MULTI-CRITERIA DECISION MAKING SUPPORT TOOLS FOR MAINTENANCE OF MARINE MACHINERY SYSTEMS

By

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Abstract

For ship systems to remain reliable and safe they must be effectively maintained through a sound maintenance management system. The three major elements of maintenance management systems are; risk assessment, maintenance strategy selection and maintenance task interval determination. The implementation of these elements will generally determine the level of ship system safety and reliability. Reliability Centred Maintenance (RCM) is one method that can be used to optimise maintenance management systems. However the tools used within the framework of the RCM methodology have limitations which may compromise the efficiency of RCM in achieving the desired results.

This research presents the development of tools to support the RCM methodology and improve its effectiveness in marine maintenance system applications. Each of the three elements of the maintenance management system has been considered in turn. With regard to risk assessment, two Multi-Criteria Decision Making techniques (MCDM); Vlsekriterijumska Optimizacija Ikompromisno Resenje, meaning: Multi-criteria Optimization and Compromise Solution (VIKOR) and Compromise Programming (CP) have been integrated into Failure Mode and Effects Analysis (FMEA) along with a novel averaging technique which allows the use of incomplete or imprecise failure data. Three hybrid MCDM techniques have then been compared for maintenance strategy selection; an integrated Delphi-Analytical Hierarchy Process (AHP) methodology, an integrated Delphi-AHP-PROMETHEE (Preference Ranking Organisation METHod for Enrichment Evaluation) methodology and an integrated Delphi-AHP-TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) methodology. Maintenance task interval determination has been implemented using a MCDM framework integrating a delay time model to determine the optimum inspection interval and using the age replacement model for the scheduled replacement tasks. A case study based on a marine Diesel engine has been developed with input from experts in the field to demonstrate the effectiveness of the proposed methodologies.

Keywords: maintenance strategy, MCDM, decision criteria, VIKOR, TOPSIS Reliability Centered Maintenance, Delay time model.

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Dedication

This thesis is dedicated to God Almighty, the creator of Heaven and earth who gave me life, energy, knowledge and wisdom to carry out this research.

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Glossary of Terms

ABS	American Bureau of Shipping
AHP	Analytical Hierarchy Process
ANP	Analytical Network Process
ARM	Age Replacement Model
AVRPN	Averaging Technique integrated with Risk Priority Number
AVTOPSIS	Averaging Technique integrated with Technique for Order Preference by Similarity to an Ideal Solution
BBA	Basic Belief Assignment
BRM	Block Replacement Model
CBM	Condition Based Maintenance
CM	Corrective Maintenance
CMMS	Computerised Maintenance Management System
CARCMS	Computer Aided Reliability Centered Maintenance
CP	Compromise Programming
CVR	Content Validity Ratio
DEMATEL	Decision Making Trial and Evaluation Laboratory
DFTA	Dynamic Fault Tree Analysis
DTA	Delay Time Analysis
DTM	Delay Time Model
D-S	Dempster-Shafer evidence theory
ELECTRE	Elimination and Et Choice Translating Reality
ETA	Event Tree Analysis
FM	Failure Mode
FMEA	Failure Modes and Effects Analysis
FMECA	Failure Modes, Effects and Criticality Analysis
FST	Fuzzy Set Theory
FTA	Fault Tree Analysis

GDP	Gross Domestic Product
HAZOP	Hazard And Operability study
MAUT	Multi-Attribute Utility Theory
MCDM	Multi-Criteria Decision Making
MSG	Maintenance Steering Groups
MTBF	Mean Time Between Failure
MTTR	Mean Time To Repair
MSI	Maintenance Significant Items
OEE	Overall Equipment Effectiveness
OEM	Original Equipment Manufacturers
OFCBM	Offline Condition Based Maintenance
ONCBM	Online Condition Based Maintenance
OREDA	Offshore Reliability Database
PROMETHEE	Preference Ranking Organisation METHod for Enrichment Evaluations
RBM	Risk Based Maintenance
RCM	Reliability Centered Maintenance
RPN	Risk Priority Number
RTF	Run To Failure
SRP	Scheduled Replacement
TOPSIS	Technique for Order Preference by Similarity to an Ideal Solution
TPM	Total Productive Maintenance
VIKOR	Vlsekriterijumska Optimizacija Ikompromisno Resenje, meaning: Multicriteria Optimization and Compromise Solution
WET	Weighted Evaluation Technique

Nomenclature

$C(t_p)$	Cost function per unit time
GP	Good product
TP	Total product
P_r	Quality rate of product from system
T_L	Loading time
α_i	Failure mode ratio
β_i	Failure effect probability
λ_i	Failure rate
CN_i	Criticality number
S	Severity rating
O	Occurrence probability
D	Detection rating
$N(t_p)$	Number of failures expected between replacement intervals
T_{PF}	P-F intervals
C_a	Cost of unit failure replacement
C_b	Cost of unit scheduled replacement
t_p	Scheduled replacement interval and
$f(t)$	Probability density function
$R(t_p)$	Reliability function
T_a	Time taken for unit failure maintenance
T_b	Time taken for unit preventive maintenance
β	Shape parameter
$\emptyset$	Scale parameter
γ	Location parameter
F(t)	Cumulative density function
B(T)	Probability of defect occurring as a breakdown failure
h_f	Delay time
T	Inspection time interval
∂	Downtime as a result of inspection
k_r	Arrival rate of defects per unit time
$f(h_f)$	Probability density function
D(T)	Downtime per unit time
R(T)	Company reputation per unit time

C(T)	Maintenance cost per unit time
d_a	Average downtime due to breakdown repair
C_{br}	Cost of breakdown repair
C_{ii}	Cost of inspection repair
C_{ic}	Cost of inspection
L_c	labour cost
P_c	Penalty cost
D_{dc}	Dry-docking cost
E_{dc}	Equipment downtime cost
N_{cm}	Number maintenance personnel
P_{rm}	Pay rate per hour per person
T_{dm}	Time duration of repair
T_d	Duration of inspection
R_{br}	Company reputation due to breakdown repair
R_{ii}	Company reputation due to inspection repair
Ds	Net inferior values
Cs	Net superior values
HLA	How long since fault was first observed
HML	duration of time could fault stay before parts may fail

Publications

The following papers have been published from this research work.

(1) Emovon, I., Norman, R.A., Murphy A.J. & Pazouki, K. (2015). An integrated multicriteria decision making methodology using compromise solution methods for prioritising risk of marine machinery systems. *Ocean Engineering*, *105*, 92-103.

(2) 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*, DOI10.1007/s10845-015-1133-6

(3) Emovon, I, Norman, R.A. & Murphy A.J. (2014) A New Tool for Prioritising the Risk of Failure Modes for Marine Machinery Systems. *In the proceedings of ASME 33rd International Conference on Ocean, Offshore and Arctic Engineering*. (OMAE 2014), San Francisco, USA.

(4) Emovon, I., Norman, R.A., Murphy, A.J. & Kareem, B. (2014) Delphi-AHP based methodology for selecting the optimum maintenance strategy for ship machinery systems. *In the proceedings of the 15th Asia pacific industrial engineering and management* (APIEMS 2014), Jeju, Korea.

(5) Emovon, I, Norman, R.A. & Murphy A.J. The development of a model for determining scheduled replacement Intervals for marine machinery systems, submitted to the "*Journal of Engineering for the Maritime Environment"*.

(6) Emovon, I, Norman R.A. & Murphy A.J. An integration of multi-criteria decision making technique with delay time model for determination of inspection interval for marine machinery systems, submitted to the Journal of "*Applied Ocean Research*".

Chapter 1 Introduction

1.1 Introduction

The role of the shipping industry in its contribution to the growth of the world Gross Domestic Product (GDP) cannot be over emphasized as it is responsible for the movement of the bulk of the world economic raw materials and commodities. However despite the large market that it serves, the business environment remains highly competitive because there are many service providers in the shipping industry and for any service provider to remain in business, reliable and quality services must be provided to its customers at a minimum cost and at the same time maintaining a safe operational environment. Unfortunately the costs of operating a ship and its systems keeps rising and one of the major contributors to operational cost is the maintenance cost which can vary from 15 to 70 % of the total operational cost (Sarkar et al., 2011, Bevilacqua and Braglia, 2000). Alhouli et al. (2010) showed in a case study of a 75,000 tonne bulk carrier, that its maintenance cost accounted for 40 percent of the total operational cost, based on a sample survey. In the US industries alone, over $3.2 billion is lost annually due to energy wastage caused by poor maintenance management of compressed air systems (Vavra, 2007). It is also reported that approximately one third of the total maintenance expenses of most industries is unnecessarily expended due to poor maintenance practice (Wireman, 1990). It is thus obvious that one major factor that influences operational cost is maintenance cost, and that reducing this cost will invariably reduce the overall operational cost. From the above, two fundamental factors are clearly essential in order to keep a service provider operational in a highly competitive business; namely service reliability and reduced operational cost. These two factors are, unfortunately, generally conflicting. Either reliability increases or cost decreases and vice versa. However in order to strike a balance, an efficient maintenance system must be in place that will yield high system reliability at a minimum acceptable cost.

However great care must be taken in reducing maintenance costs in order not to compromise safety, reliability, availability of the system functionality and safety of the environment. To achieve this aim, the various components that make up a maintenance system must be optimized. The three main components of a maintenance system are as follows:

(1) Risk assessment

(2) Maintenance strategy selection, and

(3) Maintenance strategy interval determination

Risk is generally defined as being the "product of probability of failure of a system and the consequences of the failure occurring". Risk assessment of each item of equipment that makes up the full integrated system is carried out and based on the assessed level of risk the maintenance strategy that is the most suitable to mitigate the potential consequences of failures is selected. There are several different maintenance strategies that are available for ship system maintenance practitioners to choose from and these are generally divided into three groups; corrective maintenance, preventive maintenance and condition-based maintenance. The corrective maintenance philosophy is the approach in which an item of equipment is allowed to run until failure occurs before any corrective action is performed. The preventive maintenance type is an approach in which the maintenance action (replacement or overhaul) to be carried out on an equipment item is scheduled on a regular basis. Condition-based maintenance is the approach in which the maintenance action is performed based on the observed condition of the equipment. The condition of an item of equipment can be monitored using one of two approaches; continuous or periodic (Mishra and Pathak, 2012). The periodic approach is generally the one that is preferred because it is cheaper than the continuous monitoring approach. In a maintenance management system after the determination of the optimum maintenance strategy for each item of equipment in a system the next step is to determine the appropriate interval for performing the maintenance task. There are however, other components of a maintenance system such as spare parts inventory management and personnel management that have not be considered in this thesis due to time limitations.

Different techniques have evolved for the optimisation of the components of a maintenance system namely; Reliability Centered Maintenance (RCM), Total Productive Maintenance (TPM) and Risk Based Maintenance (RBM). Each of these techniques aims at maintaining a plant or a system at an improved level of reliability and availability and at a lower risk with the minimum cost. In the maritime sector Reliability Centered Maintenance (RCM) has been applied to a greater or lesser extent in the optimization of maintenance strategies (Conachey, 2005, American Bureau of Shipping, 2004, Aleksić and Stanojević, 2007, Conachey, 2004, Conachey and Montgomery, 2003). However each of the various tools that have been utilized within the RCM framework in the optimization of these three major components of a maintenance system has several limitations. For example in the area of risk assessment, RCM utilizes Failure Mode and Effects Analysis (FMEA) in prioritizing the risk of failure modes of a system. With this analysis tool, risk is represented in the form of a Risk Priority Number

(RPN) which is computed by multiplying the severity rating (S) by both the occurrence probability (O) and the detection rating (D) for all failure modes of the system. However FMEA has been criticized by many authors in having limitations such the inability of the technique to take into account other important factors such as economic cost, production loss and environmental impact (Braglia, 2000, Sachdeva et al., 2009b, Zammori and Gabbrielli, 2012, Liu et al., 2011) and employing the use of only precise data in expressing the opinions of experts whereas in many practical situations the information may only be an imprecise estimate.

Another example is the tool that is utilised within the framework of RCM for the selection of the maintenance strategy. The RCM logic tree that is utilised for the selection of maintenance strategies has been criticized as being a very time consuming exercise (Waeyenbergh and Pintelon, 2004, Waeyenbergh and Pintelon, 2002). Furthermore, the technique does not make provision for the ranking of alternative maintenance strategies and as such selecting the optimum maintenance strategy apparently becomes difficult. Alternative techniques have been developed by previous researchers in the literature. For example Lazakis et al. (2012) proposed an integrated fuzzy logic set theory and the use of TOPSIS, Goossens and Basten (2015) and Resobowo et al (2014) proposed the use of AHP. Nevertheless, these alternative approaches all have one limitation or another such as some doubts remain on the practical use of the fuzzy set theory method because of the computational complexity it introduces into the decision making process (Zammori and Gabbrielli, 2012, Braglia, 2000). The limitations of RCM can further be proven in the area of maintenance strategy interval determination as there is no provision for such an area within the classical RCM framework, although some modified RCM models have been developed and utilised for maintenance strategy interval determination (Almeida, 2012, Gopalaswamy et al., 1993). However most of these mathematical models are either too abstract or are based on a single decision criterion whereas the problems in practical situations are generally multi-criteria based and as such are better addressed by using a multi-criteria decision making method.

From this brief review and assessment it can be concluded that there is the need to develop alternative tools that will enhance the decision making process in these three areas of the maintenance system within the framework of RCM. In this research, a multi-criteria decision making approach is proposed in solving the problems of (1) risk assessment (2) maintenance strategy selection and (3) maintenance strategy interval determination. The multi-criteria decision making approach is proposed because there are numerous decision criteria, which are in conflict with one another, generally involved in the decision making process of each of the three problems.

1.2 Research Aim and Objectives

The overall aim of this research was to develop an enhanced RCM methodology based on the combination of multi-criteria decision making methods with RCM concepts in order to formulate a more efficient maintenance system for application to marine machinery systems.

The objectives of this research, were:

(1) The development of a methodology for the assessment of the level of risk of marine machinery systems based on the integration of RCM FMEA with multi-criteria decision making techniques.

(2) The development of a methodology for maintenance strategy selection based on the integration of the RCM concept with multi-criteria decision making methods.

(3) The development of a methodology for maintenance interval determination using multi-criteria decision making approaches within the RCM framework.

1.3 Research methodology

From the literature survey that was undertaken, as described in Chapter 2, it is obvious that the tools that are currently utilized within the framework of RCM and RBM in the optimization of the three major elements of a maintenance system have limitations which negatively impact on the reliability of the system. The inadequacy of the tools has also resulted in potentially increasing maintenance costs without a commensurate increase in ship machinery system availability. Hence there is the need to develop alternative tools that will enhance the current methodologies such that maintenance of a system can be more efficiently optimized for improved ship machinery reliability at a reasonable cost. Since in the marine industry failure data and maintenance data, as required for performing failure statistical analyses, are not easily available, the proposed methodology has been developed with the inbuilt capability of using a combination of expert's opinions, a reliability data bank and data from similar plants. Some of the reasons that are given in the literature as to why failure and maintenance data are difficult to come by in the marine industry are (Mokashi et al., 2002): (1) Within the RCM framework analysis is performed at failure mode level whereas in most marine industries failure data is kept at the component level, (2) In the RCM methodology maintenance is centered on the function of the system being maintained and for some function failures, having multiple failure modes, the collecting and keeping of quality and useful statistical information is nearly impossible, (3) In many shipping industries, failures are largely mitigated through a preventative approach and in such cases data availability for statistical analysis may be inadequate and (4) Even if such data is available, in some cases, due to commercial sensitivity, the shipping industries, insurance companies and flag societies are prevented from the sharing this information.

