected charge amplifier converts it into a (positive) voltage.

Advantage →

The piezoelectric principle is suited chiefly for measuring rapid dynamic and quasistatic pressure phenomena, and it therefore enjoys preference in engine pressure measurements.

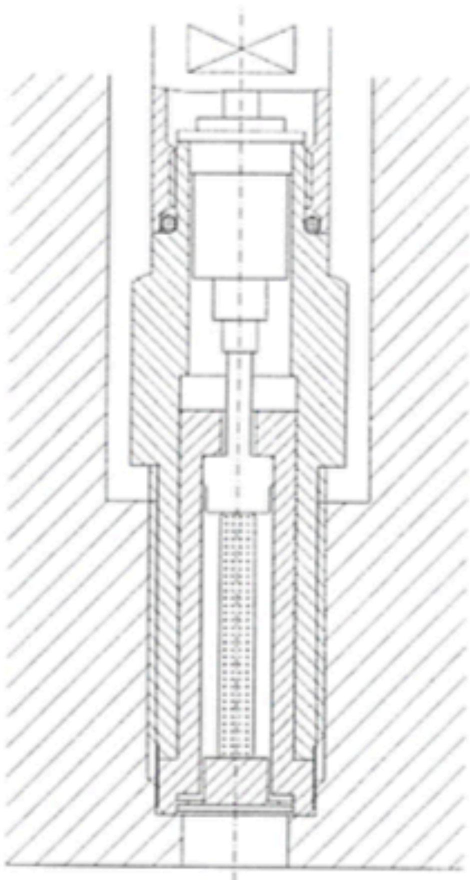


Fig. 3: Schematic section through the measuring element

6. Technical Data

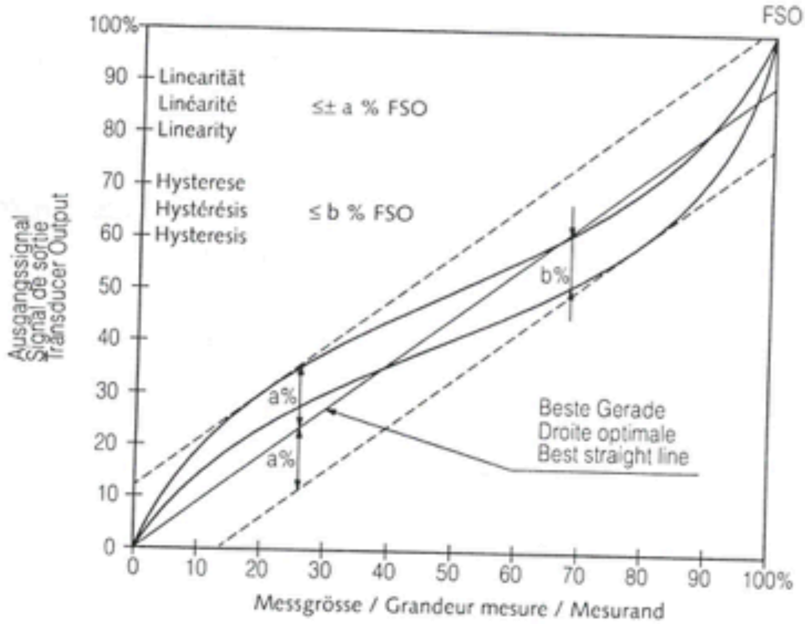
(some of the terms are explained in more detail in subsection 1.4)

Sensor Type		**6052B...** **6053BB...** **6055BB...**
Measuring range	bar	0 ... 250
Calibrated partial range	bar	0 ... 50, 0 ... 100, 0 ... 150
Overload	bar	300
Sensitivity	pC/bar	≈–20
Natural frequency	kHz	≈130
Linearity	% FSO	<±0,4
Operating temperature range		
without cooling: continuous	°C	-50 ... 400
Sensitivity shift		
200 ±50 °C	%	±0,5
200 +150 °C/-177 °C	%	±2
Tightening torque	Nm	1,5
Short term drift *)	bar	<±0,5
Load change drift *)	bar/s	1,5
Relative deviation of p_{mi} *)	%	<±2
Relative deviation of p_{max} *)	%	<±1,5
Insulation resistance at 20 °C	Ohm	>10^{13}

*) measured on test engine at 1500 rpm and 9 bar IMEP

Measuring range

The data stated relate to the corresponding measuring range.



Measurand

Physical value, state or characteristic which is measured.

Measuring chain

Interconnection of several individual components to perform measurements. A measuring chain normally consist of sensors, amplifiers, indicating and analytical instruments and recorders (e.g. printers).

Medium Term Drift (Load Change Drift)

The medium term drift is defined as gradient of signal drift due to an ignition cut-off. This measurement is absolute. It doesn't need a reference sensor.

Natural frequency

Frequency of free (not forced) oscillations of the sensor element of a fully assembled sensor.

Operating Temperature Range

The operating temperature is equivalent to the mean temperature at the installation point of the transducer. The operating temperature range extends between the limits at which the sensor may be used. If these limits are exceeded, the sensor may be damaged.

Overload

Range above the measuring range up to which the dynamometer can be loaded without sustaining damage. This is not an extended measuring range but a safety range. The measurand tolerances listed apply only within the measuring range and are not guaranteed in the overload range! Nevertheless, such measurands can in most cases be evaluated as useful measurements.

Sensor datasheets – Vibration sensor

Extracts relevant to the work presented in this thesis.

PRODUCT DATA

Miniature DeltaTron® Accelerometer — Type 4397A
DeltaTron Accelerometers — Types 4398A, 4399A

DeltaTron is the generic name for the family of accelerometers and signal conditioning products from Brüel & Kjær that operate on a constant-current power supply and give output signals in the form of voltage modulation on the power supply line.

FEATURES

- All DeltaTron products operate on constant-current line-drive (CCLD) ICP® principles
- All accelerometers have:
  - Integral preamplifiers
  - All-welded construction
  - Delta Shear Uni-Gain® design
  - Low sensitivity to all environments
  - Individual standard-traceable calibration
  - Individual data for best fit to measured frequency response

USES

- Shock and vibration measurement
- Vibration analysis
- Vibration monitoring
- Vibration test control
- Product and quality control

Description

The DeltaTron name identifies products that operate with a constant-current power supply and give output signals in the form of voltage modulation on the power supply line. These DeltaTron accelerometers are constructed to the proven Brüel & Kjær Delta Shear design with the addition of an integral DeltaTron preamplifier. They require an external constant-current power supply and operate as voltage sources. They are specially designed to withstand rough environment

Miniature Accelerometer Type 4397A

Suitable for measurements on lightweight structures where relatively high-level, high-frequency vibrations are encountered. Type 4397A uses a M3 connector.

Shock and Vibration Accelerometer Type 4398A

Designed for the measurement of relatively high levels of continuous vibration and mechanical shock up to 7500 ms^{-2}. Type 4398A uses a 10–32 UNF Connector.

General Purpose Accelerometer Type 4399A

For general purpose vibration measurements. Type 4399A uses a 10–32 UNF Connector.

Type numbers without an A-suffix include a connection cable.

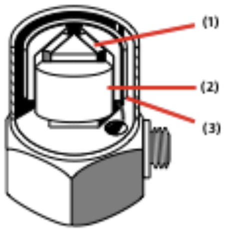
4397A/–8A/–9A

Brüel & Kjær

Design

DeltaShear® design

Fig. 1 Exploded view of DeltaShear design (preamplifier not shown)

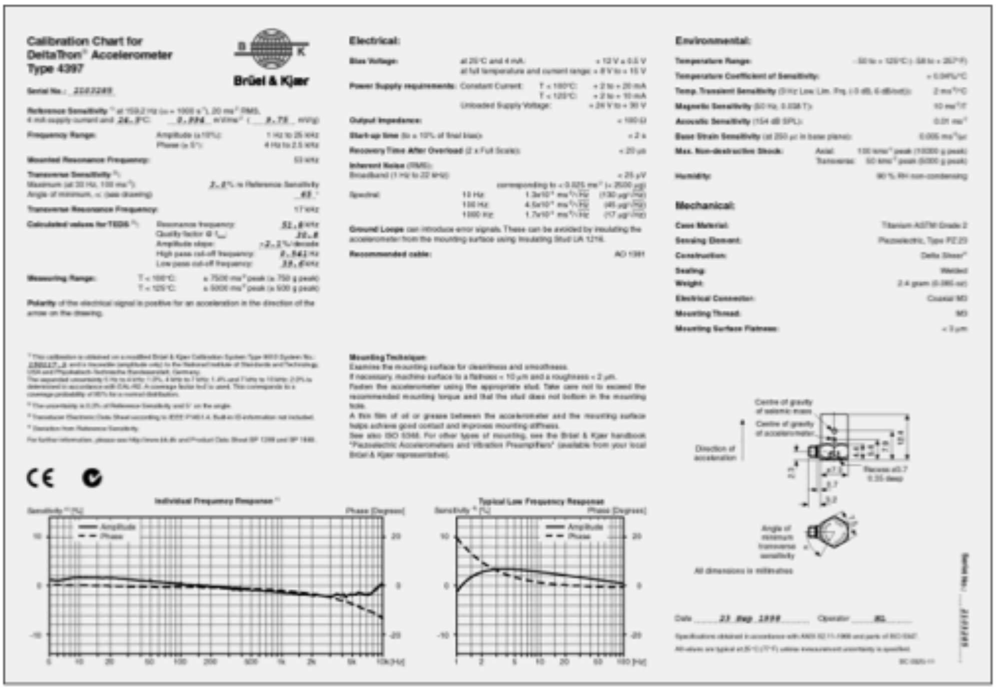


Three piezoelectric elements (1) and three seismic masses (2) are arranged in a triangular configuration around a triangular centre post. They are held in place using a high-tensile clamping ring (3). The DeltaShear design gives a high sensitivity-to-mass ratio compared to other designs, and has a relatively high resonance frequency and high isolation from base strains and temperature transients. The excellent overall characteristics of this design make it ideal for both general purpose accelerometers and more specialised types. A single-pole filter at the input of the built-in preamplifier extends the accelerometer's usable frequency range to approximately 50% of the mounted resonance frequency. Special efforts have been made to minimise interference from RF (radio frequency) electromagnetic fields.

Characteristics

The accelerometers are supplied with individual calibration charts.

Fig. 2 Example of the calibration chart supplied with Brüel & Kjær DeltaTron accelerometers



ZigBee datasheet

Extracts relevant to the work presented in this thesis.

Telegesis	SILICON LABS	TG-ETRX35X-PM-010-110
ETRX351 and ETRX357		Product Manual 1.20

ETRX35x ZIGBEE MODULES

PRODUCT MANUAL

Image not shown actual size; enlarged to show detail.

The Telegesis ETRX351 and ETRX357 modules are low power 2.4GHz ZigBee modules, based on the latest Ember EM351 and EM357 single chip ZigBee™ solutions.

These 3rd generation modules have been designed to be integrated into any device without the need for RF experience and expertise. Utilizing the EmberZNet ZigBee stack, the ETRX35x enables you to add powerful wireless networking capability to your products and quickly bring them to market.

The module's unique AT-style command line interface allows designers to quickly integrate ZigBee technology without complex software engineering. For custom application development the ETRX35x series integrates with ease into Ember's InSight development environment.

Module Features

- Small form factor, SMT module 25mm x 19mm
- Side Castellations for easy soldering and optical inspection
- 2 antenna options: Integrated chip antenna or U.FL coaxial connector
- Industry's first ARM® Cortex-M3 based family of ZigBee modules
- Industry standard JTAG Programming and real time network level debugging via the Ember InSight Port
- 192kB (ETRX357) and 128kB (ETRX351) flash and 12kbytes of RAM
- Lowest Deep Sleep Current of sub 1µA and multiple sleep modes
- Wide supply voltage range (2.1 to 3.6V)
- Optional 32.768kHz watch crystal can be added externally
- Module ships with standard Telegesis AT-style command interface based on the ZigBee PRO feature set
- Can act as an End Device, Router or Coordinator
- 24 general-purpose I/O lines including analogue inputs (all GPIOs of the EM35x are accessible)
- Firmware upgrades via serial port or over the air (password protected)
- Hardware supported encryption (AES-128)
- CE, FCC and IC compliance, FCC modular approval
- Operating temperature range: -40°C to +85°C
- Long range version with a link budget of up to 124dB available in the same form factor

Radio Features

- Based on the Ember EM351 or EM357 single chip ZigBee solutions
- 2.4GHz ISM Band
- 250kbit/s over the air data rate
- 16 channels (IEEE802.15.4 Channel 11 to 26)
- +3dBm output power (+8dBm in boost mode)
- High sensitivity of -100dBm (-102dBm in boost mode) typically @ 1% packet error rate
- RX Current: 26mA, TX Current: 31mA at 3dBm
- Robust Wi-Fi and Bluetooth coexistence

Suggested Applications

- AMR – ZigBee Smart Energy applications
- Wireless Alarms and Security
- Home/Building Automation
- Wireless Sensor Networks
- M2M Industrial Controls
- Lighting and ventilation control
- Remote monitoring
- Environmental monitoring and control

Development Kit

- New Development kit containing everything required to set up a mesh network quickly and evaluate range and performance of the ETRX35x and its long-range version.
- AT-style software interface command dictionary can be modified for high volume customers.
- Custom software development available upon request.

Example AT-Style Commands

AT+BCAST	Send a Broadcast
AT+UCAST:<address>	Send a Unicast
AT+EN	Establish PAN network
AT+JN	Join PAN

At power-up the last configuration is loaded from non-volatile S-Registers, which can eliminate the need for an additional host controller.

ETRX35x Pad	Name	EM35x Pin	Default use	Alternate Functions
1	GND	GND	GND	
2	PC5 {1}	11		TX_ACTIVE
3	PC6	13	I/O	OSC32B, nTX_ACTIVE
4	PC7	14	I/O	OSC32A, OSC32_EXT
5	PA7 {5}	18	I/O	TIM1C4
6	PB3 {2,3}	19	I/O, CTS	SC1nCTS, SC1SCLK, TIM2C3
7	nReset {6}	12	nReset	
8	PB4 {2,3}	20	I/O, RTS	TIM2C4, SC1nRTS, SC1nSSEL
9	PA0	21	I/O	TIM2C1, SC2MOSI
10	PA1	22	I/O	TIM2C3, SC2SDA, SC2MISO
11	PA2	24	I/O	TIM2C4, SC2SCL, SC2SCLK
12	PA3	25	I/O	SC2nSSEL, TRACECLK, TIM2C2
13	GND	GND	GND	
14	PA4	26	I/O	ADC4, PTI_EN, TRACEDATA
15	PA5 {4}	27	I/O	ADC5, PTI_DATA, nBOOTMODE, TRACEDATA3
16	PA6 {5}	29	I/O	TIM1C3
17	PB1 {3}	30	TXD	SC1MISO, SC1MOSI, SC1SDA, SC1TXD, TIM2C1
18	PB2 {3}	31	RXD	SC1MISO, SC1MOSI, SC1SCL, SC1RXD, TIM2C2
19	GND	GND	GND	
20	GND	GND	GND	
21	JTCK	32		SWCLK
22	PC2	33	I/O	JTDO, SWO
23	PC3	34	I/O	JTDI
24	PC4	35	I/O	JTMS, SWDIO
25	PB0	36	I/O, IRQ	VREF, IRQA, TRACECLK, TIM1CLK, TIM2MSK
26	PC1	38	I/O	ADC3, SWO, TRACEDATA0
27	PC0 {5}	40	I/O	JRST, IRQD, TRACEDATA1
28	PB7 {5}	41	I/O	ADC2, IRQC, TIM1C2
29	PB6 {5}	42	I/O	ADC1, IRQB, TIM1C1
30	PB5	43	I/O	ADC0, TIM2CLK, TIM1MSK
31	GND	GND	GND	
32	Vcc	Vcc	Vcc	
33	GND	GND	GND	

Table 3: Pin Information

Notes:

{1} When the alternate function is selected, TX_ACTIVE becomes an output that indicates that the EM35x radio circuit is in transmit mode. PC5 is not usable on the long range version of the ETRX35x as this GPIO is used internally as TX_ACTIVE to control the external RF frontend.

{2} The serial UART connections TXD, RXD, CTS and RTS are PB1, PB2, PB3 and PB4 respectively. The device sends its data on TXD and receives on RXD.

{3} When using the Telegesis AT Commandset, RTS/CTS handshaking is selectable in firmware. See the AT Command Manual.

{4} If PA5 is driven low at power-up or reset the module will boot up in the bootloader

{5} PA6, PA7, PB6, PB7 and PC0 can drive high current (see section 8)

{6} nRESET is level-sensitive, not edge-sensitive. The module is held in the reset state while nRESET is low

See also the table "Module pads and functions" in the ETRX357 Development Kit Product Manual. Refer to Ember's EM357 manual for details of the alternate functions and pin names.