The methodology that this study has evolved is a decision support tool that has been developed within the RCM framework for prioritizing the risk of failure modes of a marine machinery system and maintenance strategy is selected based on the prioritized risk. The tool also determines the interval for performing the selected maintenance strategy. The flow chart of the decision support tool is presented in Figure 1.1. The methodological steps are as follows:

Step (a) Risk assessment: This begins with the identification of the specific system to be investigated. In this research the ship machinery system was considered because, from accident data analysis that has been performed for data collected from 1994-1999, it was observed that over 50% of ship accidents were caused by machinery failures (Wang et al., 2005). However since the full machinery system was considered to be too large, a marine diesel engine which is a sub-system of the full marine machinery system was chosen as the case study for this research. The failure modes of the individual equipment/components that collectively make up the marine diesel engine were then determined. This was then followed by the development of a risk prioritisation tool for the ranking of the risk of the individual failure modes of the system under investigation. Experts' opinions were sought in assigning values to the failure modes which were then used as input data into the risk prioritisation tools. Chapters 3 and 4 discuss the risk prioritisation methodologies that are proposed for the risk assessment of marine machinery systems.

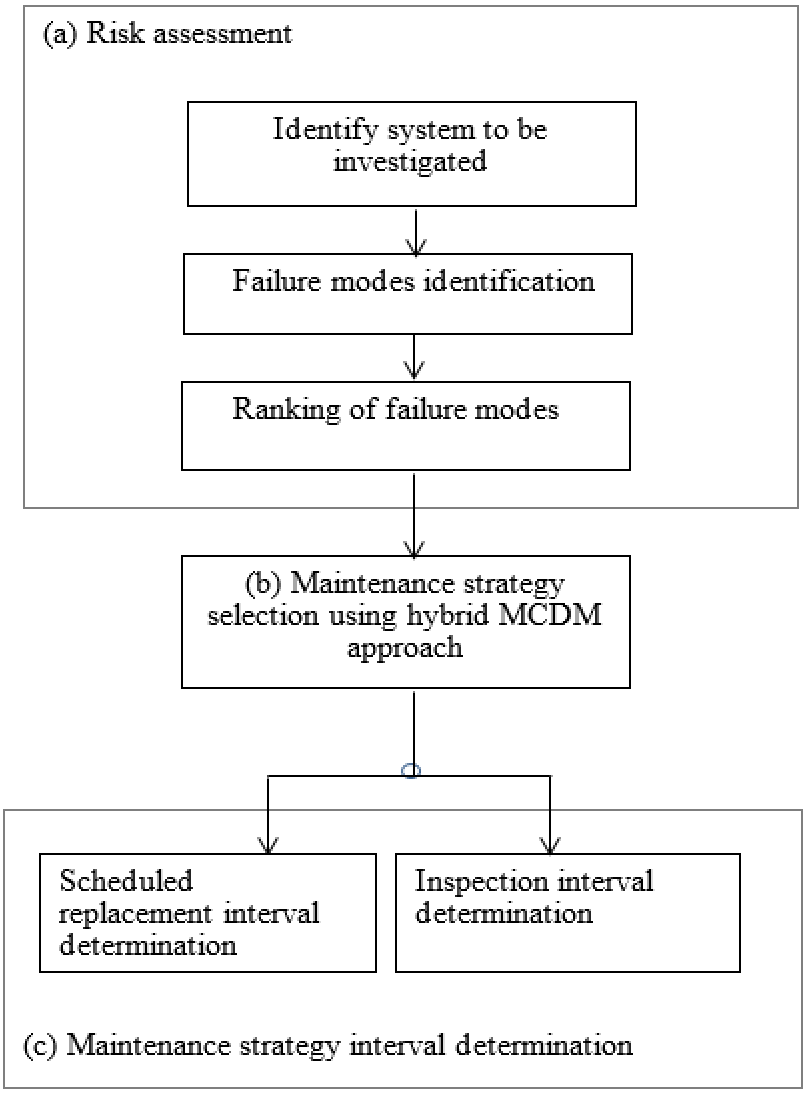


Figure 1.1: Decision support methodology for maintenance system management

Step (b) Maintenance strategy selection: The maintenance strategy selection process commences after the determination of the level of risk of each of the failure of modes of the machinery system. Since individual components/equipment items of the system can have multiple failure modes the most critical failure modes of the equipment items are identified such that maintenance strategy is determined for the equipment items based on their most critical failure mode. For example if the most critical failure mode for the high pressure oil pump is injection seizure, then the maintenance strategy to be selected for that pump will be based on mitigating failure effects that are caused by injection seizure. A maintenance selection methodology based on a hybrid MCDM technique was developed as an alternative to the RCM logic tree that is normally used in the classical RCM framework and other alternatives, proposed in the literature. Although a considerable number of critical equipment items and failure modes were identified based on the risk ranking of failure modes performed in Step (a) only the high pressure fuel oil pump maintenance strategy was determined in Step (b) in validating the proposed methodologies. The maintenance strategy selection process started with the identification of decision criteria upon which the optimum strategy is selected. This was followed by the identification of alternative maintenance strategies for marine machinery systems. The next task was the formulation of the maintenance strategy problem and associated data collection. The collected data was then used as input into the MCDM ranking tools in order to assign weights to the alternative maintenance strategies. The strategy with the highest weight was deemed to be the optimum solution that the maintenance practitioners should select if there are sufficient funds to be able to implement it, otherwise the alternative with the second highest weight can be chosen. Chapter 5 presents the methodologies for selecting an optimum maintenance strategy for marine machinery systems.

Step (c) Maintenance strategy interval determination: Another important component of maintenance management which must be optimised for greater plant reliability at a minimum cost is the maintenance strategy interval determination. Having considered the maintenance strategy that is the most suitable for each of the equipment items/most critical failure modes, the next step is to determine the optimum interval for performing the assigned maintenance strategy. Although five maintenance strategies were considered as being potential alternatives for a marine machinery system in Step (b) only the interval determination for two of them was studied in this research due to time limitations. The two maintenance strategies studied are scheduled replacement (SRP) and inspection also referred to, as in this thesis, as Offline Condition Based Maintenance (OFCBM). The methodology proposed for determining the optimum interval for scheduled replacement is presented in Chapter 6 while that of OFCBM is presented in Chapter 7.

1.4 Overview of the Thesis

The work undertaken and described in this research is presented in 8 chapters and the contents of chapters 2 to 8 are briefly described as follows:

In Chapter 2 the results are given of an extensive literature review that was undertaken with respect to all issues relating to maintenance management of marine machinery systems. Firstly an overview of maintenance is described. This is followed by a discussion of the various maintenance strategies that are employed for maintaining an asset. The three basic types of maintenance strategies that are discussed are; corrective, preventive and condition based maintenance. A discussion of the various maintenance optimisation techniques, such as RCM, RBM and TPM, is also given in this chapter. Finally the three major elements of maintenance management which are generally optimised within the RCM and RBM frameworks are extensively discussed with a view to identifying the challenges of the various tools that are currently applied and proffering alternative solutions.

In Chapter 3 a risk assessment methodology based on the FMEA technique that was developed is described. The essence was to produce an enhanced version of FMEA by eliminating some of the limitations of the classical technique. In order to establish the limitations of FMEA and to consider some of the enhanced approaches presented in the literature, an FMEA background study and a state of the art review were undertaken. This resulted in identification of the limitations of the current approaches and, development of hybrid risk prioritisation methodologies. The proposed methodologies were validated using three case studies. Finally in this chapter, it was concluded, that that the two proposed methodologies can effectively be utilised either individually or in combination in prioritising the risk of failure modes of machinery systems.

In Chapter 4 two more alternative risk assessment tools based on a compromise solution method are presented. The chapter starts with a review of MCDM tools and their relevance to the marine industry. The review then led to identification of the limitations of the techniques proposed in chapter 3 and other MCDM techniques that have been applied by other researchers in the literature. The methodological steps for the two techniques are then presented. To test the applicability of the proposed techniques three case studies are also presented.

In Chapter 5 a novel methodology for the selection of maintenance strategies is presented. This chapter starts with a review of the MCDM methodology for maintenance strategy selection. Based on the review, various hybrid MCDM methods are presented. An analysis of data using the various tools in the hybrid method is then performed.

In Chapter 6 a methodology for the determination of the optimum interval for a scheduled replacement task is presented. The methods that are proposed utilise three decision criteria;

reliability, cost and downtime. An MCDM technique is introduced for the aggregation of the three decision criteria models. In order to validate the proposed methodology, a case study of a marine diesel engine crankshaft was conducted. A sensitivity analysis is also presented to investigate the impact of the decision criteria variables on the rankings of the various alternative scheduled replacement intervals.

In Chapter 7 a methodology based on the integration of a delay time concept with the MCDM technique is presented for the determination of the optimum inspection intervals. The delay time concept was used to model three decision criteria; cost, downtime and company reputation, while MCDM techniques were used in converting the three decision criteria into a single analytical model. A case study of a cooling system water pump is presented in order to determine the suitability of the methodology for the selection of the inspection interval for marine machinery systems. A sensitivity analysis is also presented in order to investigate the influence that changes to decision criteria weights will have on the ranking of the alternative inspection intervals.

In Chapter 8 general conclusions are presented together with the contribution of the study, limitations of the current study and with recommendations for future work.

Chapter 2 Literature Review

2.1 Introduction

The aim of this chapter is to construct a theoretical structure upon which this research will be based. In the light of this, the research objectives are discussed in relation to the work of other researchers. This chapter has been divided into five parts: the first part deals with an overview of maintenance, the second part deals with maintenance optimization, the third part deals with risk assessment methods, the fourth part deals with maintenance strategy selection and finally, the fifth part deals with maintenance interval determination.

2.2 Maintenance overview

(Dhillon, 2002) defined maintenance as the combination of activities undertaken to restore a component or machine to a state in which it can continue to perform its designated functions. Maintenance usually involves repair in the event of a failure (a corrective action) or a preventive action. On the other hand the British Standard defines maintenance as (BS 1993) "*the combination of all technical and administrative actions, intended to retain an item in, or restore it to, a state in which it can perform a required action*". The costs incurred in this are normally a major percentage of the total operating cost in most industries including the maritime sector. (Vavra, 2007) reported that wasted energy as a result of poorly maintained compressed air systems collectively cost US industry up to $3.2 billion annually. This can be attributed to the general perception in the past that maintenance is an evil that plant managers cannot do without and that it is impossible to minimise maintenance cost (Mobley, 2004). This perception has disappeared with the invention of plant equipment diagnostic instrumentation (such as vibration monitoring devices) and computerized maintenance management information systems (CMMIS) which provide an effective means of optimizing maintenance efficiency (Mobley, 2004). The place of plant equipment diagnostic instrumentation in optimizing maintenance effectiveness cannot be overemphasized as it continuously monitors the operating condition of plant equipment and systems thereby resulting in improved plant reliability and availability (Mobley, 2004). Nevertheless the initial overall cost of setting-up such a maintenance scheme is usually very high (Shin and Jun, 2015). These costs include, among others, the purchase of diagnostic tools and the training of maintenance staff in order to effectively use the technology. Hence the technology is usually embraced by most industries only for the maintenance of critical plant equipment.

Plant equipment classically utilizes two types of maintenance management approach: run-to-failure or preventive maintenance (Mobley, 2001, Waeyenbergh and Pintelon, 2004, Li et al., 2006). The preventive maintenance approach could be time-based or condition based. Time based preventive maintenance is of two types; scheduled replacement and scheduled overhaul while condition based maintenance is also of two types; offline and on-line condition based maintenance.

As discussed in Chapter 1, there are three major elements that make up a maintenance system; risk assessment, maintenance strategy selection and maintenance task interval determination. These elements must be optimized in the maintenance management of a plant system in order to have a safe and reliable system at reasonable cost. Different maintenance methodologies have been applied in optimizing these elements of maintenance. The notable ones are; Reliability Centered Maintenance (RCM) and Risk Based Maintenance (RBM). Within these maintenance frameworks different tools such as FMEA and Fault Tree Analysis (FTA) have been applied in the optimization of the elements of maintenance (Taheri et al., 2014).

2.3 Maintenance optimization

Complex systems such as ship systems consist of many equipment items and for the system to remain safe and reliable at an optimum cost, the most appropriate maintenance strategy and optimum task interval have to be adopted for each of the equipment items. There are different maintenance strategies, such as corrective maintenance, preventive and condition based maintenance, to choose from with respect to maintaining the different equipment items of a plant system. For some items of equipment, allowing them to run to failure may be more cost effective than the preventative approach. Whereas for others the preventative approach may be more cost effective than the reactive approach. For some equipment where the preventative approach is the most appropriate, the optimum interval of the maintenance task must be determined in order to have an optimum level of overall system reliability at an optimum cost. Hence there is need for maintenance system optimization such that the most effective maintenance strategy which will result in optimum balance between cost of maintenance and the resulting asset reliability, is utilized for maintaining an asset (Karyotakis, 2011). There are basically three techniques for optimizing maintenance strategies for plant systems namely; RCM, Total Productive Maintenance (TPM) and Risk Based Maintenance (RBM) (Karyotakis, 2011). The main focus of this research is RCM because none of the other techniques can preserve the function of a machinery system in the same way that it can(Moubray, 1991).

2.3.1 Risk Based Maintenance (RBM)

Risk-based maintenance is a systematic approach which combines reliability and risk evaluation procedures in developing a cost effective maintenance strategy for reducing the overall risk of an operating plant system (Wang et al., 2012). The overall plant risk is a combination of the risk of each of the individual constituent units that make up the plant. For high risk units, an intensive maintenance effort is needed, whereas for low risk units minimal effort is required. Since maintenance is centered on risk, in determining the type and the frequency of preventative maintenance in the RBM approach a quantitative method of evaluating risk is applied. The RBM strategy generally consists of the following steps (Khan and Haddara, 2003, Wang et al., 2012, Krishnasamy et al., 2005):

(1) Identification of system scope: The system to be investigated is generally broken into manageable units. The units referred to could be sub-systems or components.

(2) RBM risk assessment: This step begins with the identification and analysis of failure scenarios and the consequences of the failures for each of the units of the system. It is generally advisable to consider one or two of the most important failure scenarios for each of the units that may lead to system failure. The risk for each of the units is then calculated by multiplying the probability of the failure scenario by the consequence of the failure scenario. A quantitative or qualitative measure of risk is finally obtained which is used to categorise risk of units into high, medium and low risk.

(3) RBM Risk evaluation: Here the first step is to determine an acceptable level of risk and which may vary from industry to industry. The risk estimated for each unit is then compared against the acceptable risk. If the estimated risk is above the acceptable risk the unit(s) may be subjected to further analysis and subsequently a different maintenance strategy and interval will be adopted to bring the risk down to the acceptable value.

(4) RBM maintenance planning: The first step is to critically examine the root cause of failures for each unit. Then for each unit the basic events' probability failures are evaluated in a reverse fault tree analysis using targeted probability of failure of the top event (unit

probability of failure). With the top event probability fixed, the fault tree is generally simulated in order to determine the probability of failure of basic events. The optimal probabilities of failure of the basic events obtained from this analysis are then used to calculate the maintenance tasks and associated inspection intervals. This process is carried out for each of the units that have an unacceptable risk value and the main aim is to reduce the overall system risk. The Risk Based Maintenance strategy has been applied in the literature by several authors as a technique for optimizing maintenance for example Krishnasamy et al. (2005)

2.3.2 Total Productive Maintenance (TPM)

With the introduction of 'Just in Time' manufacturing and assembly procedures, the need for the elimination of any plant downtime has become apparent. One technique that had been utilized in aiming to achieve this objective is TPM. TPM is a systematic approach to maintenance that maximizes equipment effectiveness and presses towards zero downtime and zero product defects through the involvement of all of the labour force. The concept of TPM was first introduced by M/s Nippon Denso CO. Ltd of Japan in 1971 and has since been applied by many industries across the globe with the major aim of maximizing equipment effectiveness (Ahuja and Khamba, 2008). Equipment effectiveness here is referred to as the rate to which equipment is performing its normal operating function. Using TPM as a maintenance methodology the equipment effectiveness can be maximised in two possible ways; (1) improving on plant total availability and (2) improving on the quality of plant output and in this case defective product numbers are reduced to the barest minimum. The equipment effectiveness is generally measured in the TPM methodology using Overall Equipment Effectiveness (OEE) which is evaluated as a product of the availability of the equipment (*As*), the equipment performance rate (*Pr*) and the quality rate of equipment product (*Qr*) and it is represented as, (Nakajima, 1989):

$$OEE = A_s \, . P_r \, . \, Q_r \tag{2.1}$$

The availability component is evaluated as follows:

$$A_s = \frac{(T_L - T_D)}{T_L} \tag{2.2}$$

Where

T_L = Loading time

T_D = Downtime

The performance rate component is evaluated as follows:

$$P_r = O/T_L \tag{2.3}$$

Where

O = output

The quality rate of the product from the system is measured as follows:

$$Q_r = GP/TP \tag{2.4}$$

Where

GP = Good product

TP = Total Product

Equipment effectiveness is potentially hampered by six major forms of loss in any organization. These losses include; machinery breakdown, setup and adjustment time, speed reduction, minor stoppages, product rejects and startup losses. The six losses can be measured within the three performance measurement indices of the OEE. The machinery breakdown and set up and adjustment losses are measured with the availability component of the OEE, the speed reduction and minor stops losses are measured with the performance rate component and the product reject and startup losses are measured with the product quality rate component. The essence of performing the measurements of these six losses with the OEE is to help to keep the company in a position to be able to constantly improve its maintenance system efficiency in order to achieve optimum performance of their machinery system.

There are eight pillars upon which TPM can be structured in order to maximize the benefit of the methodology in any organization. They are as follows (Rodrigues and Hatakeyama, 2006, Ahmed et al., 2005):

(1) 5S: The first step to the successful implementation of TPM is the adoption of the principle of 5S. The 5S is a logical procedure of good housekeeping with the main aim of having a conducive environment in the workstation with the cooperation and commitment of all of the workforce. If a workstation is tidy and organised problems become visible and this is the first step to system or process improvement. The 5S is generally performed in phases. The first S stands for “Seiri” meaning Sort out, the second S stands for “Seiton” meaning Set in order, the third S stands for “Seisio” meaning Shine the workstation, the fourth S stands for “Seiketsu” meaning Standardize and the fifth S stands for “Shitsuke” meaning Sustain and practice

(2) Autonomous maintenance: This puts the responsibility of performing basic maintenance tasks, such as lubrication and visual inspection, on the operators of the asset thereby creating room for the maintenance personnel to concentrate on the core maintenance tasks.

(3) Planned maintenance: The objective here is to have fault free machinery which is achieved by planning maintenance activities to curtail potential failures. Maintenance planning involves the following maintenance activities, among others; maintenance type determination, the interval for maintenance task determination and spare parts inventories.

(4) Education and training: The operators and maintenance personnel need constant training and education in order to enhance their maintenance skills and harmonious working relationships.

(5) Kaizen: The term kaizen is a combination of “Kai” which stands for change, and “Zen” which stands for good. The principle here is that a small improvement that is carried out on a continuous basis which involves all of the workforce is better than big changes executed once in a while. This principle should be practiced both in production units as well as administrative units. The basic objective of using this principle is to systematically eliminate losses through a detailed and thorough procedure. There are some basic tools for the implementation of this principle and some these tools are; Poka-Yoke, Why-Why analysis and a Kaizen summary sheet.

(6) Quality maintenance: The focus here is to impress the customers by producing defect free products. This can be achieved by ensuring that the parts of equipment that the affect quality of production are constantly monitored and maintained to ensure that output from the equipment or production line is defect free.

(7) Office TPM: The administrative staff commitment is one of keys to enjoying the benefit of the TPM. Hence the administrative staff must ensure that administrative functions

are optimized by reducing inventory carrying cost, administrative cost, procurement cost and idle time, among others, for improving productivity, waste elimination and reduced production cost.

(8) Safety and environment: A safe and conducive working environment should be ensured. This will help to guarantee a healthy workforce and lead to zero accidents. This will invariability result in an increase in productivity.

Based on the above pillars of TPM that have been discussed it is obvious that the successful implementation of TPM in any organization solely depends on the staff's willingness to embrace the technique and in the management's commitment to the implementation. The implementation is usually challenging, in some cases due to a long established culture of the division of labour e.g. maintenance practitioners solely responsible for maintenance of plant assets and operators solely responsible for the operation of the assets. This approach sometimes brings about rancor among maintenance personnel and operators thereby reducing overall productivity. However if this age long negative attitude is broken and TPM is successfully implemented then the benefits associated with TPM such as waste reduction, downtime minimization, and improved output quality will be appreciated by the organization.

The major difference between TPM and the traditional preventive maintenance approach which originated in the US, is that in the TPM approach the total organizations workforce is involved in the maintenance of an asset i.e. the operators ensure that the asset is in a good condition on a day to day basis by routinely carrying out some basic maintenance on the asset so that the maintenance personnel can concentrate on the less frequent core maintenance aspects, while for the traditional PM technique the maintenance of assets is limited to the maintenance personnel.

2.3.3 Reliability Centered Maintenance (RCM)

2.3.3.1 RCM overview

Moubray (1991) defined RCM as "*a process used to determine what must be done to ensure that any physical asset continues to function in order to fulfil its intended functions in its present operating context*." From this definition it is obvious that RCM focuses not on the system hardware itself rather on the system function. Maintenance practitioners are faced with challenges with respect to maintaining their asset and some of these challenges are; difficulty in selecting the most appropriate maintenance strategy for each equipment failure, difficulty in prioritizing the risk of component failure modes of the system, difficulty in ascertaining the most cost effective approach and difficulty in getting the best support from the workforce. All of these challenges are addressed by the RCM frame-work in a systematic manner. In fact Moubray (1991) categorically stated that no maintenance technique has proven to be more successful in preserving the function of a system than RCM.

The development of the RCM technique can be traced to the aviation industry where the Maintenance Steering Groups (MSG) formed within the industry developed a maintenance methodology which was reported in three documents referred to as MSG1 MSG2 and MSG3, released in the years 1968, 1970 and 1980 respectively (Dhillon, 2002). This technique evolved into classical RCM which has since been embraced by all industries ranging from manufacturing to the marine sectors and has proven to be successful in all these industries.

The first step to the successfull implementation of the RCM technique is to ask seven basic questions about the asset that the methodology is intended to be applied on. These seven questions are as follows, (Moubray, 1991):

(1) What are the intended functions and performance standards of the asset or machinery in its current operating situation?

(2) How does it fail to fulfil these intended functions?

(3) What are the causes of each failure?

(4) What are the corresponding consequences?

(5) In what way does each failure matter?

(6) What task should be performed in order to avert each failure?

(7) What should be done if no preventive task is found to be applicable?

2.3.3.2 RCM analysis steps

The basic steps of the RCM analysis are reviewed as follows (Rausand and Vatn, 1998, Dhillon, 2002, Selvik and Aven, 2011)**:**

(1) Preparatory stage: RCM is generally performed by a team and, as such, the first step in the RCM analysis is to set up the RCM team. The team should consist of experts with adequate knowledge of the system to be investigated. Generally the team should have a minimum of one person each from the maintenance and the operational units. The team should also have a

member with a vast knowledge of the RCM methodology and who could serve as the facilitator. The RCM team have the responsibility for determining; the scope of the study, the level of the assembly to be investigated (i.e. plant, system, sub-system) and the equipment or asset to be investigated. They also have the responsibility, among others, of data gathering for the analysis.

(2) Maintenance significant items (MSI) identification: FMEA is generally applied here in determining the maintenance significant items. FMEA methodology is discussed in detail in Section 2.4.2.4 below. These items are then used to populate the RCM decision diagram in order to determine the most appropriate maintenance task. For a very simple system MSI can easily be identified without resorting to any specialized tools. For the non-MSI items, the items are generally allowed to fail before repair or replacement can be implemented. However for the MSI items preventive maintenance tasks are usually more appropriate but in some cases they are allowed to fail before repair or replacement activities are performed and these are dependent on MSI items failure characteristics, the impact of the failure and maintenance costs.

(3) Maintenance strategy classification: The maintenance strategy for addressing crucial failure modes of the critical components of an asset have been classified in different ways. Rausand and Vatn (1998) considered five distinct maintenance strategies namely continuous predictive maintenance, scheduled predictive maintenance, scheduled overhaul, scheduled replacement and scheduled function testing for preventing or mitigating the effects of failures. Dhillon (2002) presented the following four maintenance strategies for use in the RCM methodology; reactive maintenance, preventive maintenance, predictive testing and inspection and proactive maintenance. Nevertheless both the five maintenance strategy types considered by Rausand and Vatn (1998) and the four maintenance strategies considered by Dhillon (2002) fall within the three basic main maintenance strategies: corrective maintenance, preventive maintenance and condition/predictive maintenance.

(4) Maintenance task selection: Here the RCM logic is designed and applied in selecting the appropriate maintenance task to the crucial failure mode of each of the critical components of the asset. The RCM logic is expressed in decision diagram form which, through a series of YES and NO questions, enables the RCM facilitator to arrive at an optimal maintenance strategy for the particular failure mode/component in question. There are various versions of

the decision RCM logic tree and a sample is shown in Figure 2.1. However all of the versions are based on the basic decision criteria of the RCM for selecting the maintenance task which are; cost effectiveness, applicability and failure characteristics. The term applicability with respect to selecting the maintenance task, means a maintenance preventive task that is capable of mitigating or preventing failure and in the case of a potentially hidden failure is capable of discovering it. The term cost-effectiveness is a decision criterion for determining the maintenance task from different alternatives that is the most cost effective. If there is no applicable preventive maintenance task available, then the only alternative is to select Run–To–Failure. In the case of cost effectiveness; the cost of the applicable preventive maintenance task to mitigate or prevent failure must be greater than the aggregate cost related with the failure itself, otherwise Run–To–Failure will be more appropriate except with a safety-related issue or a failure situation where redesign may be compulsory.

(5) Maintenance planning: Here the optimal intervals are determined for the preventive maintenance tasks assigned for the crucial failure modes of the critical components of the asset. Some of the failure modes are assigned scheduled predictive maintenance and some scheduled overhaul, etc. using the RCM logic. The process of determining the interval for a preventive maintenance task is, in many instances, very challenging and, in general, mathematical models are applied in obtaining these intervals. However in some cases mathematical models are not applied and preventive maintenance task intervals not optimized but are mainly determined based on experts' opinions, operational experience and manufacturers' recommendation. It is worth mentioning that in the traditional RCM process there is no provision for tools for use in the determination of preventive maintenance task intervals.

The outcome of steps 1 to 5 is a mix of diverse preventive maintenance tasks and intervals and in order to have an efficient maintenance system programme, at a minimum cost, for an entire system the preventive maintenance tasks and intervals are typically grouped. The grouping may include the non-MSI i.e. items that were eliminated in the screening phase (step 2).

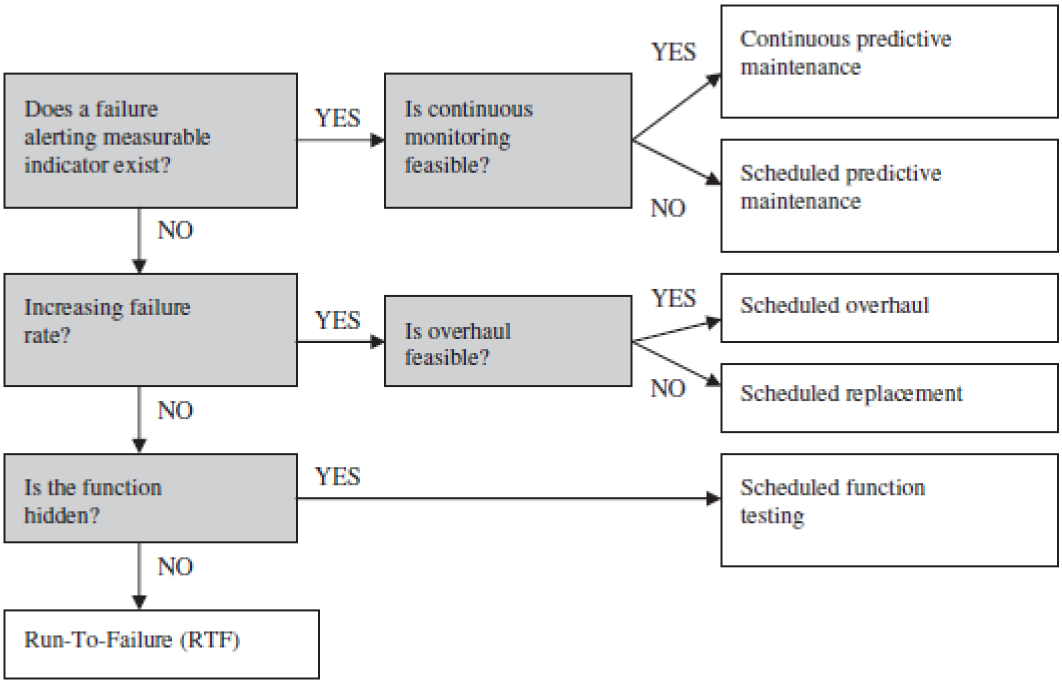


Figure 2.1: A sample of RCM logic adapted from (Rausand and Vatn, 1998)

(6) Implementation and update: Here the managerial procedures, with respect to how the results of the RCM analysis that is performed by the RCM team are applied, is described. This step includes among others; communication of the RCM analysis results from the RCM team to the management, results documentation and undertaking updating from time to time which is generally subject to availability of new relevant data.