4 Hardware Description

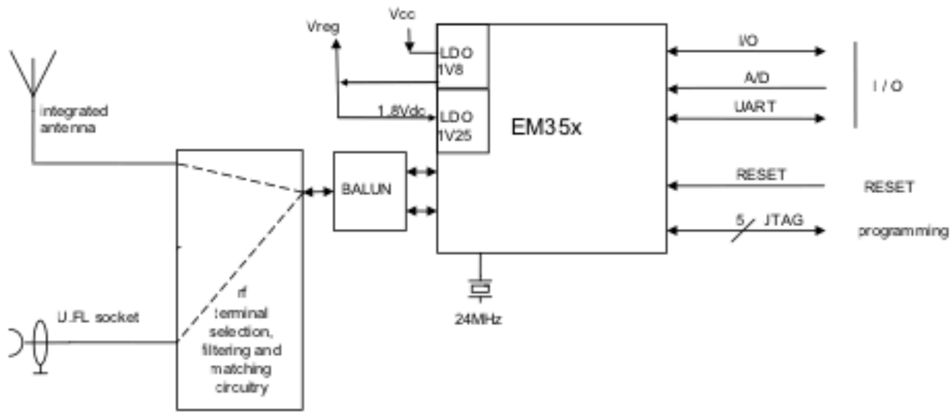


Figure 2: Hardware Diagram

The ETRX351, ETRX351HR, ETRX357 and ETRX357HR are based on the Ember EM351 and EM357 respectively. The EM351 and EM357 are fully integrated 2.4GHz ZigBee transceivers with a 32-bit ARM® Cortex M3™ microprocessor, flash and RAM memory, and peripherals.

The industry standard serial wire and JTAG programming and debugging interfaces together with the standard ARM system debug components help to streamline any custom software development.

In addition to this a number of MAC functions are also implemented in hardware to help maintaining the strict timing requirements imposed by the ZigBee and IEEE802.15.4 standards.

The new advanced power management features allow faster wakeup from sleep and new power down modes allowing this 3rd generation module to offer a longer battery life than any 2nd generation modules on the market.

The EM35x has fully integrated voltage regulators for both required 1.8V and 1.25V supply voltages. The voltages are monitored (brown-out detection) and the built in power-on-reset circuit eliminates the need for any external monitoring circuitry. An optional 32.768 kHz watch crystal can be connected externally to pads 3 and 4 in case more accurate timing is required. To utilize the external watch crystal custom firmware is required.

4.1 Hardware Interface

All GPIO pins of the EM351 or EM357 are accessible on the module's pads. Whether signals are used as general purpose I/Os, or assigned to a peripheral function like ADC is set by the firmware. When using the Telegesis AT Commandset please refer to the AT Commandset manual and the development kit manual for this information and when developing custom firmware please refer to the EM35x datasheet [2].

5.1 Token Settings

The ETRX3 Series Modules' tokens will be pre-programmed with the settings shown in the table below.

Token	Description	TG Default
MFG_CIB_OBS	Option Bytes	<not written>
MFG_CUSTOM_VERSION	Optional Version Number	<not written>
MFG_CUSTOM_EUI_64	Custom EUI	<not written>
MFG_STRING	Device Specific String	TELEGESIS
MFG_BOARD_NAME	Hardware Identifier	<Order Code>
MFG_MANUF_ID	Manufacturer ID	0x1010
MFG_PHY_CONFIG	Default Power Settings	0xFF26
MFG_BOOTLOAD_AES_KEY	Bootloader Key	<not written>
MFG_EZSP_STORAGE	EZSP related	<not written>
MFG_CBKE_DATA	SE Security	<not written>
MFG_INSTALLATION_CODE	SE Installation	<not written>
MFG_OSC24M_BIAS_TRIM	Crystal Bias	<not written>

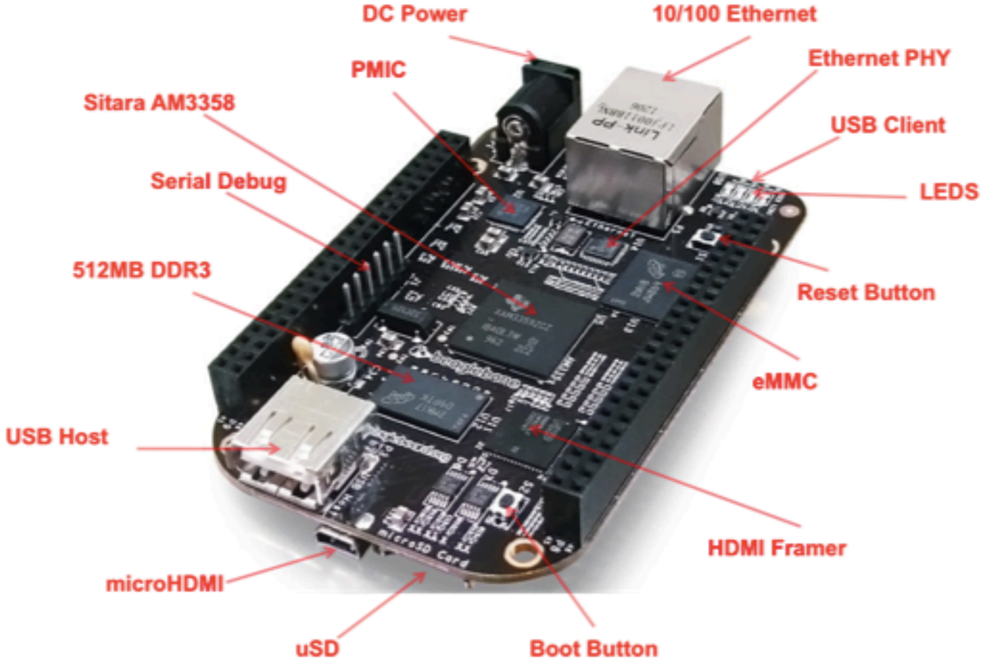
Table 4. Manufacturing tokens

5.2 Custom Firmware

For high volume customers the firmware can be customised on request. In addition to this the ETRX3 series of modules is an ideal platform for developing custom firmware. In order to develop custom firmware the Ember Insight toolchain is required.

BBB hardware spec

Extracts relevant to the work presented in this thesis. (Available: http://beagle-board.org/Support/bone101/#hardware).



Revision A5 also provides a POWER button that can be used to enter and exit hibernate modes once that feature is implemented in the software.

Headers

The expansion headers provide extensive I/O capabitilities.

Cape Expansion Headers

P9

DGND	1	2	DGND
VDD_3V3	3	4	VDD_3V3
VDD_5V	5	6	VDD_5V
SYS_5V	7	8	SYS_5V
PWR_BUT	9	10	SYS_RESETN
UART4_RXD	11	12	GPIO_60
UART4_TXD	13	14	EHRPWM1A
GPIO_48	15	16	EHRPWM1B
SPI0_CS0	17	18	SPI0_D1
I2C2_SCL	19	20	I2C2_SDA
SPI0_D0	21	22	SPI0_SCLK
GPIO_49	23	24	UART1_TXD
GPIO_117	25	26	UART1_RXD
GPIO_115	27	28	SPI1_CS0
SPI1_D0	29	30	GPIO_112
SPI1_SCLK	31	32	VDD_ADC
AIN4	33	34	GNDA_ADC
AIN6	35	36	AIN5
AIN2	37	38	AIN3
AIN0	39	40	AIN1
GPIO_20	41	42	ECAPPWM0
DGND	43	44	DGND
DGND	45	46	DGND

P8

DGND	1	2	DGND
MMC1_DAT6	3	4	MMC1_DAT7
MMC1_DAT2	5	6	MMC1_DAT3
GPIO_66	7	8	GPIO_67
GPIO_69	9	10	GPIO_68
GPIO_45	11	12	GPIO_44
EHRPWM2B	13	14	GPIO_26
GPIO_47	15	16	GPIO_46
GPIO_27	17	18	GPIO_65
EHRPWM2A	19	20	MMC1_CMD
MMC1_CLK	21	22	MMC1_DAT5
MMC1_DAT4	23	24	MMC1_DAT1
MMC1_DAT0	25	26	GPIO_61
LCD_VSYNC	27	28	LCD_PCLK
LCD_HSYNC	29	30	LCD_AC_BIAS
LCD_DATA14	31	32	LCD_DATA15
LCD_DATA13	33	34	LCD_DATA11
LCD_DATA12	35	36	LCD_DATA10
LCD_DATA8	37	38	LCD_DATA9
LCD_DATA6	39	40	LCD_DATA7
LCD_DATA4	41	42	LCD_DATA5
LCD_DATA2	43	44	LCD_DATA3
LCD_DATA0	45	46	LCD_DATA1

LEGEND
POWER/GROUND/RESET
AVAILABLE DIGITAL
AVAILABLE PWM
SHARED I2C BUS
RECONFIGURABLE DIGITAL
ANALOG INPUTS (1.8V)

Each digital I/O pin has 8 different modes that can be selected, including GPIO.

---

65 possible digital I/Os

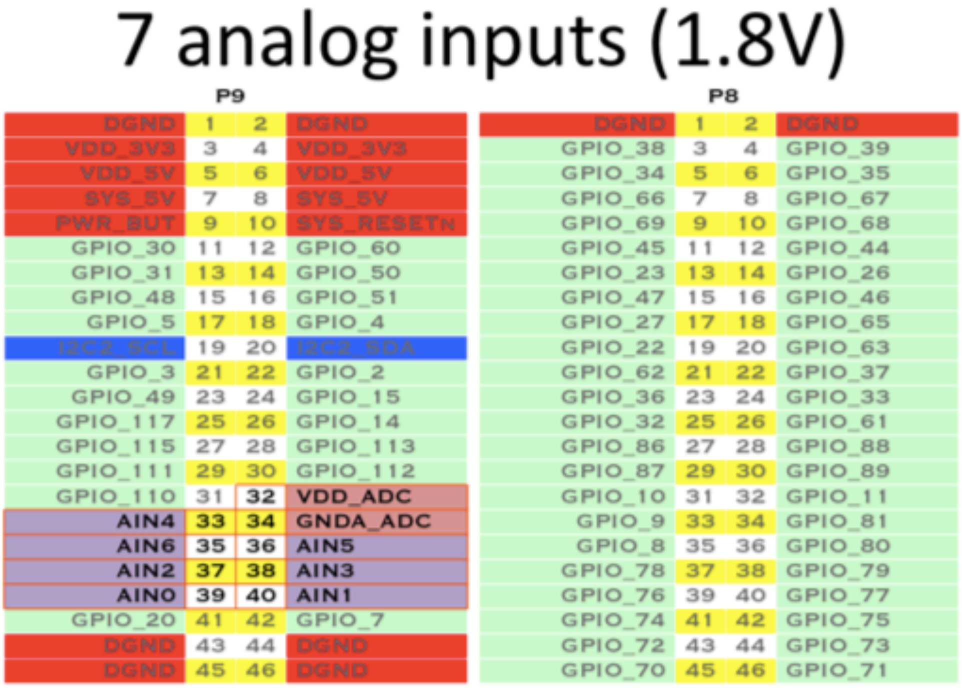
P9

DGND	1	2	DGND
VDD_3V3	3	4	VDD_3V3
VDD_5V	5	6	VDD_5V
SYS_5V	7	8	SYS_5V
PWR_BUT	9	10	SYS_RESETN
GPIO_30	11	12	GPIO_60
GPIO_31	13	14	GPIO_50
GPIO_48	15	16	GPIO_51
GPIO_5	17	18	GPIO_4
I2C2_SCL	19	20	I2C2_SDA
GPIO_3	21	22	GPIO_2
GPIO_49	23	24	GPIO_15
GPIO_117	25	26	GPIO_14
GPIO_115	27	28	GPIO_113
GPIO_111	29	30	GPIO_112
GPIO_110	31	32	VDD_ADC
AIN4	33	34	GNDA_ADC
AIN6	35	36	AIN5
AIN2	37	38	AIN3
AIN0	39	40	AIN1
GPIO_20	41	42	GPIO_7
DGND	43	44	DGND
DGND	45	46	DGND

P8

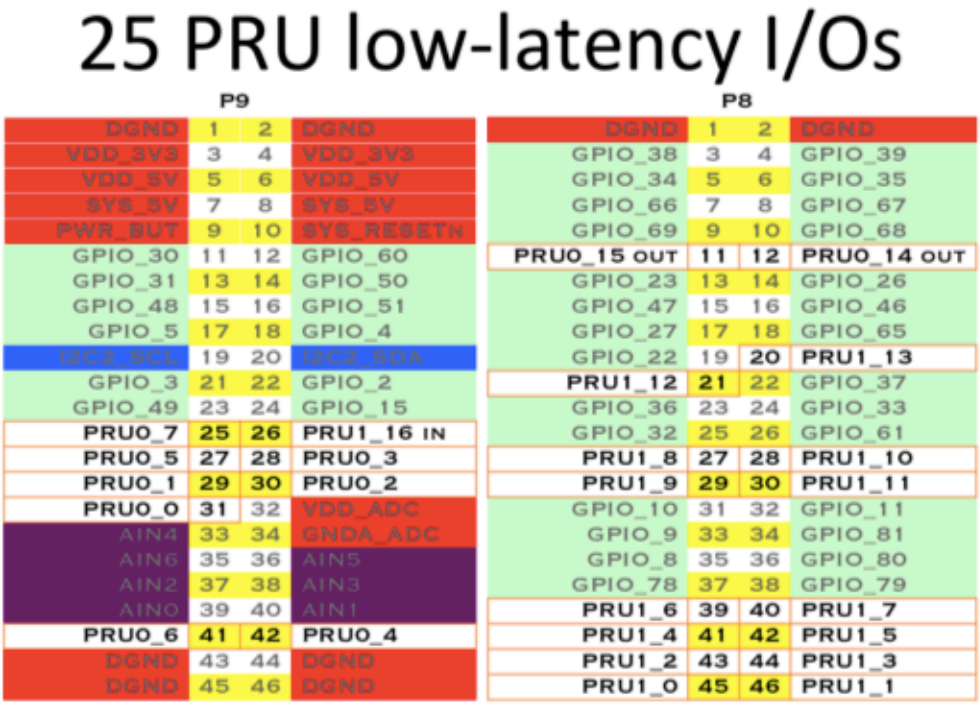
DGND	1	2	DGND
GPIO_38	3	4	GPIO_39
GPIO_34	5	6	GPIO_35
GPIO_66	7	8	GPIO_67
GPIO_69	9	10	GPIO_68
GPIO_45	11	12	GPIO_44
GPIO_23	13	14	GPIO_26
GPIO_47	15	16	GPIO_46
GPIO_27	17	18	GPIO_65
GPIO_22	19	20	GPIO_63
GPIO_62	21	22	GPIO_37
GPIO_36	23	24	GPIO_33
GPIO_32	25	26	GPIO_61
GPIO_86	27	28	GPIO_88
GPIO_87	29	30	GPIO_89
GPIO_10	31	32	GPIO_11
GPIO_9	33	34	GPIO_81
GPIO_8	35	36	GPIO_80
GPIO_78	37	38	GPIO_79
GPIO_76	39	40	GPIO_77
GPIO_74	41	42	GPIO_75
GPIO_72	43	44	GPIO_73
GPIO_70	45	46	GPIO_71

In GPIO mode, each digital I/O can produce interrupts.



Make sure you don't input more than 1.8V to the analog input pins.