2.3.3.3 RCM application areas and improvement

The conventional RCM has various limitations which have limited the effectiveness of the methodology in addressing maintenance decision making problem. Some of these limitations are (Gabbar et al., 2003): (1) the process is very demanding in-terms of time, effort and resources especially for a complex system (2) limited data availability for taking optimal decisions especially in the area of maintenance strategy selection and (3) the process involvement of non-engineering factors in the maintenance decision problem. Various improvements have been made to the conventional RCM methodology in order to make it more efficient and adaptable for optimizing maintenance systems. One improvement is the integration of the Computerized Maintenance Management System (CMMS) with RCM. Zhihong et al. (2005) proposed an integrated CMMS with the RCM. The CMMS was applied for storing and supplying the original data for undertaking the RCM analysis since one of the key challenges to the success of RCM was lack of data in many instances. The authors proposed it for application in a power system and other engineering related systems. Beni (2014) presented an enhanced RCM technique by integrating CMMS with RCM which, according to the author, has the ability to change the maintenance strategy for a system dynamically in a manner based on changing the maintenance strategy selection decision criteria data. The maintenance strategy decision criteria data are not constant because the operating condition of the asset and other factors that affect the life cycle of the asset are not themselves constant. The use of CMMS was for dynamically managing the maintenance strategy selection decision criteria data which is then applied as input data into the RCM maintenance strategy selection methodology. The methodology was proposed for application in the National Iranian Gas Company and its subsidiaries. Gabbar et al. (2003) also proposed an integration of CMMS and RCM such that the CMMS dynamically manages and updates the RCM analysis data which is then fed dynamically into the RCM methodology to subsequently change the maintenance strategies of the studied system. In order to ascertain the applicability of the technique the authors applied it to a nuclear power plant water-feed process.

Another improvement that was carried out on the conventional RCM technique was the introduction of the idea of ‘soft’ and ‘hard’ life by Crocker and Kumar (2000a) in order to optimize total system maintenance costs. The authors defined hard life as being the age at which a component of a system or sub-system has to be replaced and on attaining that age the system or sub-system housing the component is removed for subsequent salvage. They defined ‘soft’ life as being the age a component of a system or sub-system will attain, after which it will be rejected at the next opportunity the system or sub-system housing the component will be recovered. From the study the hard life is the suitable replacement age for safety-critical parts or components of an aircraft system while the soft life is ideal for comparatively cheap components that may cause costly, unplanned rejections of an engine. The author concluded that the new RCM approach can be utilized in order to select an optimal maintenance strategy for military aero-engines. In another development Cheng et al. (2008) proposed an integrated case based reasoning method combined with the RCM analysis technique and referred to as IRCMA. IRCMA, in the authors’ opinion, is a better alternative to the conventional Computer Aided Reliability Centered Maintenance (CARCMS) method and it is already being used in place of the latter as the RCM analysis tool for China’s military equipment.

The applications of RCM and the improvements carried out on the technique as discussed so far, are in the fields of nuclear power, defense and the oil and gas sectors. However RCM and improved RCM techniques have also been applied in the marine sector. Conachey and Montgomery (2003) proposed an integrated spare parts holding model combined with the conventional RCM technique for application in machinery equipment components of ship systems. After performing the first three steps of the RCM analysis such as defining systems, defining functions and functional failures and performing FMEA, the next step was to categorise risk of failure modes. The authors suggested the use of a risk matrix and gave an example of a risk matrix that classified failure modes into three risk categories; high risk, medium risk and low risk. For the three categories of risk the following maintenance strategies are applied as a means of mitigating the risk; for the high risk a one-time change or redesign, for the medium risk undertaking condition monitoring or time based preventive maintenance and for the low risk, run-to failure. The failure modes and corresponding criticality ranking for each failure mode were then used to populate the RCM logic in order to ascertain the exact maintenance strategy to be employed to detect from the onset or to mitigate or eliminate failure. This was followed by determination of the maintenance task interval and finally determination of spare parts holding. In a related paper Conachey (2005) suggested the application of conventional RCM on the machinery system of a ship together with an additional model to cater for the spare parts needs. The spare part model that was incorporated into the conventional RCM was based on risk assessment. The author recommended the basic tools such FMEA, RCM logic and a risk matrix generally applied for the conventional RCM analysis, for implementation on the machinery equipment of the ship system. It was concluded that the RCM technique is a relatively new maintenance optimization approach in the maritime industry and that the industry players (owners and operators) will fully embraced it due to the same benefits that other sectors have derived from the implementation of the technique.

Lazakis (2011) presented an enhanced RCM technique based on a combination of the managerial aspects of TPM and the technical aspects of RCM. This novel RCM approach is referred to by the author as Reliability and Criticality Based Maintenance (RCBM). The essence of the approach was to have an efficient maintenance system in place that will have the results to improve reliability and downtime minimization of a ship system. In order to achieve the aim of the study, the author applied reliability techniques and tools such as Dynamic Fault Tree Analysis (DFTA), Failure Modes, Effects and Criticality Analysis

(FMECA) and fuzzy set theory in combination with TOPSIS in solving multi-criteria decision problems. One such multi-criteria decision problem that was solved is the resolution of a maintenance strategy selection problem which the author addressed with the Fuzzy-TOPSIS methodology. The applicability of the author's proposed enhanced RCM was demonstrated with two case studies; a cruise ship diesel system and a Diving Support Vessel.

From the RCM discussion it can be seen that there are three key elements of maintenance that the methodology is used to optimize; (1) risk assessment, (2) maintenance strategy selection from different alternatives, and (3) maintenance task interval determination. A great deal of work has been carried out with respect to improving the efficiency of RCM in optimizing these three components and ensuring continuous asset reliability improvement, however there remains scope for further improvement in all three aspects.

2.4 Risk assessment

The American Bureau of Shipping (2000) defined risk as the product of the probability of the occurrence of a failure and consequence of the failure. Mathematically this is simply expressed as:

Risk = failure probability x consequence of the failure (2.5)

While risk assessment, according to Cross and Ballesio (2003), is defined as being a systematic method that combines diverse aspects of design and operation in assessing risk. Arendt (1990) described risk assessment as activities involving hazard identification, chances of the occurrence of failure estimation and the consequences of the failure estimation.

With the advent of risk-based inspection and maintenance in the 1990s in conjuction with reliability maintenance, risk assessment has gained popularity in the maintenance world and it is worth noting that risk assessment is clearly the most critical phase of risk-based maintenance since maintenance decisions to be taken will be based on the assessed level of risk (Arunraj and Maiti, 2007). Risk assessment is also a very important aspect of Reliability-Centred Maintenance (RCM) though RCM is mainly intended for preserving the reliability of plant equipment and systems. The risk assessment in the RCM process involves assessing the risk of failure of equipment items and based on the assessed risk, an appropriate maintenance strategy will be recommended. However the acceptable level of risk must be defined possibly through a retrospective study of earlier successful items etc.

Some of the factors that affect the quality of the output from a risk analysis are; data sources, human factors, methods and tools for performing the analysis itself, and the ability and experience of the analyst.

2.4.1 Risk assessment approaches

In assessing the level of risk of an asset the risk analyst has the option of selecting from among three different risk assessment approaches and, in general, the choice depends on the availability of data for performing the analysis. The three different risk assessment approaches are qualitative, semi-qualitative and quantitative (Khan et al., 2012).

2.4.1.1 Qualitative technique

In this approach risk is measured based on subjective judgement. As stated above, risk is the product of the probability of failure occurring and the subsequent consequences of the failure and these parameters should be determined using subjective judgement. In describing failure consequences, terms such as minor, major, critical and catastrophic are utilised while the probability of failure occurring is expressed using terms such as improbable, remote, occasional, probable and frequent (American Bureau of Shipping, 2003). Since the means of assessment are subjective, it follows that the mitigation measures chosen for risk reduction will also be subjective. Qualitative risk assessments are generally applied when there is a lack of quantitative data in terms of measurable quality and quantity. The techniques are usually ideal for systems where risk is relatively small and well known from experience.

2.4.1.2 Quantitative technique

The use of this technique greatly depends on the availability of quantitative data (Carter et al., 2003). As opposed to the subjective judgement used in the qualitative technique, judgement is based on using probability analysis to determine numerical values for the probability of failure occurrence and the consequences of failure (Khan et al., 2012). Some of the tools available for quantitative risk analysis are; Fault Tree Analysis (FTA) and Event Tree Analysis (ETA).

2.4.1.3 Semi-quantitative technique

In this approach the estimated numerical values necessary for the probability of failure calculations and the corresponding consequences of failure are based on expert opinions using available data from similar plants (Khan et al., 2012). With this assessment methodology, scores are assigned, based on expert judgement, to each of the variables that affect the probability of failure and the corresponding consequences and these are summed up in order to give an estimate of the probability of failure and of its consequences (Khan et al., 2012). This technique can supplement traditional tools such as FMEA, Hazard Operability Analysis (HAZOP) and others tools used for quantitative techniques such as FTA and ETA (Hauptmanns, 2004).

2.4.2 Risk assessment methods and tools

An analyst has the option of choosing from a variety of tools for performing risk analysis in each of the three major phases of risk assessment; hazard identification, risk estimation and risk evaluation. Some of the commonly used tools/methods will be discussed in the following text with emphasis on the tools that will be subsequently used in this research. It should be noted that one of the keys to successful risk assessment lies in the ability of the analyst to choose the right method or combination of methods for a particular problem (American Bureau of Shipping, 2000).

2.4.2.1 Checklist Analysis technique

A checklist is simply a list of questions about the plant system operation, maintenance, etc. and the essence is to systematically check if functional need and requirements are fulfilled. They are usually prepared based on the company's experience, codes and standards employed and are the simplest method for risk identification (Khan and Abbasi, 1998). The list indicates items of conformance and non-conformance and for the non-conformance items carefully prepared recommendations are made in terms of correcting whatever items are found to be wrong or faulty. Khan and Abbasi (1998) identified some of the limitations of the checklist approach which include:

(1) It takes a long time to develop a checklist and the result does not give full insight into the system. The status of each analysis item are in the form of 'Yes' or 'No'.

(2) The quality of the result is a function of the ability and the experience of the analyst who compiled the checklist and interpreted the result.

(3) It cannot identify a hazard that has to do with system mis-operation such as leaks or excessive heat generation nor can it tell the severity of operating conditions.

2.4.2.2 Hazard Operability Analysis (HAZOP)

HAZOP is a risk analysis and assessment tool that was developed by British Imperial Chemical Engineering in the 1960s (Zhan et al., 2012). The basic principle of a HAZOP study is that once there is a deviation from standard operating conditions of a system the result is a potential hazard (Khan and Abbasi, 1998). Once a deviation has been identified (detected) the next step is to find out the cause of the deviation and rank the corresponding level of risk in the system. Lastly steps will be taken to mitigate the effect of the risk on the system (Zhao, 2008).

According to Khan and Abbasi (1998) HAZOP has some limitations. These include:

(1) Just like a checklist the quality of the result and actions will depend on the ability and experience of the analysis team involved.

(2) The method assumes that the equipment has been built in accordance with appropriate codes and standards; this is not always the case as there can be faulty designs and installations as well.

Despite these limitations it is still one of the most common of tools that is used used for hazard identification and risk assessment in the chemical processing industry, the manufacturing industry and the power industry. In spite of its popularity in all of these sectors only one application of HAZOP in the area of ship risk assessment has been reported in the literature (Zhan et al., 2012).

2.4.2.3 Fault Tree Analysis

Geoff (1996) defined “fault tree as a method by which a particular undesired system failure mode can be expressed in terms of component failure modes and operator actions. The system failure mode to be considered is termed the top event and the fault tree is developed in branches below this event showing its causes”.

The information that is fed into the fault tree will determine whether the approach is quantitative or qualitative. Quantitative analysis is used if the occurrence or failure probability of the top event is calculated based on the estimated or measured occurrence probability of each basic event (Xing and Amari, 2008). The qualitative fault tree, on the other hand only gives a description of the combination of the basic events causing the potential problem of interest (American Bureau of Shipping, 2000). The qualitative techniques thus cannot quantify or estimate the level of risk but could help in identifying potential hazards and their significance (Halme and Aikala, 2012). The fault tree analysis technique is most suited for analysing top events (system failures) resulting from relatively complex combinations of component failures (American Bureau of Shipping, 2000).

Just like every other risk analysis tool it has some limitations according to (Khan et al., 2012) which include:

(1) The assumption in the quantitative technique is that the likelihood of basic events is precisely known which is not true because the data collection mode is characterised by a high degree of uncertainty.

(2) The assumption that component failures or basic event failures are independent is absolutely untrue in real life systems.

These two assumptions will translate to having an inaccurate risk level analysis assessment thereby resulting in potentially wrong maintenance decisions for the particular failure mode under consideration.

2.4.2.4 FMEA

Siddiqui and Ben-Daya (2009) defined Failure Mode and Effect Analysis (FMEA) “as a systematic failure analysis technique that is used to identify the failure modes, their causes and consequently their fallouts on the system function”. The development and application of the FMEA methodology dates back to 1949 and the United States Army and in the 1970s its was embraced by the automotive, aerospace and manufacturing industries (Scipioni et al., 2002). Today FMEA is a commonly used risk assessment tool in the production of hardware such as mechanical and electronic components (Scipioni et al., 2002). “The introduction of FMEA to on–board ship operations can be considered as a step in a new direction” according to Cicek and Celik (2013). When FMEA is combined with criticality analysis (CA) it is referred to as Failure Mode Effect and Criticality Analysis (FMECA) and its essence is to rank the impact of each of the failure modes for the various components that make up the entire system (Headquarters Department of the Army, 2006, Sachdeva et al., 2009a).

According to Ben-Daya (2009) FMEA basically performs three functions. These are:

(1) To identify and recognize potential failures including their causes and effects.

(2) To evaluate and prioritize identified failure modes.

(3) To identify and suggest actions to either eliminate or reduce the chance of the potential failures from occurring.

The technique can be applied to any well-defined system but it is best suited for the risk assessment of mechanical and electrical systems (e.g. fire suppression systems, propulsion systems) and the approach can either be quantitative or qualitative, (American Bureau of Shipping, 2000, Headquarters Department of the Army, 2006). The availability or non-availability of failure data will determine to a large extent the approach that is used in carrying out FMEA risk assessment. A quantitative approach is used when variables such as failure rate (λ_i), failure mode ratios (α_i), failure effect probability (β_i) and its operating time (t) are known and are used to generate the criticality number (CN) which can then be used to rank ith failure mode (Headquarters Department of the Army, 2006, Braglia, 2000). This can be represented mathematically as:

$$CN_i = \alpha_i \, x \, \beta i \, x \, \lambda_i \, x \, t \tag{2.6}$$

In applying the qualitative method each failure mode is rated or ranked by developing a risk priority number (RPN) which is computed by multiplying the severity rating (S) by both the occurrence probability (O) and the detection rating (D):

$$RPN = S \; x \; O \; x \; D \tag{2.7}$$

Qualitative terms are used to determine these three parameters, usually on a numerical scale of 1 to 10 having been determined based on collective expert opinion (Sachdeva et al., 2009b, Siddiqui and Ben-Daya, 2009, Ling et al., 2012, Kahrobaee and Asgarpoor, 2011, Zammori and Gabbrielli, 2012, Braglia, 2000). Tables 2.1 to 2.3 show the qualitative scales that are commonly used for occurrence ranking, severity ranking and detection ranking.

Table 2.1: Occurrence ranking, copied from (Headquarters Department of the Army, 2006)

Ranking	Occurrence	Comment
1	1/10,000	Remote probability of occurrence; unreasonable to expect failure to occur
2	1/5,000	Very low failure rate. Similar to past design that has, had low failure rates for given volume/loads
3	1/2,000	Low failure rate based on similar design for given volume/loads
4	1/1000	Occasional failure rate. Similar to past design that has had similar failure rates for given volume/loads.
5	1/500	Moderate failure rate. Similar to past design having moderate failure rates for given volume/loads
6	1/200	Moderate to high failure rate. Similar to past design having moderate failure rates for given volume/loads.
7	1/100	High failure rate. Similar to past design having frequent failures that caused problems
8	1/50	High failure rate. Similar to past design having frequent failures that caused problems
9	1/20	Very high failure rate. Almost certain to caused problems
10	1/10+	Very high failure rate. Almost certain to cause problem

Table 2.2: Severity ranking, copied from (Headquarters Department of the Army, 2006)

Ranking	Severity	Comment
1	None	No reason to expect failure to have any effect on Safety, Health, Environment or Mission
2	Very low	Minor disruption to facility function. Repair to failure can be accomplished during trouble call.
3	Low	Minor disruption to facility. Repair to failure may be longer than trouble call but does not delay mission.
4	Low Moderate	Moderate disruption to facility. Some portion of Mission may need to be reworked or process delayed
5	Moderate	Moderate disruption to facility. 100% of Mission may need to be reworked
6	Moderate high	Moderate disruption to facility function. Some portion of mission is lost. Moderate delay in restoring function.
7	High	High disruption to facility function. Some portion of mission is lost. Significant delay in restoring function
8	Very high	High disruption to facility function. All of mission is lost. Significant delay in restoring function.
9	Hazard	Potential Safety, Health or Environmental issue. Failure will occur without warning
10	Hazard	Potential Safety, Health or Environmental issue. Failure will occur without warning

Table 2.3 Detection ranking, copied from (Headquarters Department of the Army, 2006)

Ranking	Detection	Comment
1	Almost Certain	Current control(s) almost certain to detect failure mode
2	Very high	Very high likelihood current control(s) will detect failure mode
3	High	High likelihood current control(s) will detect failure mode
4	Moderately High	Moderately high likelihood current control(s) will detect failure mode
5	Moderate	Moderate likelihood current control(s) will detect failure mode
6	Low	Low likelihood current control(s) will detect failure mode
7	Very low	Very low likelihood current control(s) will detect failure mode
8	Remote	Remote likelihood current control(s) will detect failure mode
9	Very Remote	Very remote likelihood current control(s) will detect failure mode
10	Almost Impossible	No know control(s) available to detect failure mode

FMEA is generally the preferred tool for reliability and risk assessment studies, probably because it can easily be understood and applied (Braglia, 2000). Some other reasons why it is frequently employed, according to Ben-Daya (2009), are that it can:

(1) Help to reduce the chances of a catastrophic failure that can result in injuries and/or have an adverse effect on the environment.

(2) Optimize maintenance efforts by suggesting applicable and effective preventive maintenance tasks for potential failure modes.

Despite the popularity of FMEA, it has serious flaws (Bowles, 2003). For example a particular failure mode might have a high severity ranking, a high occurrence and a very low detection ranking, because it can easily be detected and which may result in having a low overall risk ranking i.e RPN (Ling et al., 2012). The result may be that the analyst recommends preventive maintenance instead of predictive maintenance or requiring redesign because of the misleading RPN. Some authors have suggested the removal of the detectability element from the RPN calculation (Bowles, 2003, Fleming and Wallace, 1986, Bowles, 1998) as a solution to this potential problem. Conversely some authors are of the opinion that the three attributes are equally important and thus as such the detection attribute should not be removed (Narayanagounder and Gurusami, 2009). Other limitations of FMEA are:

(1) The technique takes into account only three attributes in rating risk whereas there are other important factors such as economic cost, production loss, environmental impact etc. which are not taken into consideration (Braglia, 2000, Sachdeva et al., 2009b, Zammori and Gabbrielli, 2012, Liu et al., 2011)

(2) Different combinations of three attributes can yield the same RPN number but the risk level may be totally different (Sachdeva et al., 2009b, Kutlu and Ekmekçioğlu, 2012, Liu et al., 2012, Sharma and Sharma, 2012).

(3) It requires the services of very experienced and well trained teams (Teng and Ho, 1996).

(4) The RPN formula is questionable and debatable (Liu et al., 2012, Liu et al., 2011, Kutlu and Ekmekçioğlu, 2012, Geum et al., 2011, Chin et al., 2009b)

FMEA is, however a key component of the Reliability-Centered Maintenance methodology and ABS specifically require the bottom-up FMEA approach when performing RCM analyses (Conachey, 2005).

The traditional FMEA has some limitations just like every other risk assessment tool however many alternative variations and methods have been advocated in the literature in order to overcome or minimise some of these challenges. (Souza and Alvares, 2008) applied the traditional FMEA in conjunction with Fault Tree Analysis (FTA) as a risk assessment tool for the application of Reliability Centred Maintenance. The methodology was used to study and analyse the failure mode of a hydraulic Kaplan turbine of a hydroelectric plant. The comparative study showed that the two tools can complement each other for the execution of an effective predictive maintenance plan on the basis that the FMEA analysis provided the information required for the FTA basic event. However when the results of the risk analyses of the FTA and the FMEA were compared some of the items that the FTA identified as being critical were shown to be non-critical in the FMEA and vice versa. The discrepancy was considerable and this could be attributed to the author using the results of only the probability of failures of the basic event in the FTA in comparing the results of the FMEA instead of using the probability of failures multiplied by the consequence of failures. Other improvements in literature to the classical FMEA and limitations that prompted the need to develop new tools for prioritising risk of failure modes are discussed in Chapters 3 and 4.

2.5 Maintenance strategy selection

One of the main challenges of maintenance management is the selection of the appropriate maintenance strategy for each equipment item in the system because not all maintenance strategies are applicable and cost effective for different components. Hence choosing the right maintenance strategy for the system will help maintain a balance between the system availability and cost of performing the maintenance. However when choosing the type of maintenance strategy for a ship machinery system or other complex related ship systems, several conflicting decision criteria must be taken into consideration such as cost, reliability, availability and safety. These make maintenance strategy selection analysis critical and complex and the investigation fundamental and justifiable (Bevilacqua and Braglia, 2000). Despite the significance of the subject, only a few studies have dealt with maintainance selection policy problem (Bertolini and Bevilacqua, 2006).

There are different maintenance strategies that can be used for mitigating the different failure modes of a marine machinery system. Generally there are three types of maintenance strategy that are available for maintenance practitioners to choose from. The three maintenance strategies and a review of the methods utilised for the selection of the optimum strategy for each of the different component/failure modes of the system are discussed next.

2.5.1 Maintenance strategies

According to Pintelon et al. (2006) a maintenance strategy is generally viewed from the perspective of maintenance policies such as breakdown maintenance, preventive maintenance and predictive maintenance and sometimes RCM or TPM. It is worth noting that the maintenance strategy is one of the most influential factor affecting the effectiveness of a maintenance system (Stanojevic et al., 2000, Stanojevic et al., 2004) and the process of estimating the optimal combination of maintenance strategies for different plant system equipment items is a very hard and complex task as the maintenance program must combine both technical and management requirements (Sachdeva et al., 2009b, Bertolini and Bevilacqua, 2006, Bevilacqua et al., 2000). The selections usually require a vast amount of information relating to the following decision criteria (Bertolini and Bevilacqua, 2006): manpower utilization, cost and budget constraints, safety factors, environment factors and Mean Time Between Failure (MTBF) for each piece of equipment.

2.5.1.1 Run-to-Failure

The rationale of the run-to-failure management approach is simple and straightforward. When a machinery equipment item fails it is fixed. That is to say equipment is allowed to fail before any maintenance (repair or replacement) is carried out and, as such, resources are not deployed until equipment breaks down. It is, in fact, a no-maintenance approach to maintenance management of an asset and it is generally the least cost effective technique of maintenance management, since the maintenance costs are higher and plant availability is lower. In fact maintenance cost analysis revealed that repair carried out in reactive mode is nearly three times higher in cost than that carried out in preventative mode (Mobley, 2001)
This type of maintenance is usually effective for non-critical and low cost components and equipment in a system (Pride, 2008). For the plant manager to know that a component is non-critical, criticality analysis is carried out and, based on the result, an appropriate maintenance strategy is recommended for the plant equipment.

2.5.1.2 Preventive Maintenance

Preventive maintenance is defined as maintenance actions performed on plant systems at a definite interval with the aim of preventing wear and functional degradation, extending the useful life and mitigating the risk of catastrophic failure (Sullivan et al., 2004) and it concerns itself with such activities as the replacement and renewal of components, inspections, testing and checking of working parts during their operation (Ebrahimipour et al., 2015). In utilising this approach for maintenance management, equipment repairs or replacement are performed at pre-established intervals. The length of the intervals is usually based on equipment items' industrial average-life such as Mean Time Between Failures (MTBF). However some plant managers rely on machine or component manufacturer's recommendation to schedule preventive maintenance activities.

For the shipping industry, the IMO in 1993 set the foundations for preventive maintenance implementation by releasing the International Safety Management (ISM) code (IMO 1993). Chapter 10 of the ISM code clearly states the procedure and the duties of the shipping industry for preventive maintenance implementation in such a way that international regulations are adhered to strictly.

The major merit of PM is its ability to increase the average life of equipment items and to reduce the risk of catastrophic failure (Sullivan et al., 2004). However despite the numerous benefits of PM, the major limitation is that it often results in unnecessary repair or replacement. Another limitation is the difficulty in evaluating the optimum interval of performing the maintenance task as this may take years of data collection and analysis (Chen, 1997).

The time based preventive maintenance approach can further be divided into two categories as follows:

(1) Scheduled overhaul: a maintenance approach where equipment overhaul or repair is carried out on a specified interval basis. This policy is suited to equipment or machinery with identifiable age when failure rate function rapidly increases and large elements of the equipment or machine must survive to that age and also where reworking can restore the machine to an acceptable operational condition (Rausand, 1998).

(2) Scheduled replacement: This refers to maintenance techniques in which equipment or a unit of it is replaced on a scheduled basis. This is usually ideal when equipment or machines

are exposed to critical failure; large units of the equipment or machines must survive to at least the replacement time and the failure type must be of major economic consequences (Rausand, 1998).

2.5.1.3 Condition Based Maintenance

This refers to the maintenance approach in which the condition of an item or piece of equipment is monitored in order to detect potential failure and recommend appropriate corrective action. The CBM are generally of two types; the continuous on-condition task and the scheduled on-condition task (Rausand and Vatn, 1998). The continuous on-condition task which is referred to as online condition based maintenance (ONCBM) in Chapter 5 is the approach where the condition of an equipment item is monitored uninterruptedly using diagnostics devices. The major disadvantage of this type of approach is that it is expensive (Jardine et al., 2006). The scheduled on-condition task is referred to as offline condition based maintenance (OFCBM) in Chapter 5, is an inspection performed on an equipment item at regular interval with the aim of detecting potential failure (Rausand and Vatn, 1998). The check carried out on equipment items is performed by maintenance practitioners or operators with or without the use of diagnostic tools. This approach is effective and yet more cost effective than the continuous on-condition task and as such more attractive to most industries and the maritime industry inclusive. However the major challenge of the scheduled on-condition task is the problem of determining the appropriate interval for performing inspection task (Jardine et al., 2006).

In designing a condition monitoring program for ship machinery systems, general procedures to be followed had been put in place by BSI/ISO 17359 (2003). The standard includes procedures for equipment auditing, criticality assessment and overview of the condition monitoring procedure and the determination of the maintenance action to be used.

The technique for scheduling maintenance tasks is the major difference between time based preventive maintenance and condition based maintenance. While the time based preventive maintenance activity is scheduled based on average life evaluated using historical data of the particular piece of equipment, the condition based maintenance activity is scheduled in response to a performance degradation observed from diagnostic device readings and/or human sensing which deviate from standard equipment operating conditions (Noemi and William, 1994).

2.5.2 Maintenance strategy selection methods

The use of the Multi-Criteria Decision Making (MCDM) such as such as the Analytical Hierarchy Process (AHP), the Analytical Network Process (ANP) and the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) in making optimum decision for when faced with multi-criteria decision problem is becoming popular (Gandhare and Akarte, 2012, Bevilacqua et al., 2000). One of such multi-criteria decision problem is the maintenance strategy selection. These techniques have either been applied singly or integrated with one another or they have been used in conjunction with other tools such as fuzzy set theory and mathematical programming. (Bevilacqua and Braglia, 2000) applied AHP to select the ideal maintenance strategy for an integrated gasification and combined cycle plant. The analysis took into consideration five possible alternatives: preventive, predictive, condition-based, corrective and opportunistic maintenance. The authors used AHP in conjunction with Failure Mode Effect and Criticality Analysis (FMECA) principles in order to choose the ideal maintenance strategy for each analysed item in the plant. Other examples of the application of AHP for maintenance strategy selection are: Triantaphyllou et al. (1997) proposed an AHP technique for the selection of a maintenance strategy taking into consideration four maintenance decision criteria; Nyström and Söderholm (2010) presented a methodology based on AHP for prioritising different maintenance actions in railway infrastructure, and Labib et al. (1998) developed a model based on AHP for optimum maintenance decision making for an integrated manufacturing system.

Bertolini and Bevilacqua (2006) presented an integrated AHP and Goal Programming (GP) technique such that the best strategies for the maintenance of centrifugal pumps in an oil refinery is chosen. The model that was proposed considered decision criteria such as account budget and number of man-hour constraints in comparring three alternative maintenance strategies (corrective, preventive and predictive). The authors concluded that the application of an integrated AHP and GP methodology proved to be a viable tool for minimization of maintenance cost (Bertolini and Bevilacqua, 2006). Similar to this approach, Arunraj and Maiti (2010) used AHP and a GP method for the selection of a maintenance strategy for a benzene extraction unit within a chemical plant. Equipment failure risk and the cost of performing maintenance were considered as the relevant decision criteria. AHP was used to assign weights to the decision criteria by means of pairwise comparison and the GP considered the assigned weight to rank the alternative maintenance strategies (corrective, time based, condition based and shutdown maintenance). The main improvement to the work of Bertolini and Bevilacqua (2006) was the use of the Fussell-Vesely (F-V) importance measure by the authors in order to estimate the risk contributions of different items of equipment. Zaim et al. (2012) reported on the use of a combination of AHP and ANP techniques for selecting the optimum maintenance strategy for a newspaper printing facility located in Turkey. From the comparative study, the two techniques yielded almost the same results.

The use of integrated fuzzy logic and MCDM (such as AHP) for maintenance strategy selection has also been reported in literature. Al-Najjar and Alsyouf (2003) used integrated fuzzy logic and AHP techniques to select the most cost effective maintenance strategy for a pump station. Wang et al. (2007) also proposed a fuzzy logic-AHP technique in order to select optimal maintenance strategies for different equipment items in a manufacturing firm.