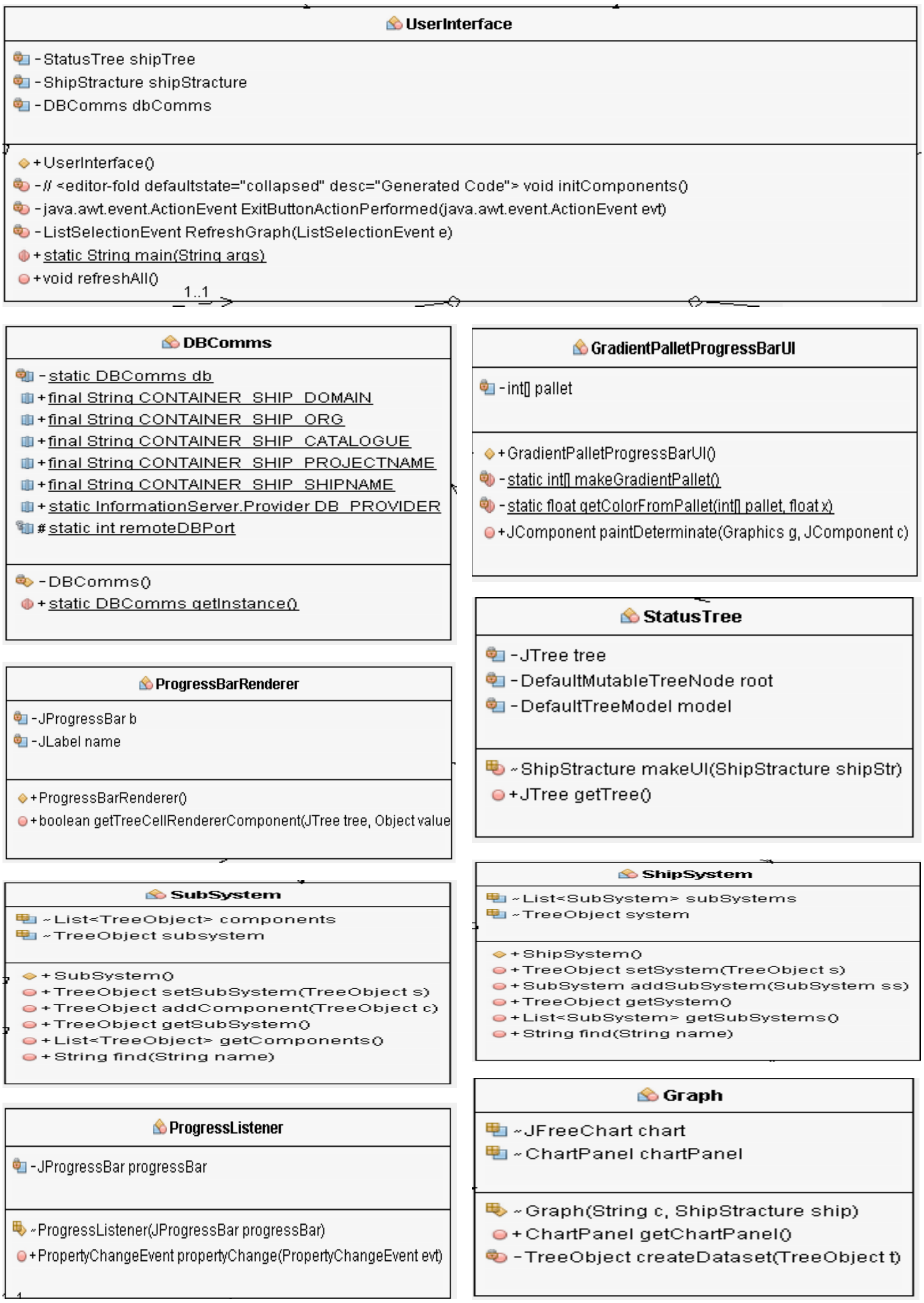
This is a single 12-bit analog-to-digital converter with 8 channels, 7 of which are made available on the headers.

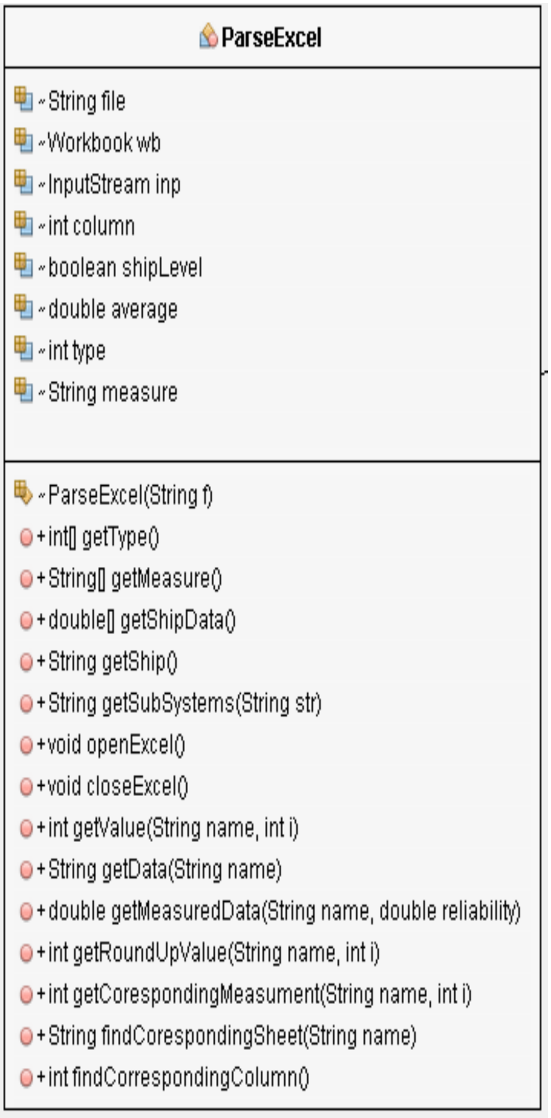


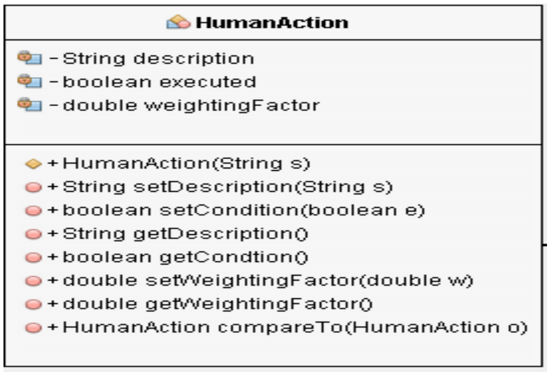
Advanced users can also make use of 2 built-in 32-bit 200-MHz microcontrollers called Programmable Real-time Units (PRUs) for performing real-time tasks. Each PRU has some pins associated with it tied directly to registers for super-low-latency access.

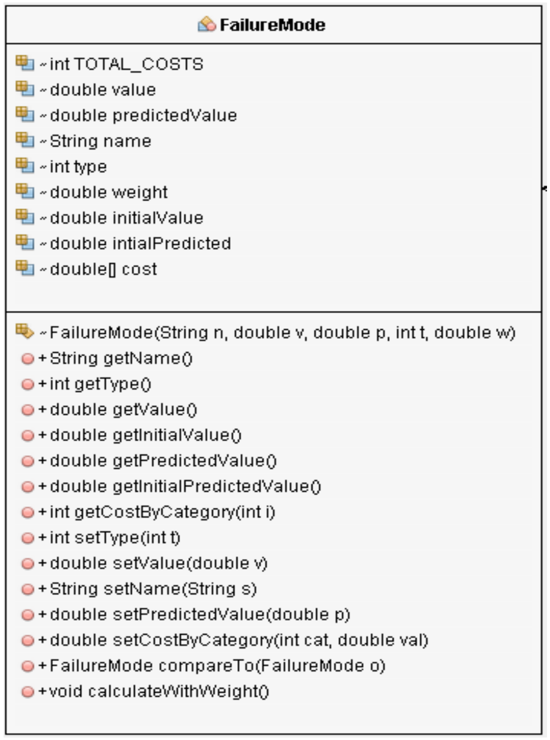
Appendix E – DSS UML diagram

The classes presented in this appendix were implemented for the DSS GUI.

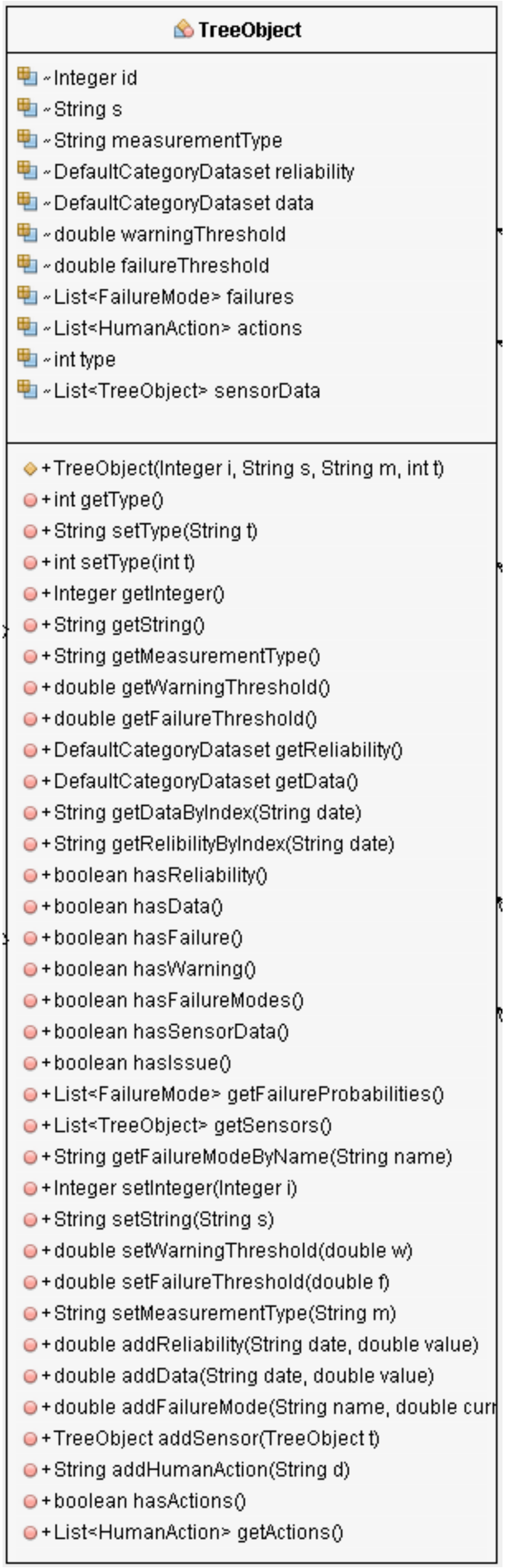



ParseExcel
~String file
~Workbook wb
~InputStream inp
~int column
~boolean shipLevel
~double average
~int type
~String measure
~ParseExcel(String f)
+int[] getType()
+String[] getMeasure()
+double[] getShipData()
+String getShip()
+String getSubSystems(String str)
+void openExcel()
+void closeExcel()
+int getValue(String name, int i)
+String getData(String name)
+double getMeasuredData(String name, double reliability)
+int getRoundUpValue(String name, int i)
+int getCorespondingMeasument(String name, int i)
+String findCorespondingSheet(String name)
+int findCorrespondingColumn()


HumanAction
-String description
-boolean executed
-double weightingFactor
+HumanAction(String s)
+String setDescription(String s)
+boolean setCondition(boolean e)
+String getDescription()
+boolean getCondtion()
+double setWeightingFactor(double w)
+double getWeightingFactor()
+HumanAction compareTo(HumanAction o)


FailureMode
~int TOTAL_COSTS
~double value
~double predictedValue
~String name
~int type
~double weight
~double initialValue
~double intialPredicted
~double[] cost
~FailureMode(String n, double v, double p, int t, double w)
+String getName()
+int getType()
+double getValue()
+double getInitialValue()
+double getPredictedValue()
+double getInitialPredictedValue()
+int getCostByCategory(int i)
+int setType(int t)
+double setValue(double v)
+String setName(String s)
+double setPredictedValue(double p)
+double setCostByCategory(int cat, double val)
+FailureMode compareTo(FailureMode o)
+void calculateWithWeight()


ShipStracture
-TreeObject selected
-String selectedWarnOrFail
~List<ShipSystem> systems
~TreeObject ship
+ShipStracture()
+TreeObject getShip()
+List<ShipSystem> getStracture()
+String findSystem(String name)
+TreeObject getSelected()
+String getSelectedWarnOrFail()
+boolean hasSelection()
+String findShipStructure(String name)
+String getComponentNamesAfterStructure(String name)
+String selectShipStructure(String name)
+String selectionOfWarnOrFail(String s)
+double addDataTo(String name, double pPast, double pCurrent, dou
+double addFailureModeDataTo(String name, String n, double c, doub
+String addHumanActionDataTo(String name, String d)
+int calculateFailureProbabilities(DefaultListModel lm, int listType)
+ParseExcel addData(ParseExcel pef)

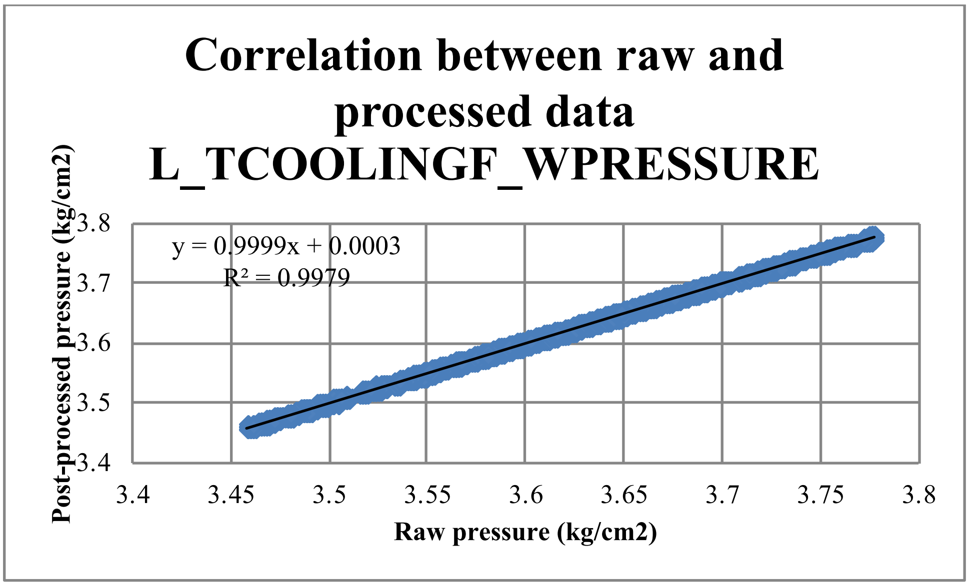

TreeObject
~Integer id
~String s
~String measurementType
~DefaultCategoryDataset reliability
~DefaultCategoryDataset data
~double warningThreshold
~double failureThreshold
~List<FailureMode> failures
~List<HumanAction> actions
~int type
~List<TreeObject> sensorData
+TreeObject(Integer i, String s, String m, int t)
+int getType()
+String setType(String t)
+int setType(int t)
+Integer getInteger()
+String getString()
+String getMeasurementType()
+double getWarningThreshold()
+double getFailureThreshold()
+DefaultCategoryDataset getReliability()
+DefaultCategoryDataset getData()
+String getDataByIndex(String date)
+String getRelibilityByIndex(String date)
+boolean hasReliability()
+boolean hasData()
+boolean hasFailure()
+boolean hasWarning()
+boolean hasFailureModes()
+boolean hasSensorData()
+boolean hasIssue()
+List<FailureMode> getFailureProbabilities()
+List<TreeObject> getSensors()
+String getFailureModeByName(String name)
+Integer setInteger(Integer i)
+String setString(String s)
+double setWarningThreshold(double w)
+double setFailureThreshold(double f)
+String setMeasurementType(String m)
+double addReliability(String date, double value)
+double addData(String date, double value)
+double addFailureMode(String name, double cur
+TreeObject addSensor(TreeObject t)
+String addHumanAction(String d)
+boolean hasActions()
+List<HumanAction> getActions()

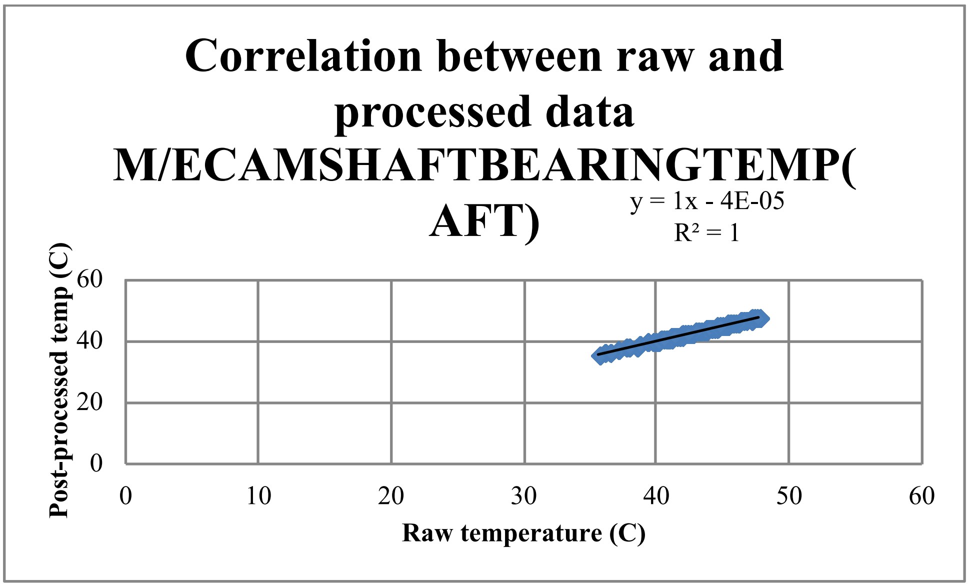
Appendix F – Third Case Study Correlation Analysis Results for All Instances

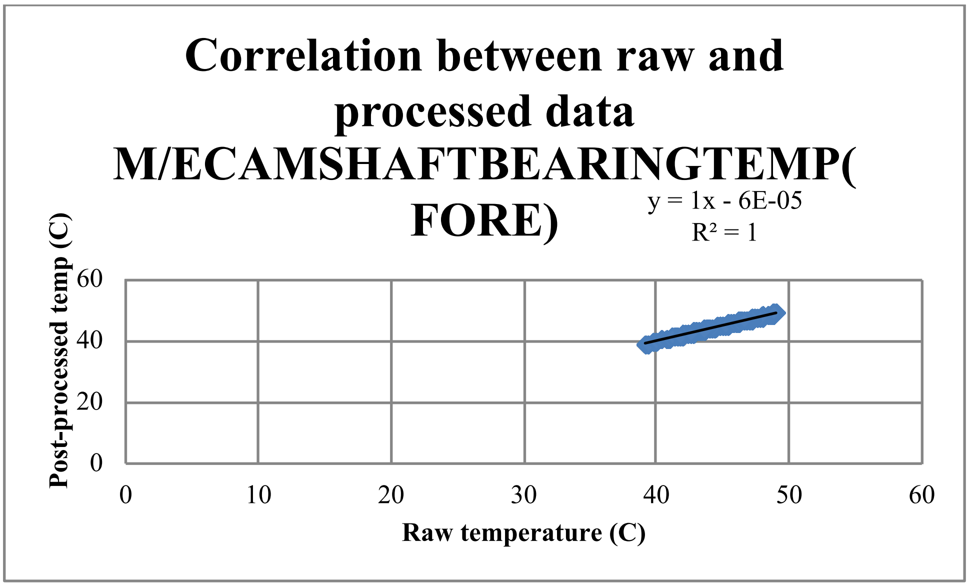
The following table presents the unique instance numbers used in the case study and their respective names in the input dataset.