The Reliability Centered Maintenance (RCM) technique is also widely used (Bevilacqua and Braglia, 2000, Mohan et al., 2004). "RCM represents a method for preserving functional integrity and it is designed to minimise overall maintenance costs by balancing the higher cost of corrective maintenance against the cost of preventive maintenance" (Crocker and Kumar, 2000b). RCM has been applied to a greater or lesser extent in the maritime industry for example the use of RCM logic diagrams in order to select the most appropriate maintenance strategy for different components of a system from the failure modes perspective (Conachey, 2005, American Bureau of Shipping, 2004). However the use of RCM is a very time consuming exercise and generally limited to some specific equipment (Waeyenbergh and Pintelon, 2004). Another limitation of the RCM technique in selecting maintenance strategies is that it does not allow for ranking of maintenance alternatives such that the optimum solution can easily be selected. This prompted Lazakis et al. (2012) to develop a maintenance strategy selection methodology based on the integration of fuzzy set theory and TOPSIS for the selection of the maintenance strategy for a diesel generator in a cruise ship. The maintenance strategy selection model that the authors proposed compared three alternative maintenance strategies (corrective, preventive and predictive maintenance) against eight decision criteria: maintenance cost, efficiency/effectiveness, system reliability, management commitment, crew training, company investment, spare parts inventories and operation loss.

From the analysis, condition based maintenance (CBM) was considered as the optimum maintenance strategy for the cruise ship diesel generator. However some doubts remain with regard to the practical use of the fuzzy approach because of the difficulty in testing and developing extensive sets of fuzzy rules (Zammori and Gabbrielli, 2012, Braglia, 2000). Additionally some important decision criteria such as applicability for maintenance strategy selection especially when dealing with the problem from the system failure modes perspective were not taken into account in Lazakis et al. (2012). In further work, Lazakis and Olcer (2015) aimed to improve the performance of the fuzzy-TOPSIS methodology by integrating AHP into it. AHP was introduced to assist in the weighting of the decision criteria. The result of the enhanced technique yielded preventive maintenance as the optimum maintenance strategy for the for ship diesel generator.

Goossens and Basten (2015) utilized AHP in the selection of maintenance strategies for naval ship systems. The authors involved three different groups within the industry in the decision making process namely: the shipbuilders, the owners/operators and the Original Equipment Manufacturers (OEM). In selecting the optimal maintenance strategy for the ship system from three maintenance strategies; corrective, time/use-based maintenance and condition based maintenance, three level decision criteria were applied. The first level consisted of two decision criteria; the second level consisted of eight and the third level consisted of 29. From the analysed results, the maintenance strategy preferred by the shipbuilder, owner/operator and the OEM is condition based maintenance. However the structuring of the problem made it computationally intensive as it required formation and analysis of numerous pairwise judgements from experts.

Resobowo et al. (2014) also applied AHP in prioritizing the factors that affect military ship maintenance management. In this case, the factors considered were; cost, availability, reliability, safety, human resource, operations, types of ship and ship characteristics. These factors were ranked using planned maintenance, preventive maintenance and routine maintenance as decision criteria. According to the authors the result of the analysis revealed that the most important factor is human resource. The major interest of the authors was to identify important factors for making maintenance decisions and as such does not completely address the problem of maintenance strategy selection.

It is obvious that there is a need for a more systematic approach that can easily incorporate qualitatively and/or quantitatively the maintenance alternatives selection criteria for marine system applications. On this basis one of the objectives of this research was to develop an alternative maintenance strategy selection method which avoids the limitations of the approaches used in literature.

2.6 Maintenance interval determination

After determining the type of maintenance task for each of the failure mode/components of an asset or machinery item, the next task is to determine the interval for carrying out the maintenance tasks. This process is an essential phase of the different maintenance optimization techniques (RBM, TPM and RCM). In this research the maintenance tasks that are considered for preventing or mitigating the effects of failure are; CM or RTF, scheduled overhaul, scheduled replacement, offline condition based maintenance (physical inspection) and online condition based maintenance (use of diagnostic tools). For all of these various maintenance types, different models have been developed by researchers for determining the intervals for performing them and they have been applied in different fields with variations to suit specific industrial needs. However the basic principle for the determination of the interval is to have a balance between the cost of achieving the highest reliability and the cost of unexpected failure. In the following Sections the different models that have been developed by different researchers for determining intervals for (1) scheduled replacement and (2) offline condition based maintenance (inspection) are discussed.

2.6.1 Scheduled replacement interval determination

As previously stated, preventive maintenance involves repair or replacement activities being performed at regular intervals. Hence scheduled replacement is one of the techniques that is used in preventive maintenance in order to recover the functions of an equipment item. Bahrami-G et al. (2000) defined it as a practice that entails decision making, based on certain criteria regarding the optimal time to replace an equipment item so as to reduce or eliminate a sudden breakdown. Optimization techniques are used to define the appropriate intervals for the replacement of the equipment item in order to have a balance between availability of the equipment items and the cost of the related maintenance. Generally two conditions must be satisfied to justify the use of scheduled replacement as a strategy in maintaining equipment. These are: (1) the value of Weibull shape parameter β of the equipment/components statistical variability must be greater than 1 and (2) the cost of the replacement activity as a result of failure must be greater than the cost of planned replacement. It therefore means that data on the failure parameters of the equipment and related cost information are essential in order to ascertain whether or not there is the need for a scheduled replacement to be carried out. This information is also required as an input into the replacement model in order to determine the optimum interval for replacement. Once it is ascertained that scheduled replacement is the optimum option for performing the recovery or sustainment of items of equipment, the most appropriate interval is then to be determined. From the literature two popular models have been generally applied and these are; the Age Replacement Model (ARM) and the Block Replacement Model (BRM) (Aven and Jensen, 1999).

For the ARM, an equipment item is replaced with respect to a predetermined age (t_p) or at failure. In this respect if failure occurs before the predetermine interval time, replacement is carried out at failure otherwise replacement is at the predetermined age. Furthermore if an equipment item is replaced due to failure, the replacement equipment is assumed to be as good as new and as such the maintenance practitioner would have to wait for another t_p to elapse before carrying out the next replacement. The universal ARM mathematical model, which is generally used for determining the appropriate time interval (t_p) for scheduled replacement is the one that was proposed by Barlow and Hunter (1960) and it is represented as follows:

$$C(t_p) = \frac{C_a\left(1 - R(t_p)\right) + C_b R(t_p)}{\int_0^{t_p} t f(t)dt} \tag{2.8}$$

Where:

$C(t_p)$ is the cost function per unit time

C_a is the cost of unit failure replacement

C_b is the cost of unit scheduled replacement

t_p is the given scheduled replacement interval and

$f(t)$ is the probability density function

$R(t_p)$ is the Reliability function

The essence of this age replacement model is to evaluate cost of equipment replacement for different values of 't_p'. The value of $t_p$with the lowest cost is then chosen as the optimum replacement interval. Hence the main purpose of this model is to minimise the cost of replacement of equipment.

For the block replacement model, however equipment/components are replaced at constant time intervals and in the case of failure before the constant time interval has elapsed the equipment/components are replaced and will be replaced again once the same constant time interval has passed. This type of replacement model can then result in unnecessary replacement of equipment/components. Hence the generally accepted perception that the ARM is more cost effective than the BRM. Nevertheless the BRM can be applied for less expensive equipment items whose replacement can be carried out in a group. The only advantage of the BRM over the ARM is that BRM is easier to apply and manage since replacement is performed at regular intervals as opposed to ARM where the maintenance practitioner would have to consider the time for replacement at failure before knowing the exact date that the next preventative replacement will be performed. The general BRM mathematical model is the one developed by Barlow and Hunter (1960) represented as follows (Ahmad and Kamaruddin, 2012):

$$C(t_p) = \frac{C_b + C_a\,.N(t_p)}{t_p} \tag{2.9}$$

Where $N(t_p)$ is the number of failures expected in an interval of 0 to t_p. As in the case of ARM, the main purpose of this model is to obtain an optimum replacement interval at the least cost.

These models (ARM and BRM) and variations have been applied in solving replacement problems for both single unit and multi-unit systems in different industries. Since in this research ARM has been chosen as the scheduled replacement model, discussion with respect to review of existing work in the literature in terms of application and advancement will focus on it.

2.6.1.1 ARM and BRM applications and improvement

Huang et al. (1995) developed a standard solution for the ARM that was proposed by Barlow and Hunter (1960) and for ease of use it was organised in the form of tables and charts.

Another important feature of the solution, in addition to organising it in tables, is in the reduction of input parameters by using a cost ratio (ratio of C_a to C_b) in place of the actual cost of failure replacement (C_a) and cost of preventive replacement (C_b). The algorithm developed for the standard solution technique was applied to various hypothetical examples in order to demonstrate the applicability of the technique. In their paper Cheng and Tsao (2010) applied the standard solution for the determination of the preventive replacement maintenance interval for a rolling stock component. Das and Acharya (2004) presented two age-based replacement models for preventative replacement of an equipment item. The two preventive replacement policies included consideration of the equipment failure delay time (the time between the point of equipment failure initiation and the point at which the equipment eventually failed). In the first model, the trend of the degradation of the equipment during the delay time was utilised in order to determine the preventive replacement interval. Hence, for this policy, replacement due to failure or prevention of failure is performed after a fixed period during its delay time. The second policy, according to the authors, is an opportunistic age replacement technique where a failing equipment item or component is replaced at the next available maintenance opportunity. Finally the authors opined that the two policies although designed for a single unit system were capable of addressing a multi-unit system when there is a difficulty in tracking the whole life of each individual equipment item or component. Jiang et al. (2006) investigated the relationship between the preventive effect produced from alternative replacement intervals and corresponding cost savings. The preventive replacement models that they studied were the age and the block preventive replacement models. From the results reasonable cost savings can be derived if the system is replaced when it has reached satisfactory age. The authors also opined that the often increasing failure rate of the equipment or components does not necessarily translate to representing ‘satisfactory age’ and this has to be determined by the maintenance practitioners based on the maintenance goal.

Ahmad et al. (2011a) utilised the age based model that was developed by Hunter and Barlow in revising the preventive replacement interval for a production machine in the processing industry. The important feature of their approach was the consideration of the covariate effect on the life of the machine. In the real sense the actual state of the machine was considered in the determination of the preventive replacement interval of the machine. The authors compared the revised replacement interval (inclusion of the covariate effect) with the replacement interval (without covariate effect). From the result, the revised preventive replacement interval and the replacement interval without the covariate effect differed considerably. While the revised produced a 21 day interval for replacement of the production machine, the replacement interval without the covariate effect produced a 35 day interval for the replacement of the production machine. Bahrami-G et al. (2000) presented a new model for the preventive replacement of an equipment item or component that is experiencing an increasing failure rate. The model proposed is a simplified version of the BRM that was developed by Hunter and Barlow. A case study of an equipment item whose failure rate followed a normal distribution was applied to determine the benefits and suitability of the technique. According to the authors, the results obtained from the model almost perfectly matched the result from that of Hunter and Barlow whose approach is more computationally challenging. They concluded that the proposed model will aid the maintenance practitioner to make more cost-effective decisions.

2.6.1.2 MCDM tools application for scheduled replacement interval determination based on ARM and BRM

The essence of undertaking preventive maintenance is to reduce the chances of failure of plant equipment such that plant reliability and availability is optimised. The reliability of a system is dependent on the reliability of the individual components/equipment items that collectively make up the system and in order to achieve this aim, a suitable preventive maintenance and inspection programme should be in place (Duarte et al., 2006)

One of the greatest challenges of the preventive maintenance approach is in the selection of the optimum interval to perform preventative maintenance tasks on equipment items (Duarte et al., 2006). This is because, if the intervals are not properly timed, it can result in over-maintenance and a waste of resources and man-hours due to premature replacement or repair of equipment items or an even worse case scenario, in that under-maintenance can result in catastrophic failure and invariably production loss and the company's image being damaged. This makes the subject of interval selection for a preventive maintenance task an important issue worthy of thorough investigation. There are quite a number of articles published in the literature which are based on a single criterion for making decisions for preventive task interval selection (Almeida, 2012, Gopalaswamy et al., 1993) and yet a number of them are too abstract often requiring a high level of mathematical and statistical skills thereby limiting the practicability of their use in real life situations (Vatn et al., 1996, Duarte et al., 2006, Huang et al., 1995). In addition, the application of these single criterion based methodologies is neither reliable nor flexible for effective decision making with respect to interval selection (Gopalaswamy et al., 1993).

However there are some limited studies that deal with the use of the MCDM approach to selecting intervals for preventive maintenance tasks (Gopalaswamy et al., 1993, Chareonsuk et al., 1997) but they were applied for land based systems with no applications reported for maritime systems. Cavalcante and De Almeida (2007) presented a preventive maintenance decision model based on a combination of PROMETHEE II and Bayesian technique considering two decision criteria; cost and reliability. In a similar work (Cavalcante et al., 2010) also proposed an integrated PROMETHEE based methodology combined with Bayesian technique and, in addition, accounting for possible uncertainty in maintenance data. Chareonsuk et al. (1997) also proposed a PROMETHEE multi-criteria decision making methodology for the selection of preventive maintenance intervals. The authors applied the Huang et al. (1995) assumption that corrective replacement cost and preventive replacement cost can be in the form of a ratio in the case of a situation with a lack of data. The cost ratio was then varied for different assigned alternative replacement maintenance intervals in the expected cost replacement model in order to obtain corresponding values of cost and reliability factors. Finally PROMETHEE was applied in ranking alternative preventive maintenance intervals with respect to the evaluated decision criteria, namely cost per unit and reliability. The authors chose the replacement maintenance interval with the best PROMETHEE index. The PROMETHEE technique used by these authors, has the challenge of problem structuring thereby making the evaluation procedure complicated when more than seven decision criteria are used. This approach will limit maintenance practitioners' choice of decision criteria for selecting optimum preventive maintenance intervals. Additionally the authors' approach for weighting decision criteria lacked flexibility as it only depends on subjective rules without balancing it with an objective technique or using a compromise between them.

From this literature review it is obvious that marine industries will benefit from the application of MCDM techniques as tools for determination of optimum scheduled replacement intervals. However a more systematic MCDM approach will be used in this research that will avoid the limitations of the approach applied in the land base systems.

2.6.2 *Inspection interval determination*

In the condition based maintenance methodology there are basically two approaches for monitoring the condition of an item of equipment or component; continuous and periodic. These two approaches are also referred to as on-line condition based maintenance and offline condition based maintenance in this research and are considered in detail in chapter 5. For the continuous monitoring type, the condition of equipment is continuously monitored using some form of measurement and/or diagnostic tools. The challenge of this approach is that it is quite expensive and on this basis many maintenance practitioners prefer the periodic monitoring technique which is more cost effective. However the major difficulty in the periodic monitoring approach is in the timing of the inspection interval of the condition monitoring activity because of the possibility of failures occurring between consecutive inspections (Jardine et al., 2006). In the course of monitoring the state of an item, if a defect is found, a repair or replacement task is scheduled and if possible it is executed immediately in order to prevent the equipment from further deterioration. If inspections are not carried out then slowly developing defects will go unnoticed and this can lead to catastrophic system failure with severe economic loss for the company. However even if inspection tasks are performed, if they are not properly timed then defects can still occur between successive intervals. It is thus obvious that the determination of the optimal inspection interval is central to the effective operational monitoring of any mechanical system. In conventional practice, the inspection interval is determined by maintenance practitioners relying merely on experience and/ or on the equipment manufacturers' recommendation and the results from this approach are far from optimal and are also conservative (Christer et al, 1997).