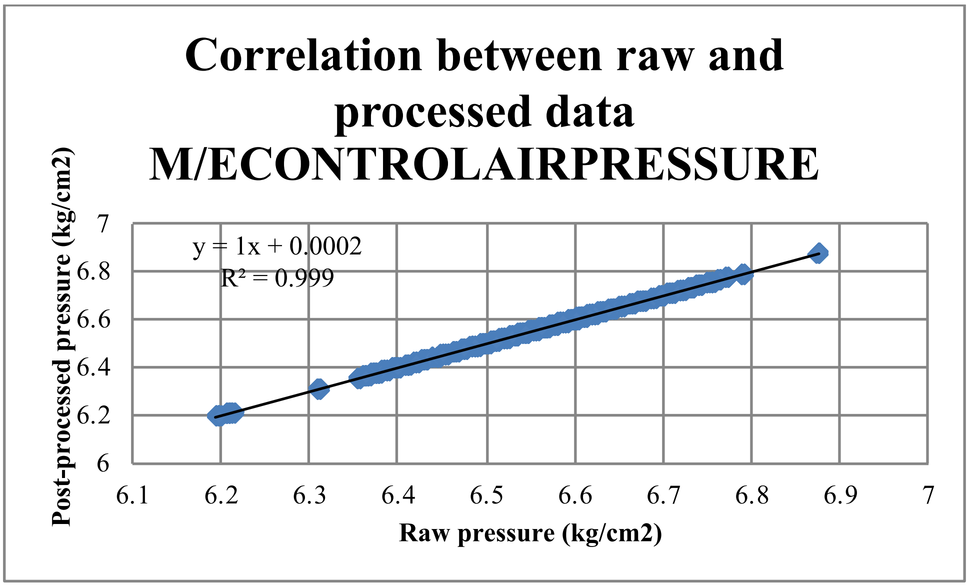
Cross-reference between unique instance numbers and input dataset measurement names.

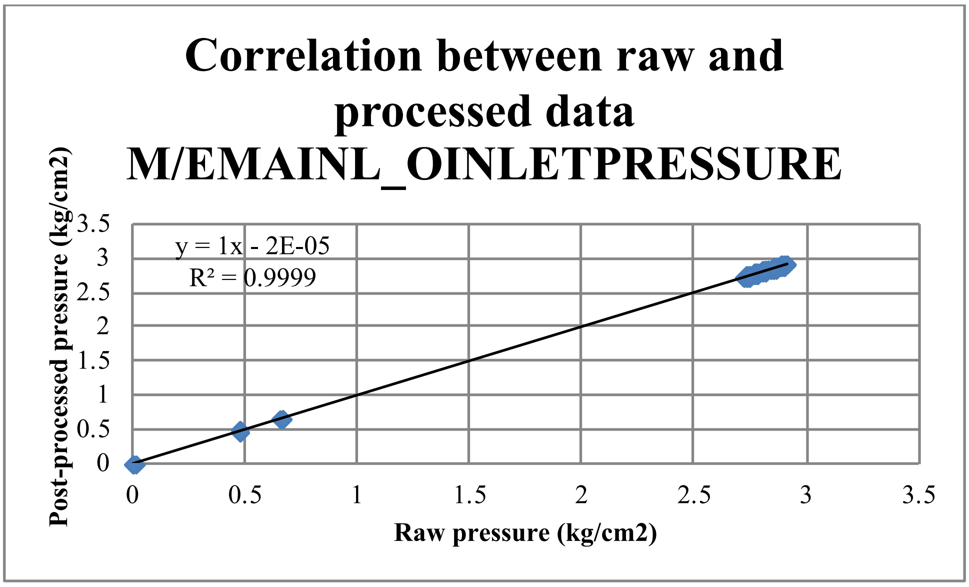
No.	Measurement	No.	Measurement
1	M/ETHRUSTBEARINGL_OOUTLETTEMP	20	NO_1INTERMEDIATESHAFTBEARINGTEMP
2	M/ENO_1T/CL_OINLETPRESSURE	21	NO_2INTERMEDIATESHAFTBEARINGTEMP
3	M/ENO_1T/CL_OINLETTEMP	22	NO_3INTERMEDIATESHAFTBEARINGTEMP
4	M/ENO_1T/CL_OOUTLETTEMP	23	M/EMAINL_OINLETPRESSURE
5	M/ENO_2T/CL_OINLETPRESSURE	24	M/EMAINL_OINLETTEMP
6	M/ENO_2T/CL_OINLETTEMP	25	L_TCOOLINGF_WPRESSURE
7	M/ENO_2T/CL_OOUTLETTEMP	26	M/ENO_1CYL_EXH_GASOUTLETTEMP
8	SCAVENGINGAIRMANIFOLDPRESSURE	27	M/ENO_2CYL_EXH_GASOUTLETTEMP
9	M/ESCAVENGINGAIRMANIFOLDTEMP	28	M/ENO_3CYL_EXH_GASOUTLETTEMP
10	M/ESTARTAIRPRESSURE	29	M/ENO_4CYL_EXH_GASOUTLETTEMP
11	M/EP_C_OINLETPRESSURE	30	M/ENO_5CYL_EXH_GASOUTLETTEMP
12	M/ENO_1CYLINDERJ_C_F_WOUTLETTEMP	31	M/ENO_6CYL_EXH_GASOUTLETTEMP
13	M/ENO_2CYLINDERJ_C_F_WOUTLETTEMP	32	M/ENO_7CYL_EXH_GASOUTLETTEMP
14	M/ENO_3CYLINDERJ_C_F_WOUTLETTEMP	33	M/ENO_8CYL_EXH_GASOUTLETTEMP
15	M/ENO_4CYLINDERJ_C_F_WOUTLETTEMP	34	M/ECAMSHAFTBEARINGTEMP(AFT)
16	M/ENO_5CYLINDERJ_C_F_WOUTLETTEMP	35	M/ECAMSHAFTBEARINGTEMP(FORE)
17	M/ENO_6CYLINDERJ_C_F_WOUTLETTEMP	36	M/ENO_1T/CEXH_GASOUTLETTEMP
18	M/ENO_7CYLINDERJ_C_F_WOUTLETTEMP	37	M/ENO_2T/CEXH_GASOUTLETTEMP
19	M/ENO_8CYLINDERJ_C_F_WOUTLETTEMP	38	M/ECONTROLAIRPRESSURE

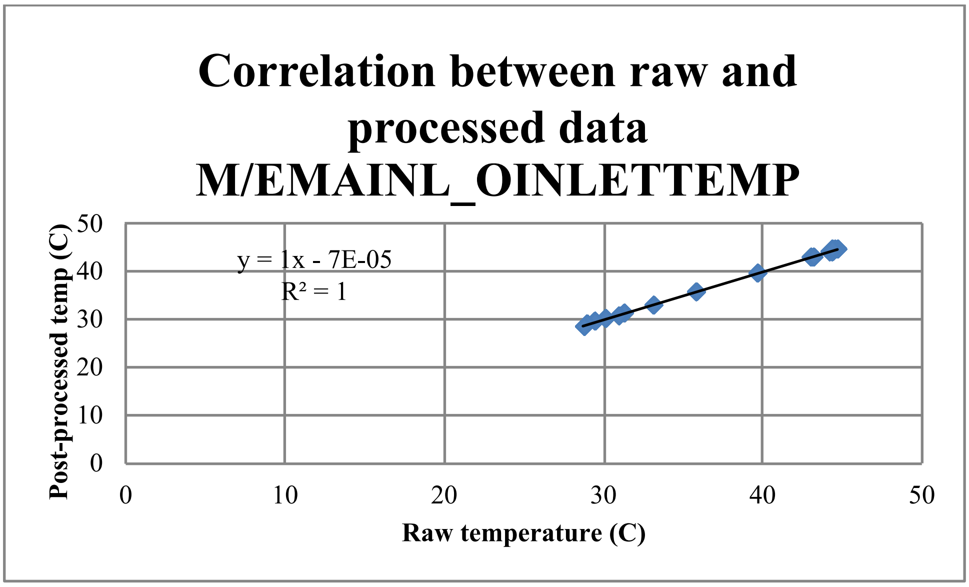


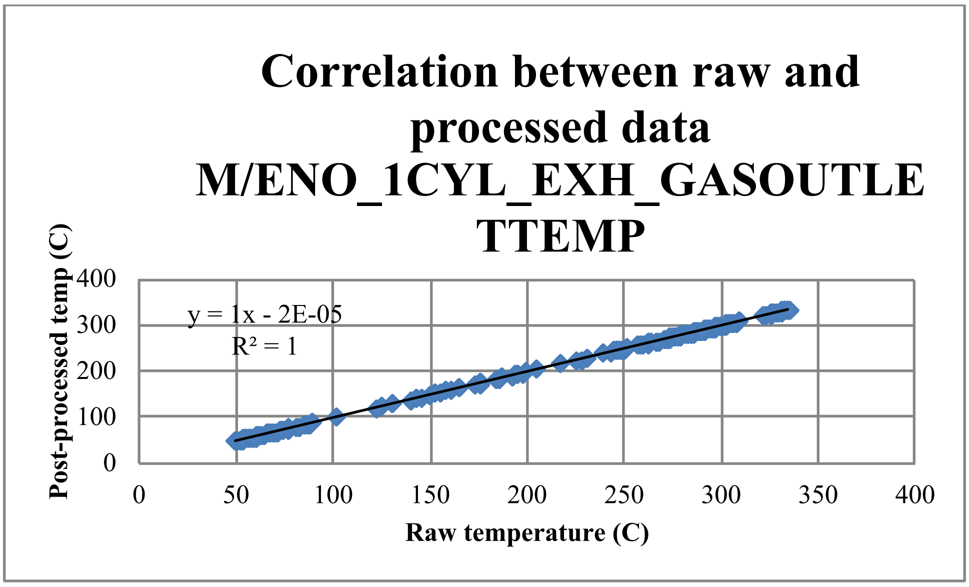

Correlation between raw and processed data M/ECAMSHAFTBEARINGTEMP(AFT)
y = 1x - 4E-05
R² = 1
Post-processed temp (C)
0
20
40
60
0
10
20
30
40
50
60
Raw temperature (C)

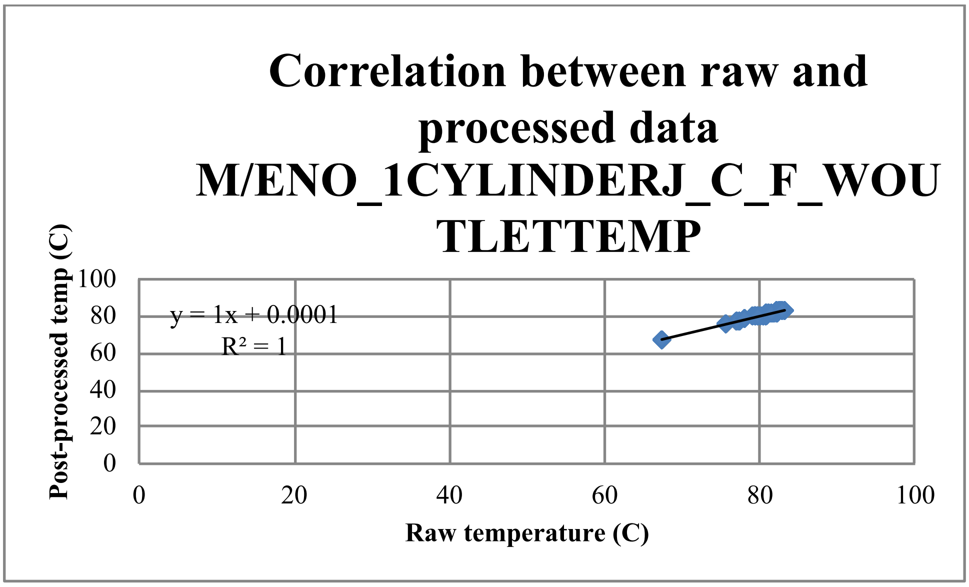

Correlation between raw and processed data M/ECAMSHAFTBEARINGTEMP(FORE)
y = 1x - 6E-05
R² = 1
Post-processed temp (C)
0
20
40
60
0
10
20
30
40
50
60
Raw temperature (C)

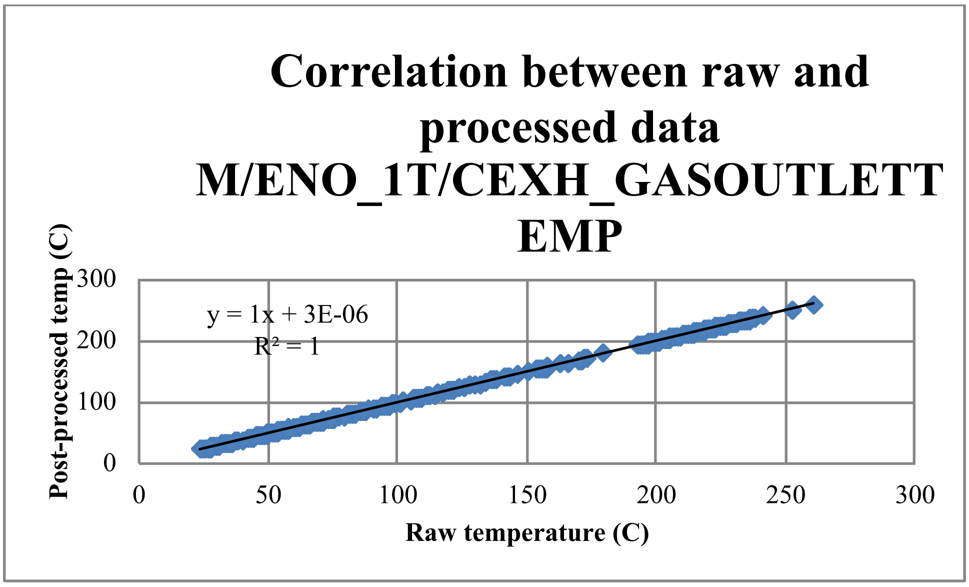

Correlation between raw and processed data M/ECONTROLAIRPRESSURE
y = 1x + 0.0002
R² = 0.999
Post-processed pressure (kg/cm2)
Raw pressure (kg/cm2)
7
6.8
6.6
6.4
6.2
6
6.1
6.2
6.3
6.4
6.5
6.6
6.7
6.8
6.9
7

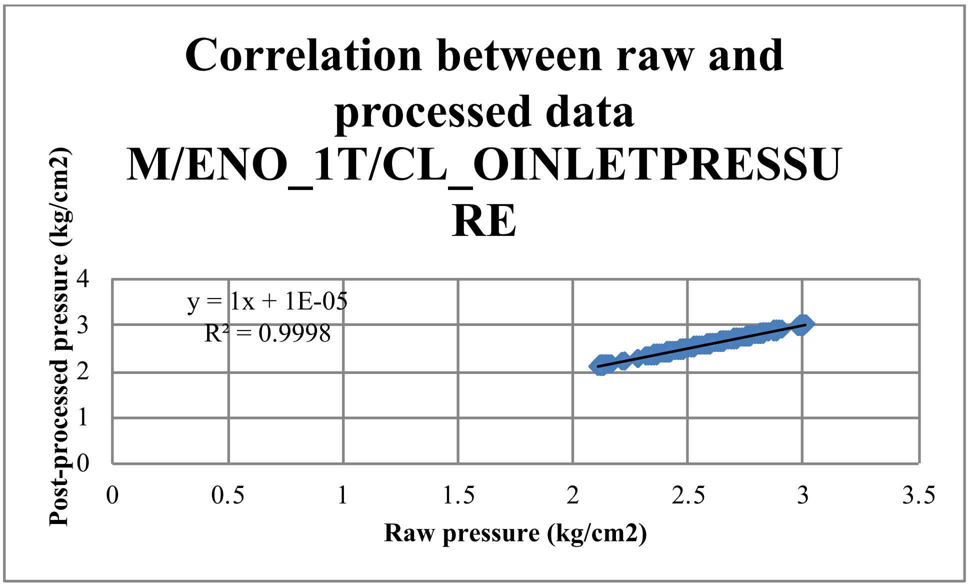

Correlation between raw and processed data M/EMAINL_OINLETPRESSURE
y = 1x - 2E-05
R² = 0.9999
Post-processed pressure (kg/cm2)
Raw pressure (kg/cm2)
3.5
3
2.5
2
1.5
1
0.5
0
0
0.5
1
1.5
2
2.5
3
3.5

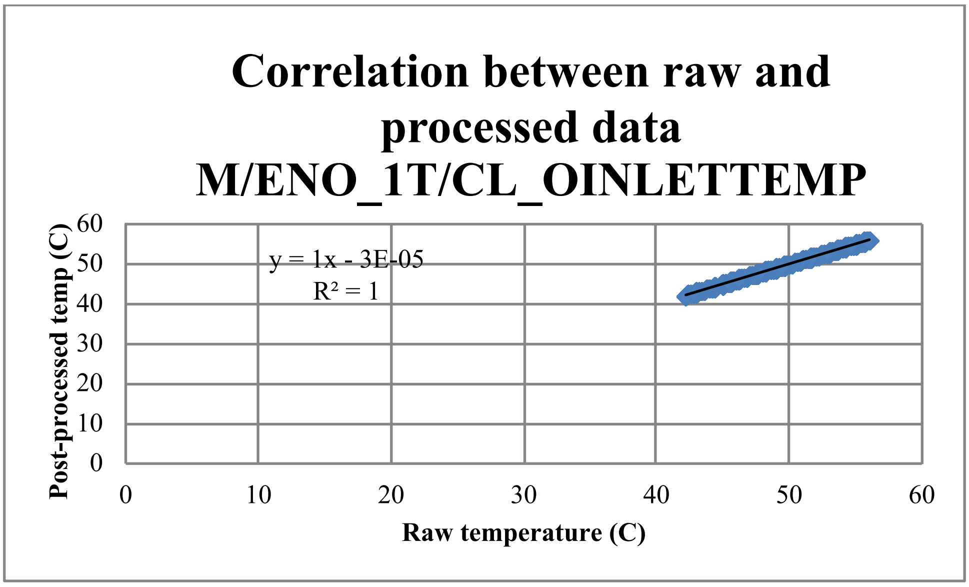

Correlation between raw and processed data M/EMAINL_OINLETTEMP
y = 1x - 7E-05
R² = 1
Post-processed temp (C)
Raw temperature (C)
0
10
20
30
40
50

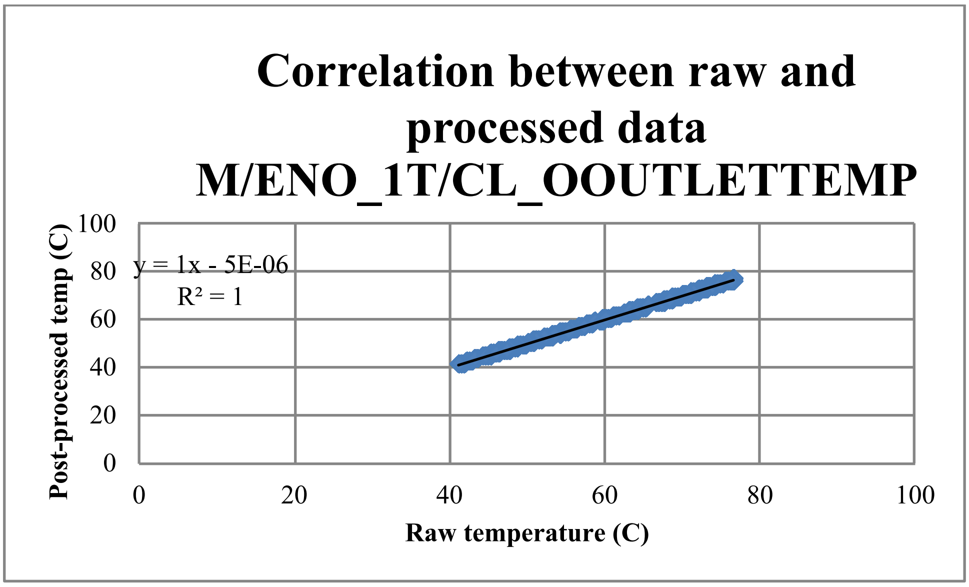

Correlation between raw and processed data M/ENO_1CYL_EXH_GASOUTLETTEMP
y = 1x - 2E-05
R² = 1
Post-processed temp (C)
Raw temperature (C)
0
50
100
150
200
250
300
350
400

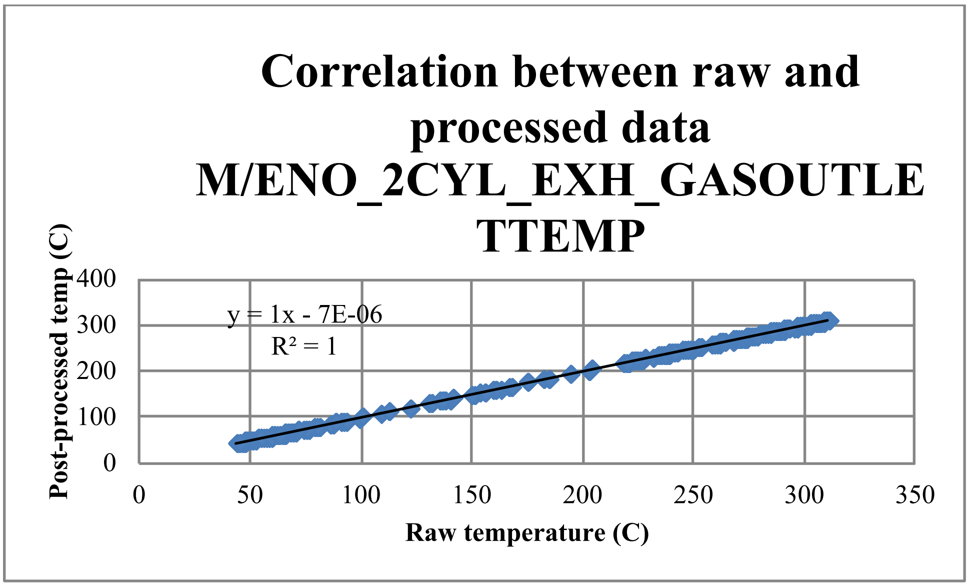

Correlation between raw and processed data M/ENO_1CYLINDERJ_C_F_WOUTLETTEMP
Post-processed temp (C)
Raw temperature (C)
y = 1x + 0.0001
R² = 1
0
20
40
60
80
100

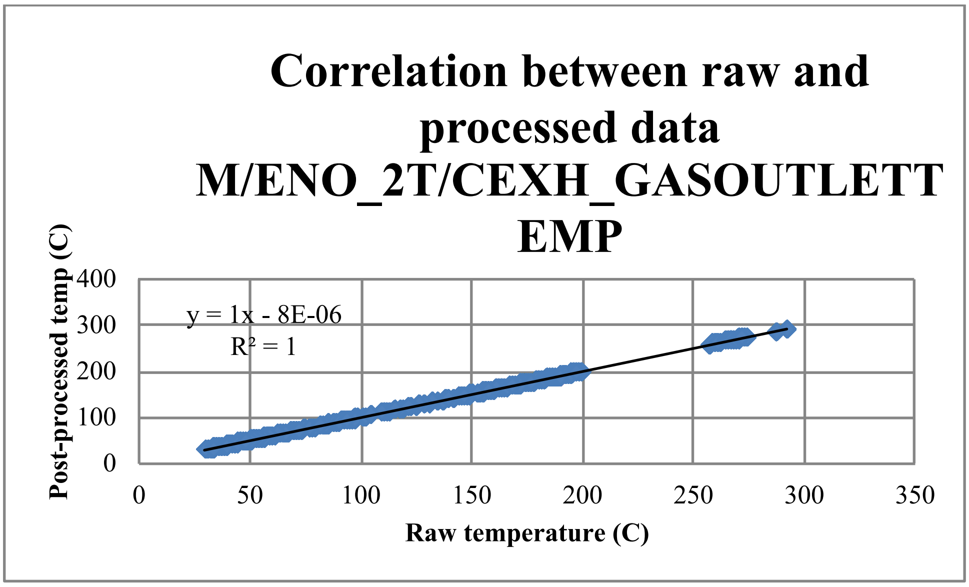

Correlation between raw and processed data M/ENO_1T/CEXH_GASOUTLETTEMP
Post-processed temp (C)
Raw temperature (C)
y = 1x + 3E-06
R² = 1
0
50
100
150
200
250
300

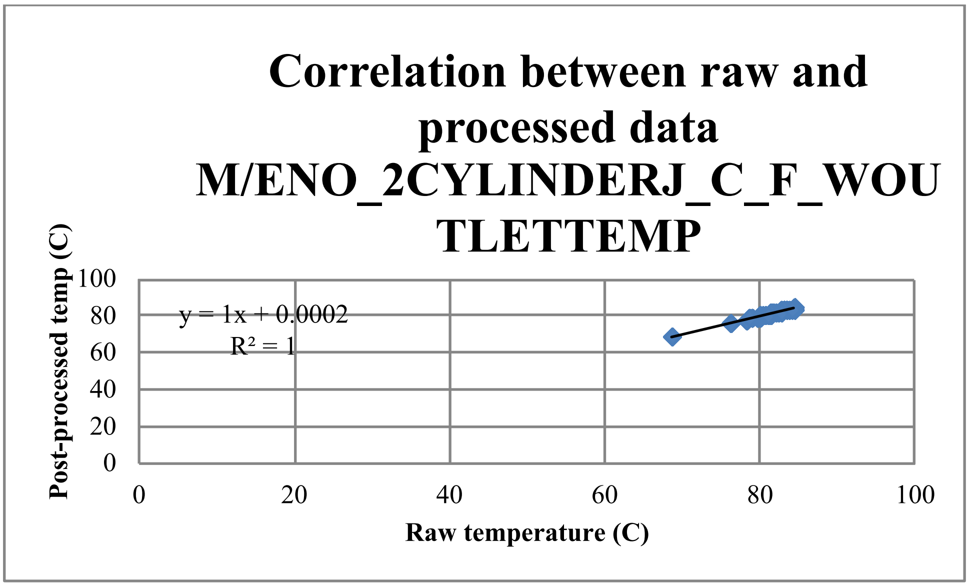

Correlation between raw and processed data M/ENO_1T/CL_OINLETPRESSURE
Post-processed pressure (kg/cm2)
y = 1x + 1E-05
R² = 0.9998
0
1
2
3
4
0
0.5
1
1.5
2
2.5
3
3.5
Raw pressure (kg/cm2)

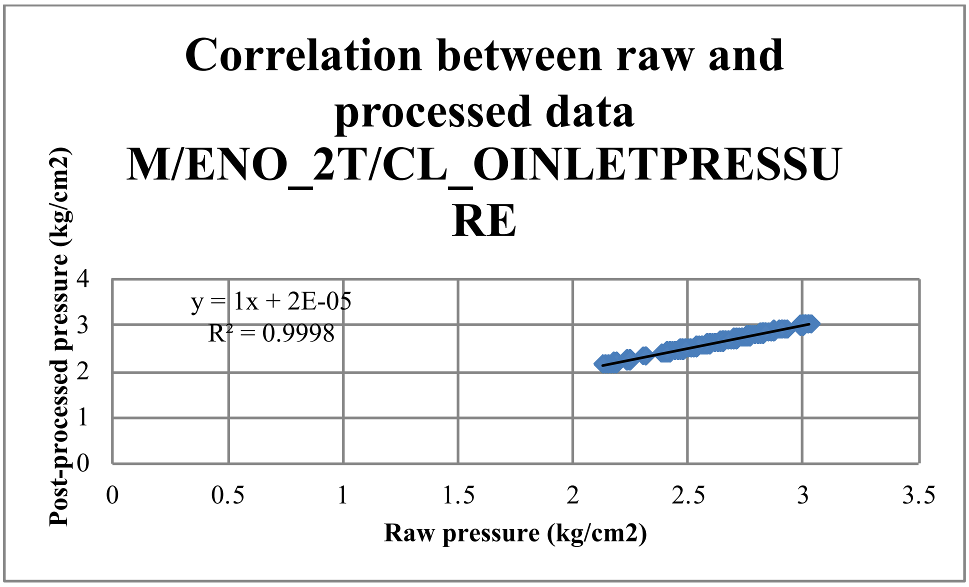

Correlation between raw and processed data M/ENO_1T/CL_OINLETTEMP
Post-processed temp (C)
y = 1x - 3E-05
R² = 1
0
10
20
30
40
50
60
0
10
20
30
40
50
60
Raw temperature (C)

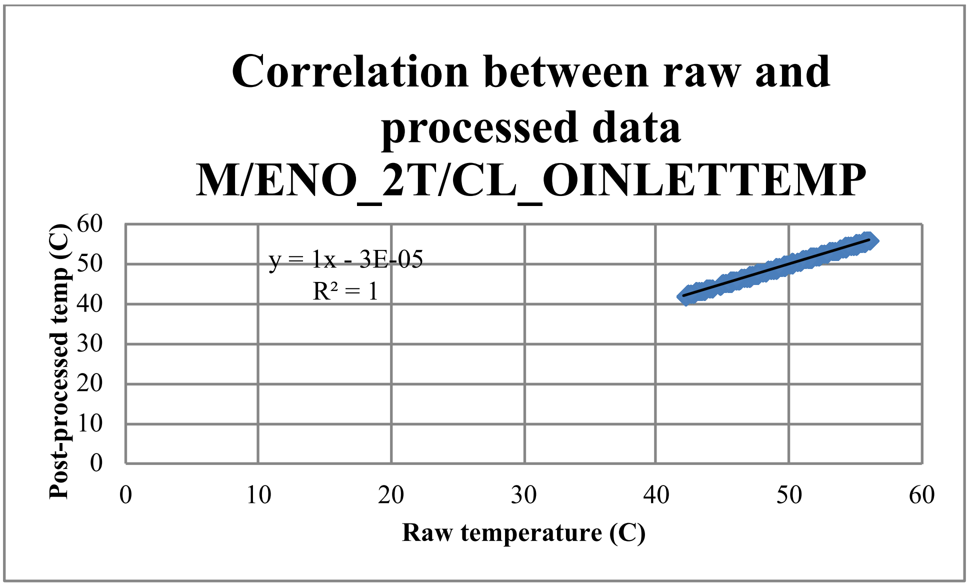

Correlation between raw and processed data M/ENO_1T/CL_OOUTLETTEMP
y = 1x - 5E-06
R² = 1
Post-processed temp (C)
Raw temperature (C)
0
20
40
60
80
100

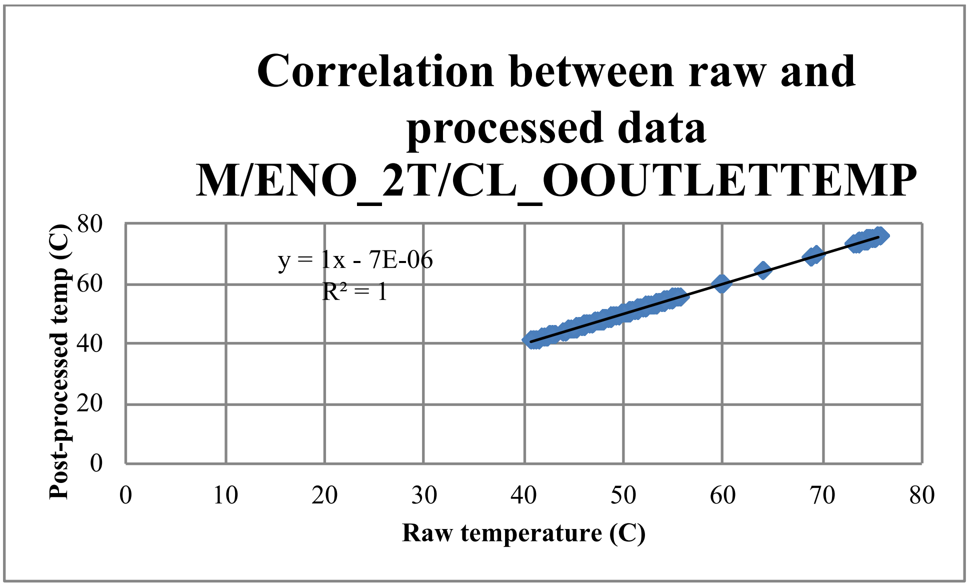

Correlation between raw and processed data M/ENO_2CYL_EXH_GASOUTLETTEMP
y = 1x - 7E-06
R² = 1
Post-processed temp (C)
Raw temperature (C)
0
100
200
300
400
50
150
250
350