Inspection tasks as an alternative maintenance approach for an equipment item can only be beneficial if there is a sufficient period between the time that a potential defect is observed and the actual time of failure of the equipment. Hence the time that elapses between point of failure initiation and the point when the failure becomes obvious is vital in estimating the inspection interval. The time that elapse between point P and F is referred to the P-F interval (T_{PF}) within the RCM frame work and is illustrated in Figure 2.2.

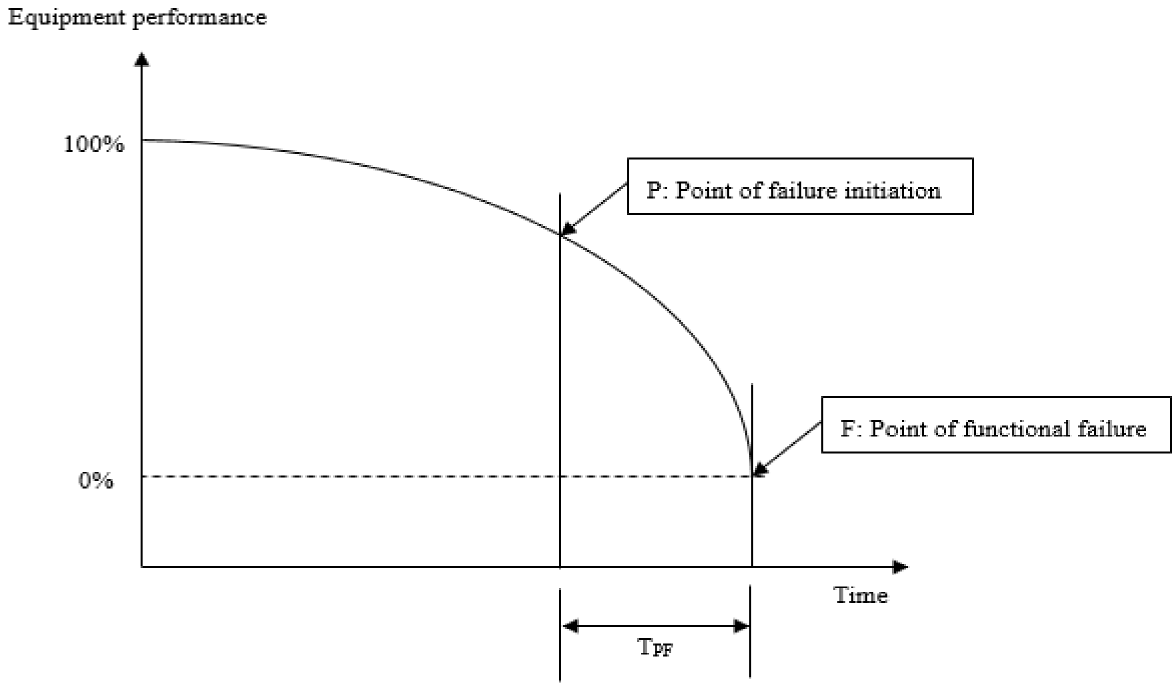


Figure 2.2: P-F interval (Rausand, 1998)

In RCM, the P-F interval principle is applied in determining the frequency of the condition monitoring of equipment and it was suggested that an inspection interval (T) be set at $T \leq T_{PF}/2$ (Arthur, 2005). The author however stated that one major challenge of the use of P-F approach is that there are usually no data to evaluate P-F interval (T_{PF}) and in most cases the evaluation based on experts opinion. Moubray (1991), on the other hand, suggested five ways of determining the inspection interval based on P-F but the author concluded that: "*it is either impossible, impractical or too expensive to try to determine P-F intervals on an empirical basis*".

Apart from this approach that is used in the conventional RCM, other approaches have been described in the literature for determining inspection intervals. In the majority of the techniques cost optimization is the main decision criterion for determining the inspection interval. Christer et al. (1997) proposed the Delay Time model and this concept has been subsequently applied by many researchers either in its original form or as a variant in the modelling of the problem of inspection intervals. This approach has surpassed alternative models developed by other researchers for enhancing inspection intervals under different situations (Wang et al., 2010). The DTM and its application in the modelling of inspection programmes is discussed next.

2.6.2.1 Inspection interval determination based on delay time

The delay time concept has been employed by many authors in the field of maintenance engineering in the modelling of inspection intervals (Scarf, 1997). The introduction of this concept can be traced to Christer (1982). The delay time categorises the failure process of machinery into two phases; the first phase is the time period from when the machinery is new to the time that it starts showing signs of some degradation. The second phase is the time period from when it starts showing some sign of performance degradation to the time when the machinery eventually fails. The elapsed time between when the machinery first shows signs of performance degradation and when it eventually fails is referred to as the delay time. The Delay Time concept is in agreement with the P-F interval principle described within the framework of the classical RCM. However the major difference is that each concept uses a different technique in the evaluation of the time that elapses between the point of failure initiation and the point failure eventually occur. For the delay time concept as proposed by Christer, statistical distribution, such as a Weibull or an exponential distribution is utilised, while the subjective technique is applied in determining P-F interval within the framework of the classical RCM. Additionally in the delay time concept approach a different mathematical modelling technique are used in the determination of the optimal inspection interval. The delay time concept is illustrated in figure 2.3.

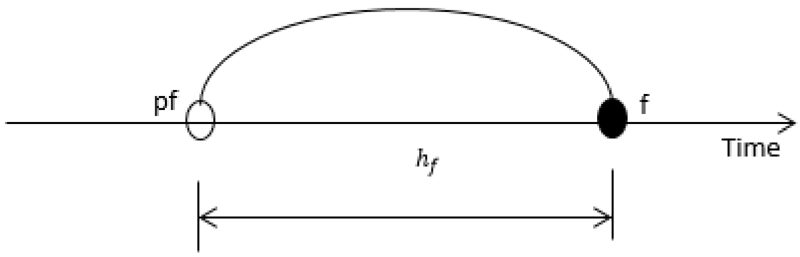


Figure 2.3: The Delay Time concept

In Figure 2.3, h_f represents the delay time; pf represents the time of the initial machinery performance sign of degradation and, f, represents the time that the machinery eventually failed. The most appropriate time to perform a maintenance inspection is within the machinery delay time and if it is performed then the fault will be detected and if the necessary preventive maintenance such as repair or replacement of the machinery is executed, failure will be averted. However if inspection is not carried out then, the machinery degradation will continue until failure occurs at point f.

The delay time concept had been applied by several researchers in solving inspection problems either for a single-unit system with a single failure mode or a multi-unit system with multiple failure modes. The majority of researchers have focussed on the multi-unit system with multiple failure modes. As stated earlier the concept of delay time was first introduced by Christer (1982). In the paper the author applied the delay time concept in the development of a cost model for building inspection maintenance. The model was utilised in determining an appropriate inspection maintenance plan for a complex building as an alternative maintenance strategy to the reactive approach. The following assumptions were made; (1) the cost function varied within the delay time period and (2) inspection is perfect. In determining the probability density function of the delay time a subjective method was proposed. On that basis the author suggested that information such as time of failure initiation and delay time of system parts should be obtained based on experts' (that is engineers and inspectors) estimates. A questionnaire developed for obtaining information from experts asked questions such as:

(1) For how long has it been since the fault was first observed (=HLA)?

(2) If repair or replacement is not performed, what duration of time could the fault stay before parts may or will eventually fail (=HML)?

The delay time is then evaluated for each fault by h_f = HLA+HML. The distribution for $f(h_f)$ is therefore then obtained by observing a sufficient number of faults or defects.

Christer and Waller (1984a) applied the delay time concept in the development of two inspection maintenance models for determining the inspection frequency for a complex industrial system. Two different models; cost function and downtime function, were constructed with the assumption that inspection is perfect. The cost function model shows the relationship between the inspection interval, t_p, and the cost for performing inspection at that particular t_p while the downtime function model shows the relationship between t_p and the resulting downtime for performing an inspection at that particular t_p. The study was further extended by introducing a model to cater for imperfect inspection. To demonstrate the applicability of these methodologies some numerical examples were provided.

Christer and Waller (1984b) proposed both an integrated delay time model and a snapshot model for determining an appropriate inspection plan for a canning-line plant in a production company in order to reduce the potential system downtime. The integrated model was used to model the downtime consequences of the system for every inspection maintenance interval. The data applied in analysing the models was obtained subjectively i.e. based on experts' estimates through the administering of questionnaires.

Wang (1997) proposed a novel model for estimating delay time distribution from a combination of experts' judgements in the face of insufficient or a lack of reliability data. The author also proposed a technique for combining experts' opinions as well as a model for updating the estimate of delay time distribution in a situation where maintenance and reliability data becomes available. One of the most important features of the approach is the suggestion of the use of probability estimates rather than point estimates in designing a questionnaire. The author compared the delay time distribution obtained using point estimates with that obtained using probability estimates using two case studies. From the results of the two case studies it was concluded that the delay time distribution obtained using a probability estimate presented a better result than the one obtained using a point estimate. In a related paper, Wang and Jia (2007) presented an integrated empirical Bayesian based technique with a delay time model for determining the inspection interval for an industrial boiler. The empirical Bayesian model was introduced for the purpose of utilising both subjective and objective data in estimating delay time distribution parameters.

Tang et al. (2014) postulated that for a part of a system subjected to wear, objective data should be applied in estimating parameters of the delay time model. On this basis they stated that there is a need for continual functional inspection and repair for such systems so as to reduce unscheduled downtime and lead to an increased record of maintenance data. Taking into consideration the wearing parts of a system, a model based on the delay time concept was developed for both perfect and imperfect inspections. To demonstrate the applicability of their proposed models two case studies were presented; a blowout preventer core and a filter element, both components of an oil and gas drilling system. Failure and maintenance data obtained relevant to both parts were used to estimate the delay time distribution parameters.

The papers reviewed were studies that had been carried out in the non-maritime sector, such as manufacturing, building and automobile industries. From the literature some limited work has also been investigated by researchers with respect to application of the delay time concept for developing inspection plans for maritime systems. Pillay et al. (2001) applied the expected downtime model based on the delay time concept in order to determine appropriate inspection periods or intervals for a fishing vessel equipment items. The inspection plan was developed with the aim to reduce vessel downtime as a result of machinery failure that could occur between discharge ports. To demonstrate the applicability of their approach, reliability data gathered from the winch system and complemented with experts' opinions, was applied to the proposed model. The case study results showed that an inspection period of 12 hours was appropriate for the system. In a related paper, Pillay et al. (2004) utilised both the expected downtime function model and the expected cost function model based on the delay time concept, in determining the optimum inspection period for the fishing vessel. In order to obtain a compromise inspection period, the expected cost was plotted against expected downtime consequences. Arthur (2005) used the delay time model in order to establish an inspection interval for condition monitoring of an offshore oil and gas water injection pumping system. The purpose of introducing the delay time concept was to produce an alternative inspection plan for the system that was more cost-effective than the current inspection regime of a one month cycle. Data was obtained from the Computerised Maintenance Management System (CMMS) and subjected to screening. From the data scrutiny, only one failure mode (bearing failure) was dominant for both the gearbox and the motor while three failure modes (bearing failure, shaft failure and impeller failure) were dominant for the pumps of the system. The author validated the observed data by comparing it with published industrial reliability data. The validated data was then used as an input into the delay time model in order to obtain the mean delay time and inspection interval for each of the components of the system. The delay time model that was proposed produced an inspection interval of 5 months against the current interval of 1 month with annual cost savings of £21,000.

The approaches reviewed so far for maritime application suggested mainly single criteria being utilised in the determination of inspection interval, however in practical situations multi-criteria are generally involved in making such vital decision. These multiple criteria are in most cases conflicting with one another and in such scenario, the use of Multi-criteria decision making tools for aggregating decision criteria into a single analytical problem becomes imperative.

2.7 Summary

In this chapter a thorough literature survey was conducted with respect to providing relevant information pertaining to the development of multi-criteria decision making tools for maintenance of marine machinery systems. The chapter introduced maintenance practitioners' definition of maintenance, the negative implication of poor maintenance systems, types of maintenance strategies and major elements of a maintenance system that must be optimised and methods available for their optimisation. Three maintenance methodologies (RBM, TPM and RCM) were discussed. Since the major focus in this study is RCM, it was discussed in more detail in terms of analysis steps, application and improvements carried out by previous researchers. It was observed that different tools are being used in optimising the different elements of maintenance system within the framework of RCM. The three elements of maintenance; risk assessment, maintenance strategy selection and maintenance interval determination were discussed in detail and for the risk assessment with a particular focus on FMEA. For the maintenance strategy selection, the three types of maintenance strategies; corrective maintenance, preventive maintenance and condition based maintenance were presented. A survey of methods used by previous researchers for the selection of the appropriate maintenance techniques was considered. For the maintenance interval determination the discussion was centered on scheduled replacement and scheduled inspection type of maintenance with respect to current approaches, limitations of these approaches and the need for multi-criteria decision making methods for application for marine systems. From the review it was obvious that the tools utilised within the framework of RCM for the optimisation of the three main elements of maintenance systems have limitations and there was a need to develop alternative approaches that avoid such limitations. On this basis alternative techniques have been developed and reported in Chapters 3 to 7.

Chapter 3 Risk Assessment using enhanced FMEA

3.1 Introduction

One of the key elements of a maintenance system is the assessment of risk of each equipment item/component of the system such that the most important equipment items/components in terms of risk criticality are given high priority in allocation of scarce resource. Risk assessment is usually performed prior to the selection of the optimal maintenance strategy that will mitigate the effect of failure since the optimal strategy to be selected is based on the assessed risk. One of the most popular tools used for risk assessment of marine machinery systems is Failure Mode and Effect Analysis (FMEA). With this analysis tool, risk is represented in the form of a Risk Priority Number (RPN) which is computed by multiplying the severity rating (S) by the occurrence probability (O) and the detection rating (D) for all failure modes of the system. As previously stated in the literature review, the conventional FMEA has been criticised as having several limitations such as inability to aggregate imprecise ratings of multiple experts and inability to incorporate more than three risk criteria (Su et al., 2012, Braglia, 2000). These challenges have been addressed in this chapter by developing two novel methodologies for prioritising the risk of failure modes of marine machinery systems. The first methodology integrates an averaging technique with RPN of the conventional FMEA. This approach eliminates one challenge of the classical FMEA which is the inability to aggregate imprecise ratings from experts. Other challenges of the classical FMEA such as the inability to incorporate more than three decision criteria cannot be addressed with this method. Hence a second approach is proposed for maintenance practitioners who need to include other decision criteria such as economic factors or company reputation in the decision making process. The second method integrates an averaging technique with TOPSIS. While the averaging technique is applied as a means of aggregating imprecise risk criteria ratings from multiple experts, RPN and TOPSIS are used in the ranking of the risk of failure modes. The applicability and suitability of these methodologies for risk prioritisation is demonstrated using two case studies.