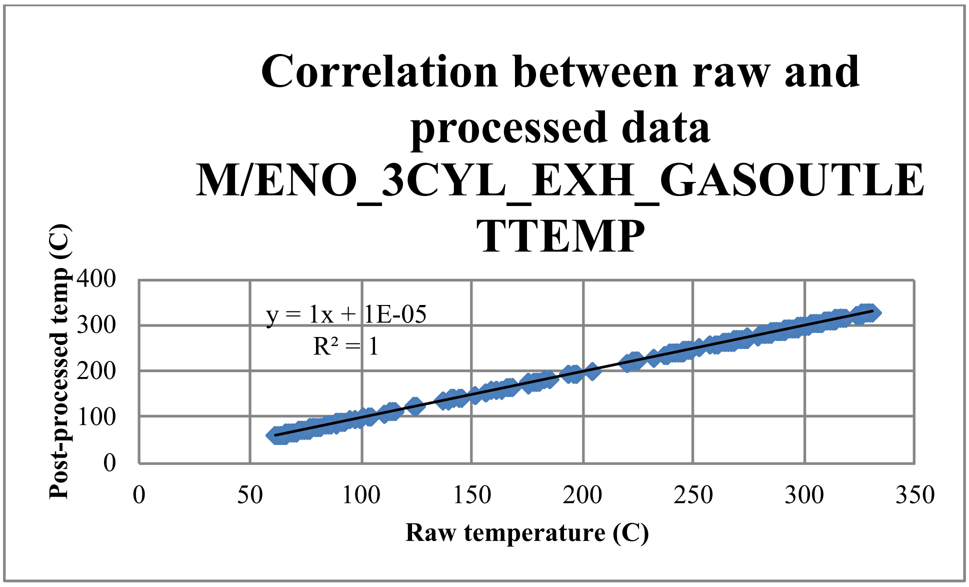

Correlation between raw and processed data M/ENO_2T/CEXH_GASOUTLETTEMP
y = 1x - 8E-06
R² = 1
Post-processed temp (C)
400
300
200
100
0
0
50
100
150
200
250
300
350
Raw temperature (C)

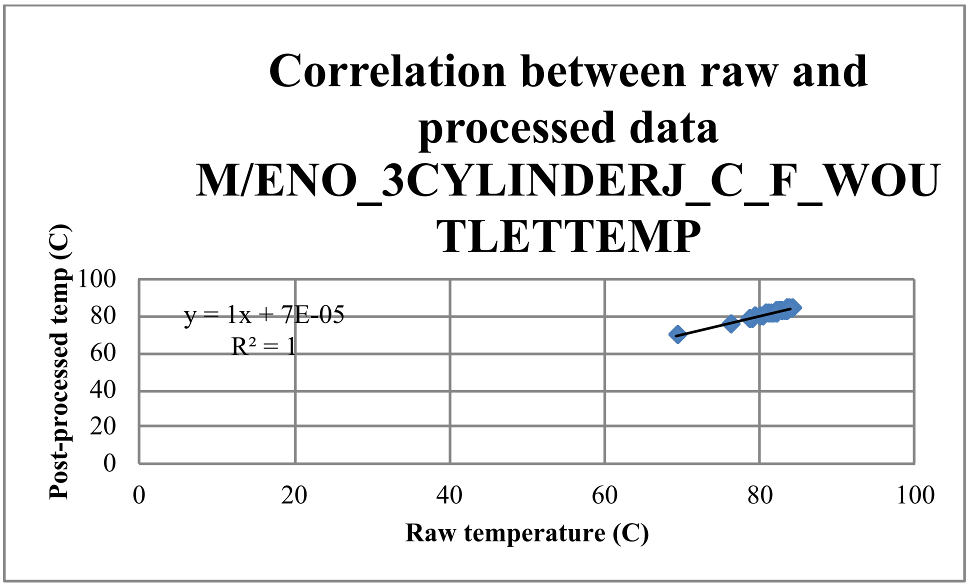

Correlation between raw and processed data M/ENO_2CYLINDERJ_C_F_WOUTLETTEMP
y = 1x + 0.0002
R² = 1
Post-processed temp (C)
100
80
60
40
20
0
0
20
40
60
80
100
Raw temperature (C)

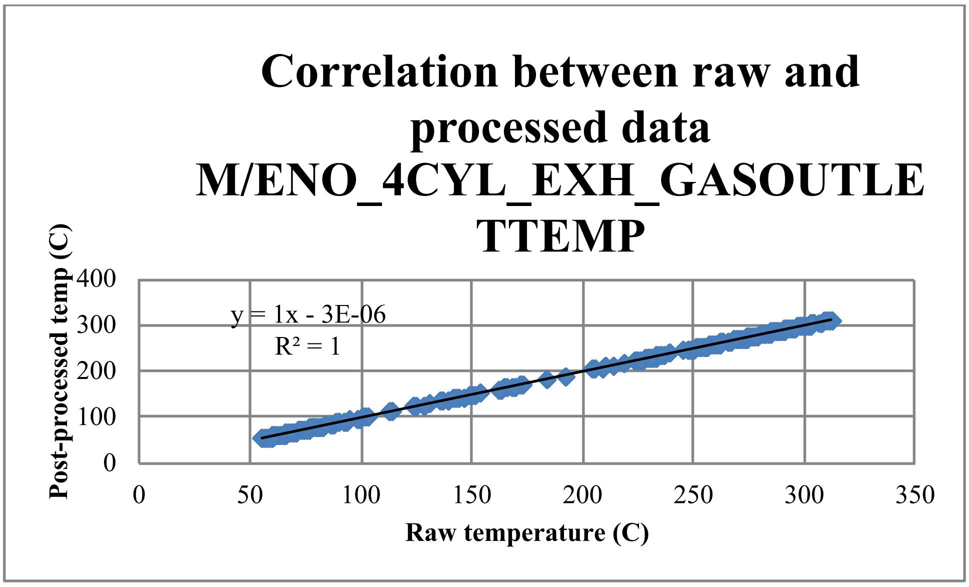

Correlation between raw and processed data M/ENO_2T/CL_OINLETPRESSURE
Post-processed pressure (kg/cm2)
4
3
2
1
0
0
0.5
1
1.5
2
2.5
3
3.5
Raw pressure (kg/cm2)
y = 1x + 2E-05
R² = 0.9998

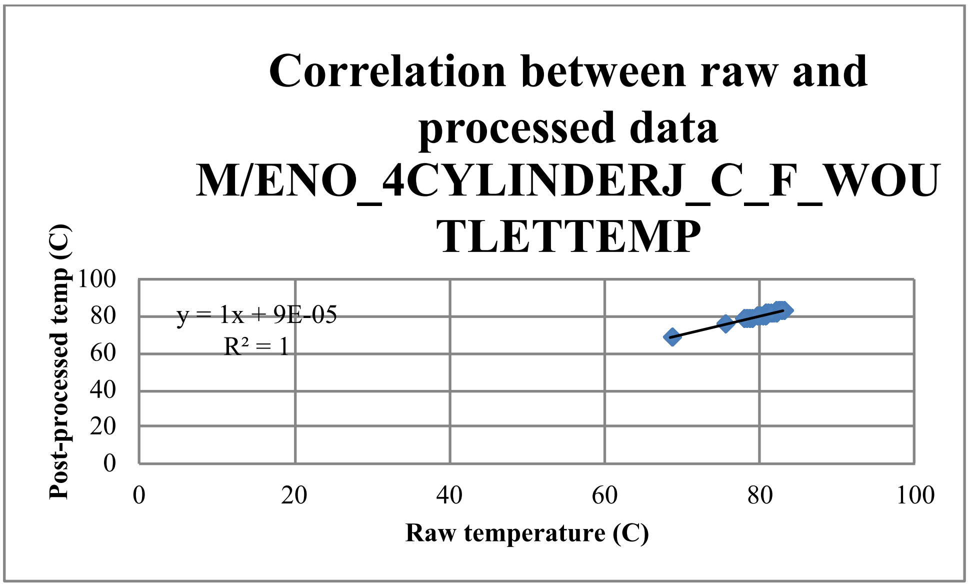

Correlation between raw and processed data M/ENO_2T/CL_OINLETTEMP
Post-processed temp (C)
60
50
40
30
20
10
0
0
10
20
30
40
50
60
Raw temperature (C)
y = 1x - 3E-05
R² = 1

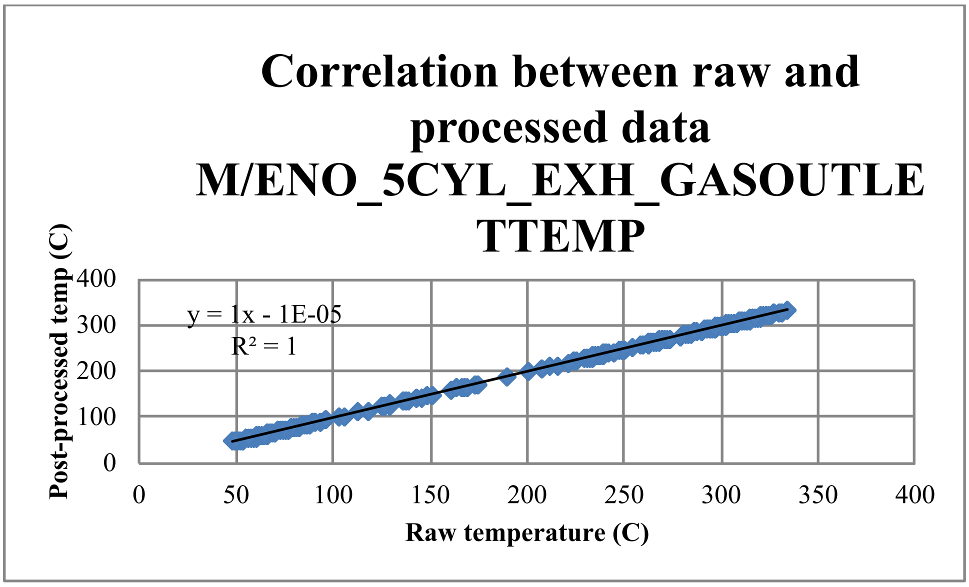

Correlation between raw and processed data M/ENO_2T/CL_OOUTLETTEMP
y = 1x - 7E-06
R² = 1
Post-processed temp (C)
Raw temperature (C)
0
20
40
60
80
0
10
20
30
40
50
60
70
80

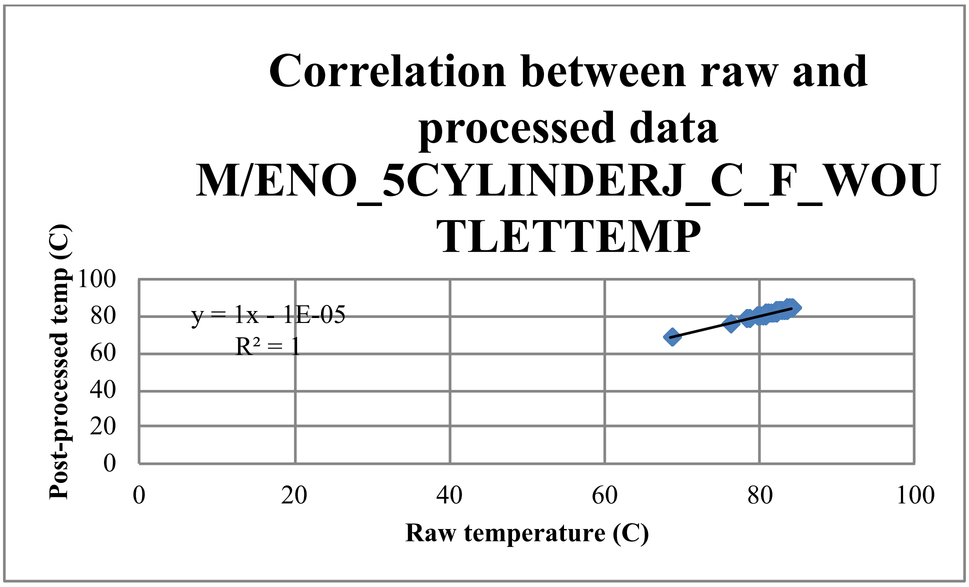

Correlation between raw and processed data M/ENO_3CYL_EXH_GASOUTLETTEMP
y = 1x + 1E-05
R² = 1
Post-processed temp (C)
Raw temperature (C)
0
100
200
300
400
0
50
100
150
200
250
300
350

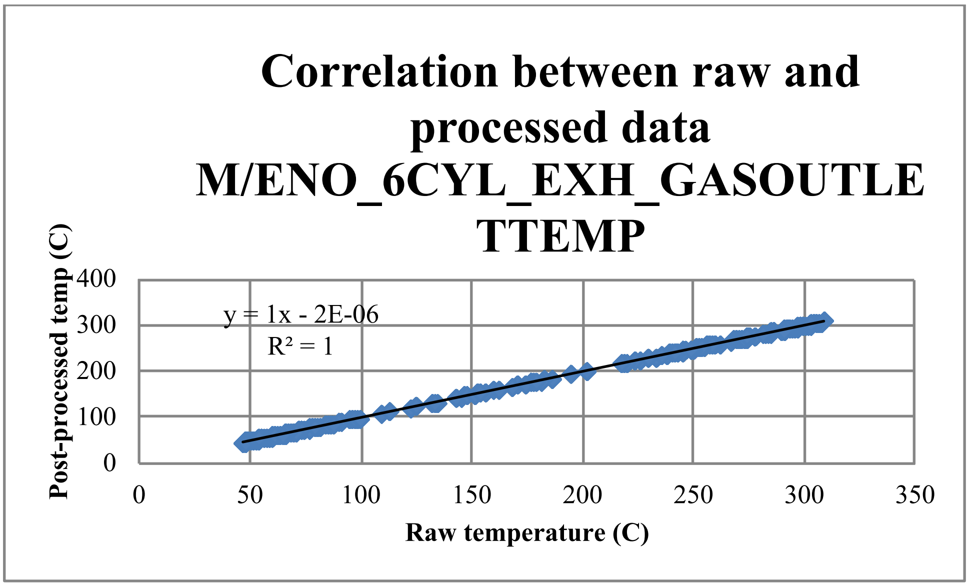

Correlation between raw and processed data M/ENO_3CYLINDERJ_C_F_WOUTLETTEMP
y = 1x + 7E-05
R² = 1
Post-processed temp (C)
100
80
60
40
20
0
0
20
40
60
80
100
Raw temperature (C)

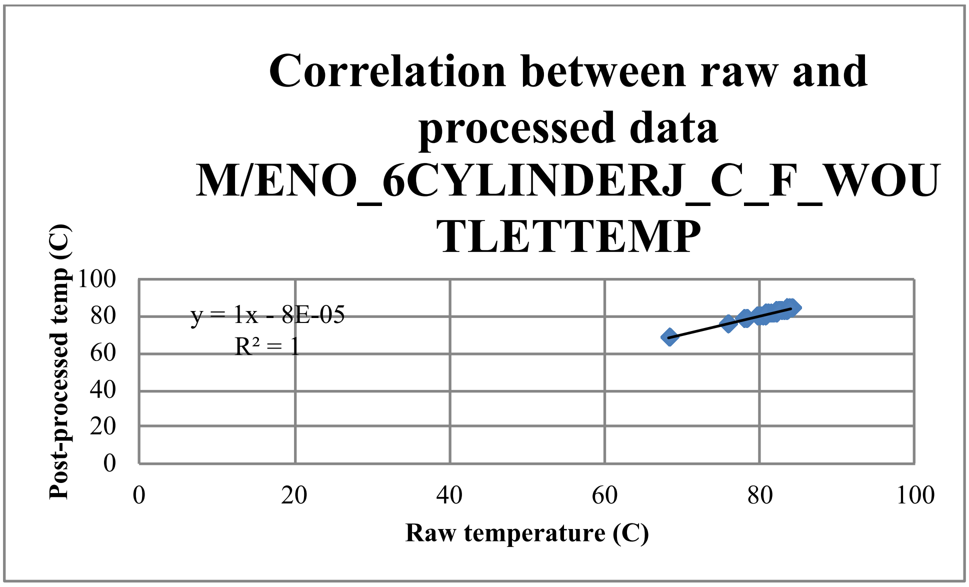

Correlation between raw and processed data M/ENO_4CYL_EXH_GASOUTLETTEMP
y = 1x - 3E-06
R² = 1
Post-processed temp (C)
400
300
200
100
0
0
50
100
150
200
250
300
350
Raw temperature (C)

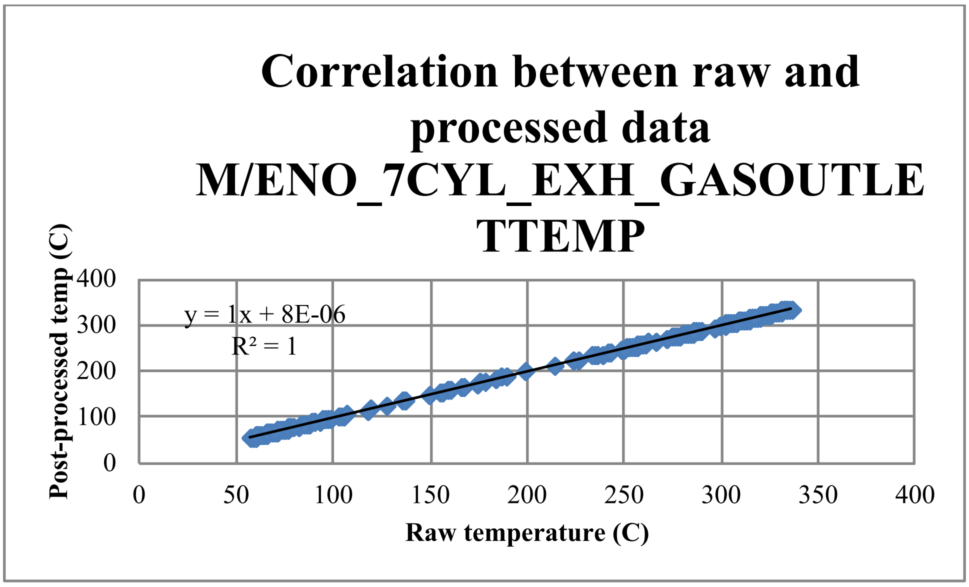

Correlation between raw and processed data M/ENO_4CYLINDERJ_C_F_WOUTLETTEMP
y = 1x + 9E-05
R² = 1
Post-processed temp (C)
Raw temperature (C)
0
20
40
60
80
100

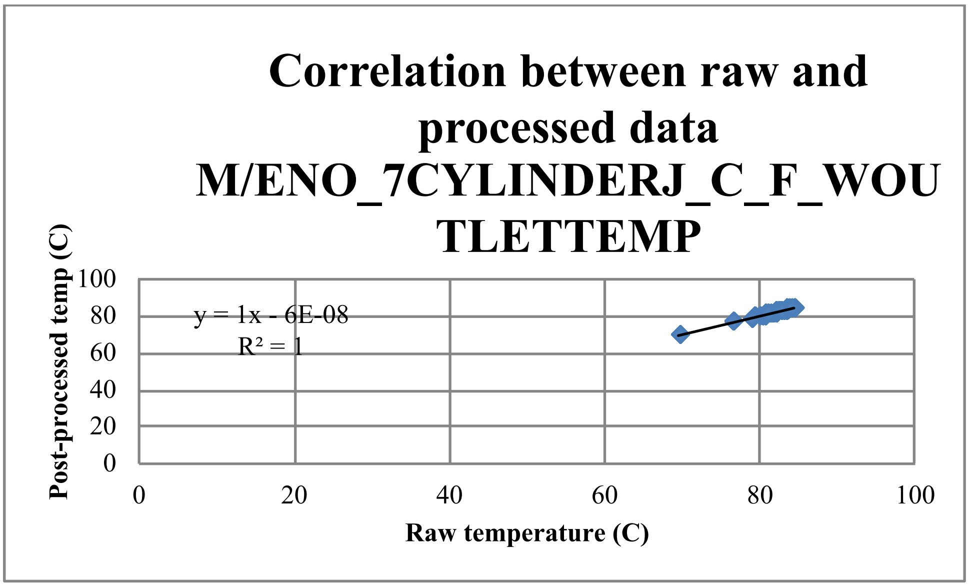

Correlation between raw and processed data M/ENO_5CYL_EXH_GASOUTLETTEMP
y = 1x - 1E-05
R² = 1
Post-processed temp (C)
Raw temperature (C)
0
50
100
150
200
250
300
350
400

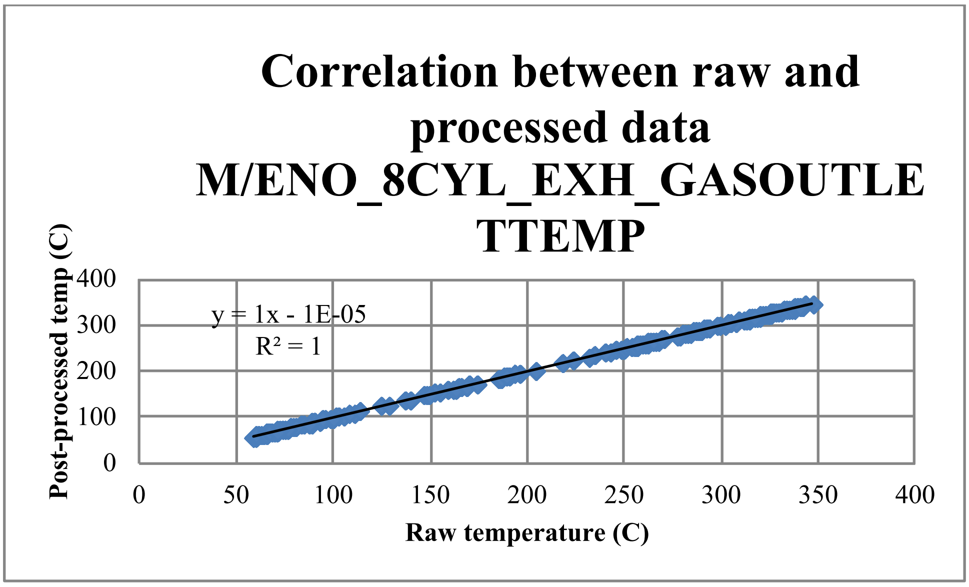

Correlation between raw and processed data M/ENO_5CYLINDERJ_C_F_WOUTLETTEMP
y = 1x - 1E-05
R² = 1
Post-processed temp (C)
Raw temperature (C)
0
20
40
60
80
100

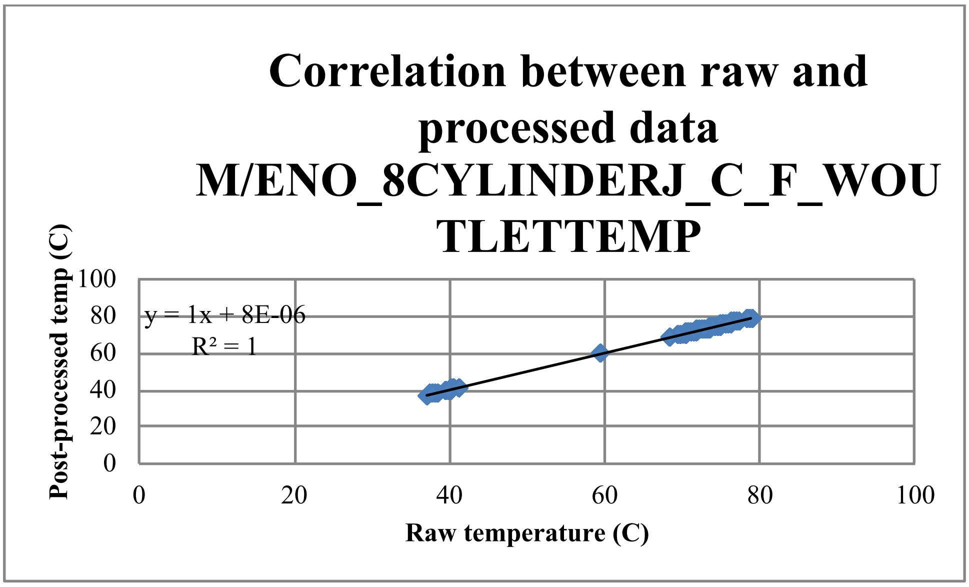

Correlation between raw and processed data M/ENO_6CYL_EXH_GASOUTLETTEMP
y = 1x - 2E-06
R² = 1
Post-processed temp (C)
Raw temperature (C)
0
100
200
300
400
50
150
250
350


Correlation between raw and processed data M/ENO_6CYLINDERJ_C_F_WOUTLETTEMP
Post-processed temp (C)
Raw temperature (C)
y = 1x - 8E-05
R² = 1
0
20
40
60
80
100

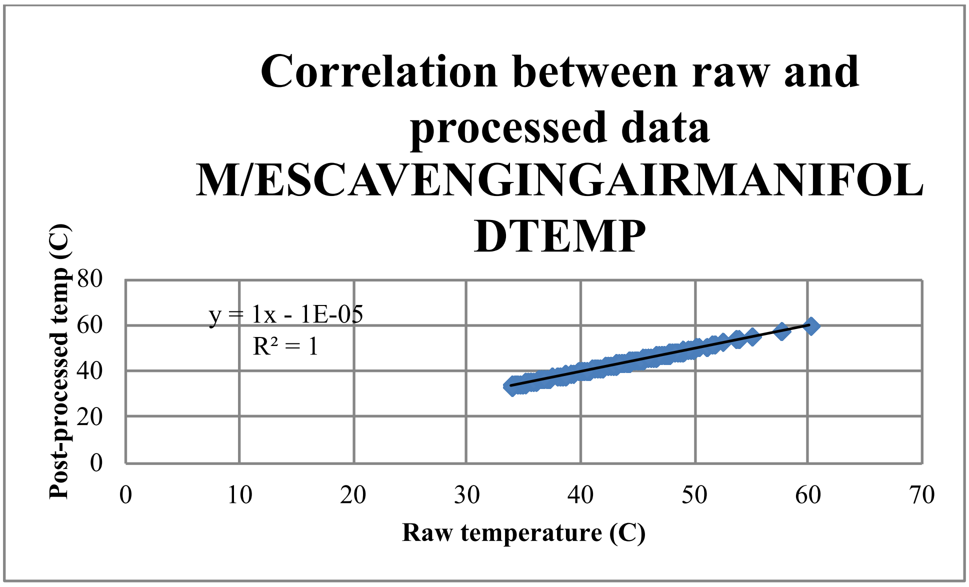

Correlation between raw and processed data M/ENO_7CYL_EXH_GASOUTLETTEMP
Post-processed temp (C)
Raw temperature (C)
y = 1x + 8E-06
R² = 1
0
50
100
150
200
250
300
350
400


Correlation between raw and processed data M/ENO_7CYLINDERJ_C_F_WOUTLETTEMP
Post-processed temp (C)
100
80
60
40
20
0
y = 1x - 6E-08
R² = 1
0
20
40
60
80
100
Raw temperature (C)

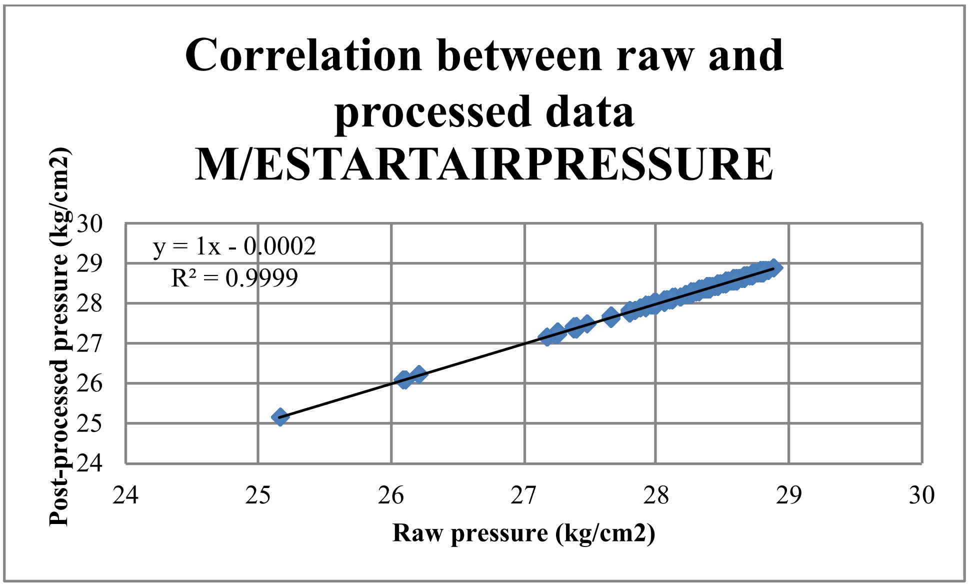

Correlation between raw and processed data M/ENO_8CYL_EXH_GASOUTLETTEMP
Post-processed temp (C)
400
300
200
100
0
y = 1x - 1E-05
R² = 1
0
50
100
150
200
250
300
350
400
Raw temperature (C)

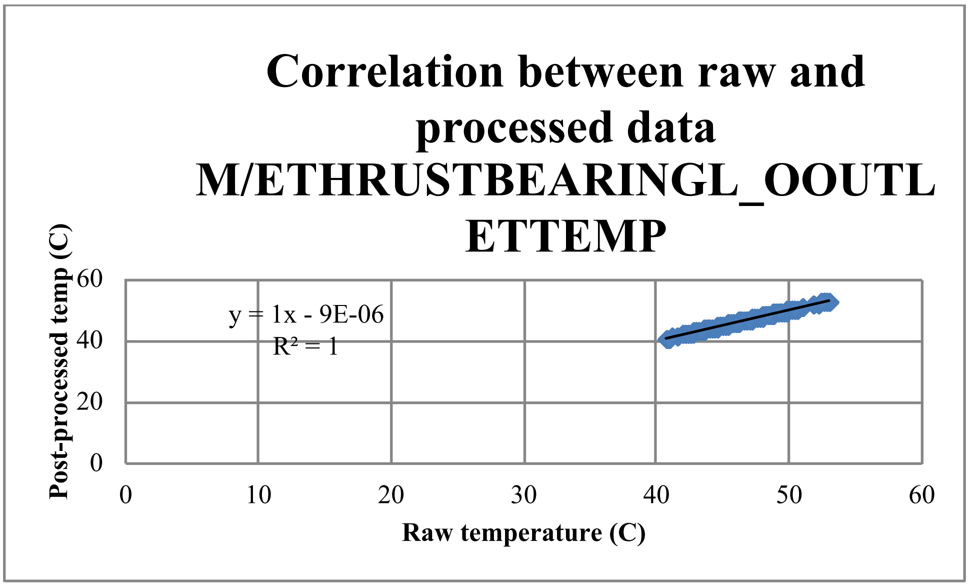


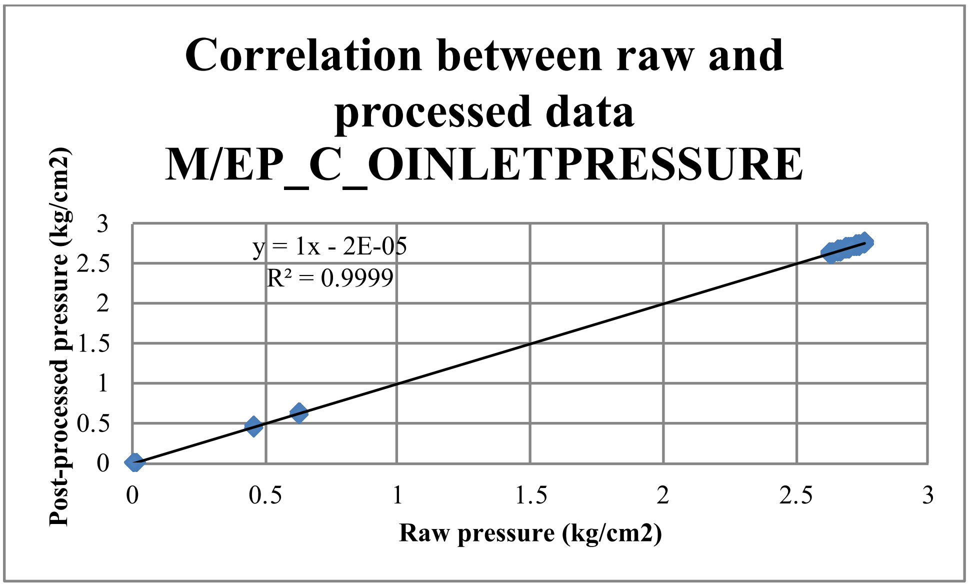
Correlation between raw and processed data M/ENO_8CYLINDERJ_C_F_WOUTLETTEMP
Post-processed temp (C)
100
80
60
40
20
0
y = 1x + 8E-06
R² = 1
0
20
40
60
80
100
Raw temperature (C)

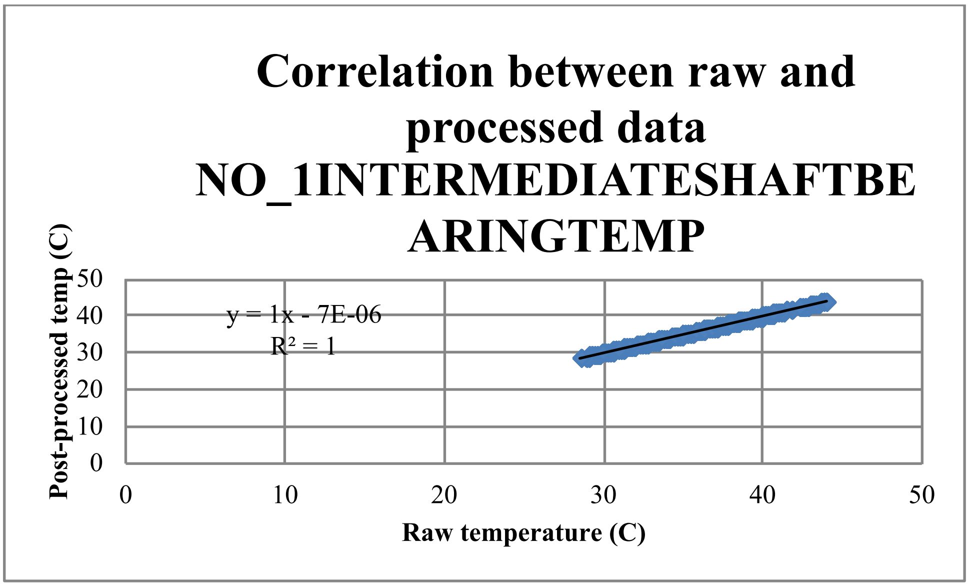


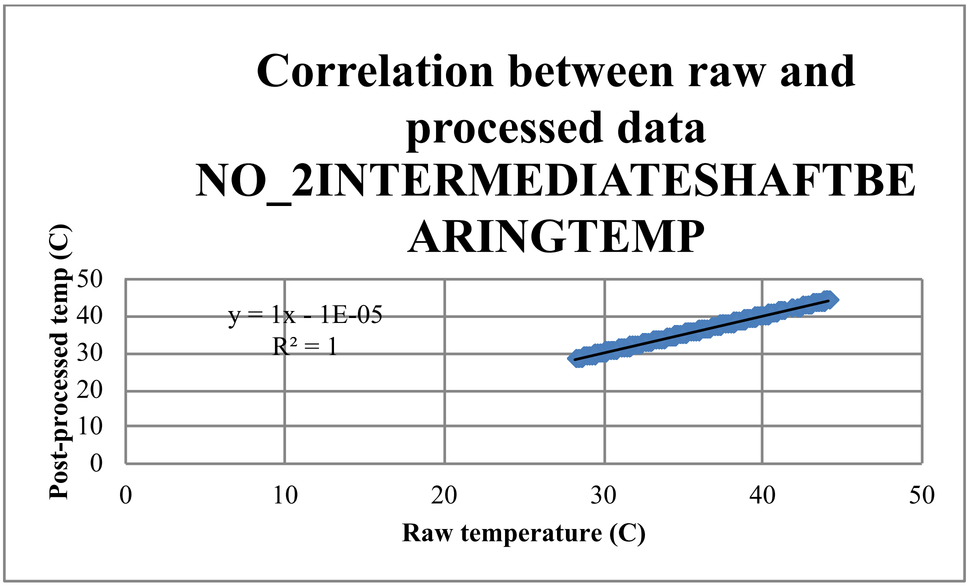
Correlation between raw and processed data M/ESCAVENGINGAIRMANIFOLDTEMP
Post-processed temp (C)
80
60
40
20
0
y = 1x - 1E-05
R² = 1
0
10
20
30
40
50
60
70
Raw temperature (C)


Correlation between raw and processed data M/ESTARTAIRPRESSURE
y = 1x - 0.0002
R² = 0.9999
Post-processed pressure (kg/cm2)
30
29
28
27
26
25
24
24
25
26
27
28
29
30
Raw pressure (kg/cm2)

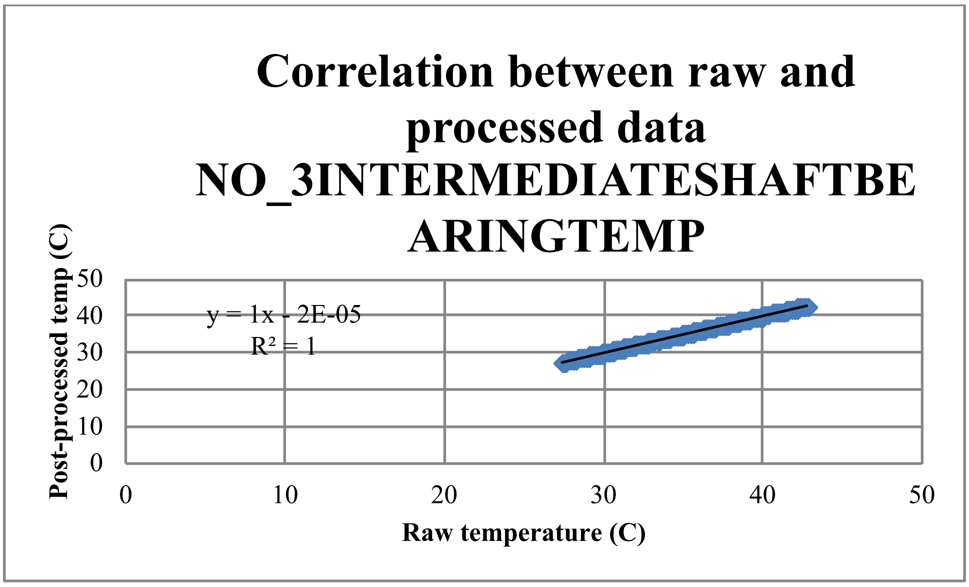

Correlation between raw and processed data M/ETHRUSTBEARINGL_OOUTLETTEMP
y = 1x - 9E-06
R² = 1
Post-processed temp (C)
60
40
20
0
0
10
20
30
40
50
60
Raw temperature (C)


Correlation between raw and processed data M/EP_C_OINLETPRESSURE
y = 1x - 2E-05
R² = 0.9999
Post-processed pressure (kg/cm2)
Raw pressure (kg/cm2)
0
0.5
1
1.5
2
2.5
3

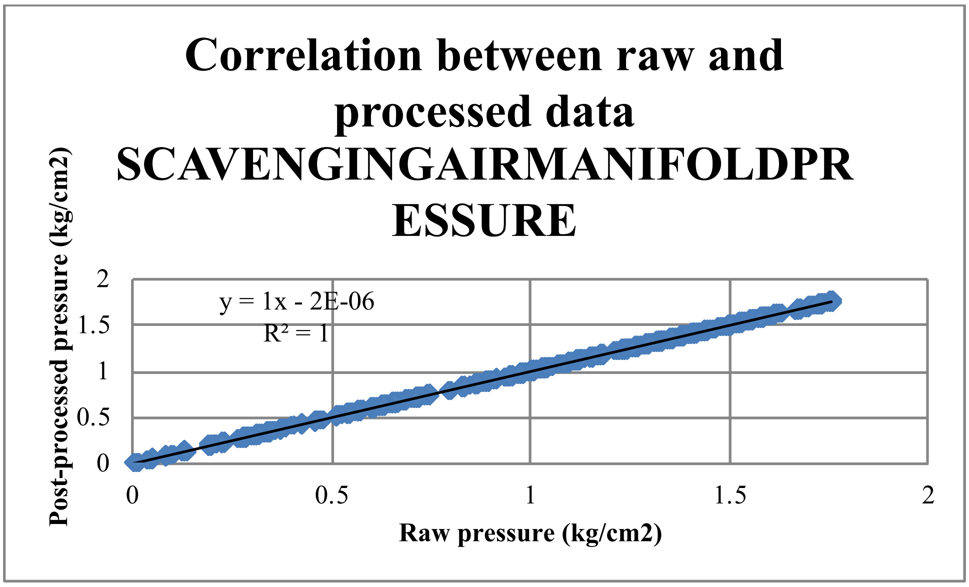

Correlation between raw and processed data NO_1INTERMEDIATESHAFTBEARINGTEMP
y = 1x - 7E-06
R² = 1
Post-processed temp (C)
Raw temperature (C)
0
10
20
30
40
50



Correlation between raw and processed data NO_2INTERMEDIATESHAFTBEARINGTEMP
y = 1x - 1E-05
R² = 1
Post-processed temp (C)
0
10
20
30
40
50
Raw temperature (C)



Correlation between raw and processed data NO_3INTERMEDIATESHAFTBEARINGTEMP
y = 1x - 2E-05
R² = 1
Post-processed temp (C)
0
10
20
30
40
50
Raw temperature (C)


Correlation between raw and processed data SCAVENGINGAIRMANIFOLDPRESSURE
y = 1x - 2E-06
R² = 1
Post-processed pressure (kg/cm2)
Raw pressure (kg/cm2)
0
0.5
1
1.5
2

Appendix G – WMN suitability validation methodology

The method for assessing the performance of the network was based on established practices such as, capacity identification, throughput estimation, graph colouring and cliques (Badis and Rachedi, 2015). Single antennal WMNs' capacity was derived through Equation N:1 known as Shannon's formula. The capacity is closely related to the interference. Thus, low capacity indicates low performance, especially if the requirements for data transfer exceed it. The signal power is dependent on the antenna and the noise on the environment. Typical values of electrical field strength of radiated noise on board a medium size cargo ship in machinery spaces are generally lower than 0,1 V/m, rising to 1 V/m near a running alternator (DNV GL, 1995). However, the noise degrades in frequencies above 2GHz (refer to Chapter 5). Thus, it can be safely assumed that it is far lower than the 54 dBμV/m emission limit for the 2GHz frequency. Also, several publications support the viability of WSNs in full ship installations both in the engine room and containers curried by ships (Koutsoubelias et al., 2016, Paik et al., 2009, Paik et al., 2007, White et al., 2010, Katsikas, 2013, Katsikas et al., 2014)

$$C = B \times \log_2\left(1 + \frac{S}{N}\right)$$

Where: B (Hz) is the bandwidth of the channel defined by the protocol, S/N is the signal to noise ratio in the ship, and C the capacity.

The throughput of the network was estimated through Bianchi's model. This equation is applicable to single hop networks, which is assumed to be the case in the proposed deployment for those nodes initiating the transmission to the collection point. This was done for reasons of economy, in both installation cost and node traffic interference. The required probabilities were statistically derived from the network, as it attempts to send messages under conditions similar to those of the engine room.

$$S = \frac{P_s P_{tr} E[P]}{(1 - P_{tr})\sigma + P_{tr} P_s T_s + P_{tr}(1 - P_s)T_C}$$

Where: P_S is the probability that a transmission is successful, P_{tr} is the probability that there is at least one transmission in a given slot time, $E[P]$

is the average packet payload size, T_S is the average time the channel is sensed busy, T_C is the average time the channel is sensed busy by each station during collision, and σ is the duration of one empty time slot.

Graph colouring refers to a technique of graph labelling and is based on graph theory. A graph is an ideal representation of a WMN as it allows for topographical and networking representation. Graph colouring has been used to assess connectivity, scheduling, resource allocation, frequency assignment, interference reduction, and capacity estimation in WMNs (Frey et al., 2016, Tushir et al., 2016, Arokia Mary and Amsalekha, 2014). Through this method, the capacity of any link of the network can be calculated. This approach is particularly useful when multiple nodes are accessed, when a message is propagated through the WMN, to reach the collection point. In that respect, this approach can be used to derive the load of the network when traffic is simultaneously initiated from various nodes.

In graph colouring each link between two wireless nodes is represented by a node in the Conflict Graph (CG). The edges of the CG are conflicts between links, i.e. traffic interference. Colours of the edges represent the time-slot allocation of this edge. Edges starting from the same node cannot have the same colour. Mutual conflict links belong to the same subgraph which is referred as a clique. The distance-H-interfering model is used to create this graph for where any link with distance H is considered a potential interference. Edges in the sale clique must have different colours. The behaviour of this network can be studied if the geography of the network is known and the flow rates of the nodes are calculated based on successful transmissions. To study this behaviour a matrix representation is required where for each clique the following Equation applies.

$$\forall i; Q_i \times F_i \leq C_i$$

Where: F_i is the average flow rate assigned to link i, C_i is the channel capacity of the link i, and Q_i is the incidence matrix.

The flow rate or any link is calculated through Equation:

$$F_i = \frac{1}{\tau}\int_{t-\tau}^{t} F_i(r)dr$$

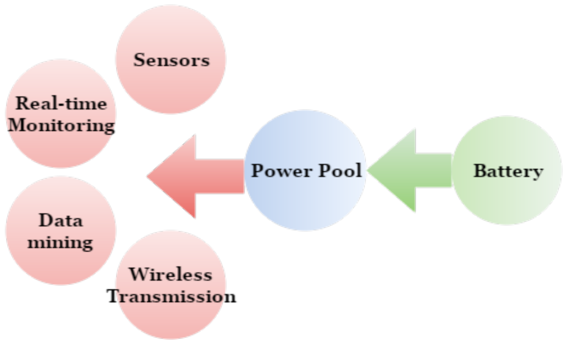
Where: $F_i(r)$ is the instantaneous flow rate utilization on link i at time r.

Assuming n number of links in the network and q the number of maximal cliques that this link i belongs to, the union of the clique matrices across all the links gives the global clique matrix Q.

For the network to be dimed as sufficiently capable of performing in the given environment, the conflict graph must be a perfect graph and a unit disk graph. A perfect graph is defined as a graph that for every clique the clique number is equal to the chromatic number (optimised chromatic allocation). A unit disk graph is defined as a planar graph where all edges must be allocated between vertices whose Euclidean distance is lower than a constant threshold of 0.46 (Gupta et al., 2007, Badis, 2007). This method could be used to establish the appropriateness of the ZigBee Pro protocol for installation in the engine room.

Appendix H – Power

When real-time monitoring and wireless communication is a necessity for an embedded system, the power consumption becomes an issue quickly. Hence, the embedded system needs to have sufficient power supply to allow both these functions and consider power saving actions or “*sleep*” states. Moreover, some sensors require power supply to operate. The figure presents the relation between supply and consumption in an embedded system. The functions that consume energy are the power supplied sensors and all the demanding software executed at regular intervals.



Power sources and power consuming functions of embedded system.

According to Costillo (2015), the power consumption can be identified as the sum presented in Equation:

$$P_{consumed} = \sum_{i=1}^{N} Psensor_i + Pprocessor_{ideal\ sampling\ rate}$$

Where: $P_{consumed}$ *is the total power consumption,* $Psensor_i$ *is the power consumed by sensor* i *for its operation,* $Pprocessor_{ideal\ sampling\ rate}$ *is the power consumed by the processor for the selected sampling rate, N is the number of sensors in the system, and the ideal sampling rate is analogous to the response requirements.*

As discussed by Gardner (2012), the power provided by a battery can support a system’s operation for several years if required. This is often referred as the operating life time of the system. Via an appropriate selection of sensors, low power electronics, and low power wireless systems, which can be optionally switched off when they are not needed, the system can increase its operating life time using low cost batteries.

Real time monitoring requires higher battery consumption. However, by managing when the sensors are enabled and disabled, or by altering sampling rates, the power consumption can be regulated. Additionally, battery changes can be implemented (e.g. at inspections) to create a balance between the two parameters. As part of this thesis, the total power consumption of the system will not be measured as it would significantly change between the benchtop model used in this thesis and final deployment hardware. However, the power consumption of the system will be taken into account when designing both the hardware and software components.

As wireless sensor networks are becoming more prevalent, many other techniques have been developed to minimise power consumption of data transmission. Proposals include harvesting power from vibration to power the wireless sensor, duty cycling to reduce operating time, implementation of wakeup calls to reduce trafficking conflicts, low power pre-processing routines to reduce transmitted data, variable sampling rates to increase sleep duty cycles, and implementation of fast data mining techniques to reduce pre-processing time (JaeHyuk et al., 2013, Baker, 2010, Yang et al., 2012).

The power management policy proposed is presented in the following section (Figure 2:10). It utilises sampling rate management, low power fast data mining and low wireless traffic. The power management policy components alone are not novel. However, it contributes to the overall system in a significant and meaningful way as it fulfils a pragmatic need of any such system.

Furthermore, to satisfy the power consumption constraints, the ideal sampling rate of the system must be identified and defined based on the duty cycles of transmission and pre-processing routines. These will be further elaborated in the data management and mining section of this thesis.