The chapter is organised as follows: in Section 3.2 FMEA relevance in the marine industry is discussed. In Section 3.3 the proposed risk prioritisation methodology is described. Section

3.4 presents the two case studies to demonstrate the applicability and suitability of the proposed methodologies. Finally conclusions are presented in Section 3.5.

3.2 FMEA relevance in the marine industry background study and state of art review

Marine machinery systems, no matter how well designed will not remain safe and reliable if not properly maintained (Cicek et al., 2010a) . How to maintain such complex systems is still a challenge in the maritime industry. One of the major problems is the selection of the appropriate maintenance strategy for each piece of equipment/component of the system. Different key players in the maritime industry have adopted various methodologies in overcoming these challenges. One of the most popular methodologies adopted is Reliability Centred Maintenance (RCM). RCM represents a method for preserving functional integrity and is designed to minimise maintenance costs by balancing the higher cost of corrective maintenance against the cost of preventive maintenance (Crocker and Kumar, 2000b) and it uses decision logic diagrams in selecting maintenance strategies (Conachey, 2004, Aleksić and Stanojević, 2007).

However in deciding on the appropriate maintenance strategy, a thorough risk analysis must be carried out because the maintenance decision depends on the assessed risk. Different techniques such as FMEA, Hazard and Operability Analysis (HAZOP) and checklist analysis are available for risk analysis and within the marine industry, the American Bureau of Shipping (ABS) requires FMEA to be employed in prioritising risk of failure modes within an RCM framework (Conachey, 2005, Conachey, 2004, Conachey and Montgomery, 2003).

FMEA is a risk analysis tool which is used to define, identify, and eliminate known and/or potential failures from the system, design, process, and/or service (Stamatis, 2003). It is one of the most powerful tools for performing risk analysis for marine machinery systems with values assigned to O, S and D by a team of experts using an ordinal scale, an example of which is shown in Table 3.1. The ordinal scales in Table 3.1 were originally generated by Ford Motor Company (Ford Motor Company, 1998) and have since been used by many authors in assigning values to risk criteria in the prioritisation of failure modes of different systems such as; marine diesel engine subsystems specifically the fuel oil system and crankcase (Cicek and Celik, 2013, Cicek et al., 2010a), aircraft turbine rotor blades (Yang et al., 2011), diesel engine turbocharger (Xu et al., 2002) and the cooling sub-system in an offshore plant (Sankar and Prabhu, 2000). The FMEA analysis usually involves a series of steps which are presented in Figure 3.1.

As mentioned previously, the classical FMEA employed by the marine industry has been criticised as having some flaws which limit the effectiveness of the tool in prioritising risk of failure modes. Some of the flaws identified in the literature are (1) the inability of the technique to take into account more than three attributes in prioritising risk thereby excluding other important factors such as economic cost, production loss and environmental impact (Liu et al., 2011), (2) the different combinations of the three decision criteria (detection, severity and occurrence) yielding the same RPN value whereas the perceived risk might be totally different (Kutlu and Ekmekçioğlu, 2012) and (3) assumption that decision criteria are of equal importance. These make the classical FMEA that uses RPN in prioritising risk unsuitable especially in the marine environment and as such a more appropriate technique is needed for the marine world.

The problem of aggregating diverse experts' information which may be imprecise and uncertain has been investigated by a few authors in recent years. Chin et al. (2009b) proposed an FMEA system/methodology which uses a data envelopment analysis (DEA) technique for capturing imprecise criteria ratings obtained from multiple experts. The decision maker has to be familiar with linear programming concepts and software in order to apply this approach for risk prioritisation. Yang et al. (2011) proposed an FMEA method which uses modified Dempster-Shafer evidence theory (D-S) to aggregate the different opinions of experts for risk prioritisation of the failure modes of rotor blades of an aircraft turbine. With this approach the authors constructed a Basic Belief Assignment (BBAs) for all failure modes with respect to risk criteria ratings from multiple experts. The BBAs of failure modes from different experts are then aggregated with a Dempster-Shafer combination model. However the Yang methodology is limited to aggregating the same complete distribution criteria rating from different experts. This situation is not practically possible. Su et al. (2012) modified the BBAs constructed by Yang in order to deal with a situation when different integer values of risk criteria are assigned by experts. The Su methodology is also limited to complete distribution criteria rating and although it is an improved version of the Yang methodology it can only deal with a situation when integer values assigned by different multiple experts differ marginally, otherwise the combination of multiple expert criteria ratings will be zero. Additionally the aggregation techniques are computationally intensive and challenging.

In this chapter some of the drawbacks in the conventional FMEA technique are addressed using two approaches for risk prioritisation: an AVeraging technique integrated with conventional Risk Priority Number (AVRPN), and an AVeraging technique integrated with TOPSIS (AVTOPSIS). The AVRPN technique is capable of aggregating precise, complete distribution data and imprecise distribution data of multiple experts' risk criteria ratings through a novel approach using averages that can easily be understood and executed by decision makers without resorting to specialised software or having the need to be familiar with any programming concepts. The result obtained from the AVRPN method when applied to a complete distribution risk criteria problem, closely matches the one generated from the Yang et al. (2011) and Su et al. (2012) modified Dempster-Shafer evidence theory method. AVTOPSIS also utilizes averages in aggregating imprecise data and, in addition to this, the technique is capable of incorporating as many risk criteria as the decision maker would want a decision to be based on.

Table 3.1: Ratings for occurrence (O), severity (S) and Detectability (D) in a marine engine system, adapted from (Yang et al., 2011, Pillay and Wang, 2003, Cicek and Celik, 2013)

Rating	Linguistic term	Occurrence (O) (failure rate measured in operating days)	Severity (S)	Likelihood of non-detection (D)
10	Very high	>1 in 2	Engine failure resulting in hazardous effects is almost certain	Very high chance control system will not and /or cannot detect a potential cause and subsequent failure mode
9		1 in 3	Engine failure resulting in hazardous effects highly probable	
8	High	1 in 8	Engine inoperable but safe	High chance control system will not detect a potential cause and subsequent failure mode
7		1 in 20	Engine performance severely affected	
6	Moderate	1 in 80	Engine operable and safe but performance degraded	Moderate chance the control system will not detect a potential cause and subsequent failure mode
5		1 in 400	Reduced performance with gradual performance degradation	
4		1 in 2000	Minor effect on engine performance	
3	Low	1 in 15,000	Slight effect on engine performance. Non-vital faults will be noticed most of the time	Low chance the control system will not detect a potential cause and subsequent failure mode
2		1 in 150,000	Negligible effect on engine performance	
1	Remote	<1 in 1,500,000	No effect	Remote chance control system will not detect a potential cause and subsequent failure mode

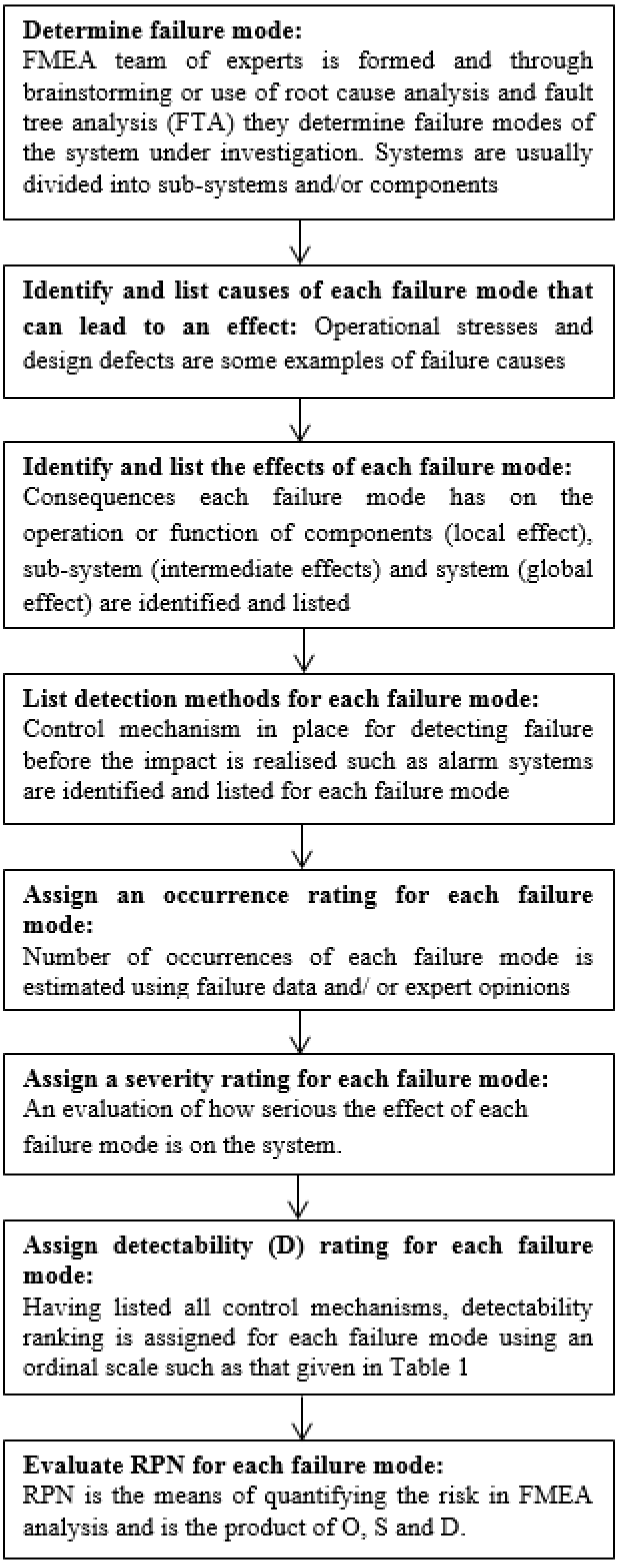


Figure 3.1: FMEA methodology, adapted from (Cicek and Celik, 2013)

3.3 Proposed Hybrid Risk Prioioritisation methodology

RPN for quantifying risk in the FMEA system has several flaws as previously explained, such as the challenge of aggregating imprecise multiple experts' information. To holistically address these FMEA challenges, two novel methods are proposed for risk prioritisation for marine machinery systems:

(1) AVRPN: AVeraging technique for data aggregation and Risk Priority Number evaluation

(2) AVTOPSIS: AVeraging technique for data aggregation with TOPSIS.

These are explained in the following sections.

3.3.1 AVRPN: AVeraging technique for data aggregation and Risk Priority Number *evaluation*

AVRPN is a combination of an averaging technique and the RPN. The averaging technique is applied in converting experts' imprecise ratings into precise ratings while the RPN is used as a tool for the ranking of the failure modes.

3.3.1.1 Averaging technique for data aggregation:

The averaging technique is a data aggregation method principally designed for aggregating imprecise values of individual expert's criteria ratings (O, S and D) such that the imprecisions are captured as an expectation interval. The mean value of the maximum and minimum bounds of the expectation interval is then used as the input to the chosen methodologies such as RPN, TOPSIS, VIKOR and CP for the ranking of the risk of each the failure modes.

The steps are as follows:

(1) Formation of decision matrix. The values assigned by an expert to failure modes against risk criteria are used to form a decision matrix (m x n). Where m is the number of failure modes and n is the number of criteria.

Risk criteria rating information obtained from experts is used to form a matrix of m-failure modes with the rating value for each of n-decision criteria.

(2) Computation of the minimum and maximum risk criteria values

The risk criteria data for producing the decision matrix can take the following form (Chin et al., 2009a)

(a) A Precise rating is identified with single confidence of 100%. For example, if the rating is 5 this can be written as 5:100%.

(b) A Complete distribution such as 5:80% and 7:20% means that a value of 5 at 80% confidence and 7 at 20% confidence is assigned to a failure mode against a risk criterion with the confidence summing to 100%.

(c) An incomplete or imprecise distribution such as 7:30% and 8:60% means a value of 7 at 30% confidence and 8 at 60% confidence with 10% confidence missing. The missing 10% confidence is usually called local ignorance and could be assigned to any rating between 1 and 10 (Shafer, 1976).

The incomplete or imprecise assessment can be represented as an expectation interval whose minimum and maximum risk criteria values are evaluated as follows (Chin et al., 2009b):

$$x_{ij}^{min} = x_{ij}^{1}.p_{ij}^{1} + x_{ij}^{2}.p_{ij}^{2} + \left[1.\left(100\% - p_{ij}^{1} - p_{ij}^{2}\right)\right] \tag{3.1}$$

$$x_{ij}^{max} = x_{ij}^{1}.p_{ij}^{1} + x_{ij}^{2}.p_{ij}^{2} + \left[10.\left(100\% - p_{ij}^{1} - p_{ij}^{2}\right)\right] \tag{3.2}$$

Where

x_{ij}^{min} is the minimum rating of failure mode i with respect to risk criterion j

x_{ij}^{max} is the maximum rating of failure mode i with respect to risk criterion j

x_{ij}^{1} and x_{ij}^{2} are the distribution ratings of failure mode i with respect to risk criterion j assigned by an expert at percentage confidence p_{ij}^{1} and p_{ij}^{2} respectively.

3. Computation of the mean rating of failure mode i with respect to risk criteria j

After determination of the minimum and maximum rating values of failure mode i with respect to risk criterion j , the average may be calculated to obtain the mean rating of failure mode i with respect to risk criterion j as follows:

$$\overline{x}_{ij} = \frac{x_{ij}^{min} + x_{ij}^{max}}{2} \tag{3.3}$$

Where $\overline{x}_{ij}$ is the mean rating of failure mode i with respect to risk criterion j

The next step is to use the value of $\overline{x}_{ij}$ as the input to the RPN calculation or any other risk of failure modes ranking tool such as TOPSIS, VIKOR and CP.

3.3.1.2 Failure mode ranking tool; RPN

The mean rating of failure modes i with respect to risk criteria j are used as inputs in the RPN model to evaluate the risk of each failure mode as follows:

$$RPN_i = \prod_{j=1}^{n} \bar{x}_{ij} \; : \; i = 1\,, 2\, \ldots, m\;, \qquad j = 1, 2, \ldots n \tag{3.4}$$

Where RPN_i is the risk priority number of the failure mode i.
An alternative approach is to feed Eq. (3.1) – (3.3) separately into the RPN model rather than feeding only Eq. (3.3) to obtain maximum, minimum and mean risks of each failure mode. However when dealing with a complete distribution risk criteria problem, Eq. (3.1) – (3.3) generate the same result as using Eq. (3.3) alone. In that case Eq. (3.1) and (3.2) are equal, since local ignorance will be zero. Where data is available from multiple experts, RPN values from the individuals are averaged to obtain the risk of each failure mode.

3.3.2 AVTOPSIS: AVeraging technique for data aggregation and TOPSIS method

AVTOPSIS is a combination of the averaging technique and TOPSIS. The averaging technique is used in aggregating imprecise rating of failure modes from experts while the TOPSIS is used in the ranking of risk of failure modes.

The averaging technique has been described in Section 3.3.1.1.

3.3.2.1 Failure mode ranking tool; TOPSIS

TOPSIS is a technique for order preference by similarity to the ideal solution and was first proposed by Hwang and Yoon in 1981 (Hwang and Yoon, 1981). The concept of TOPSIS is that the best alternative is usually the one which is closest to the ideal solution and farthest from the negative ideal solution (Yoon and Hwang, 1995). In this chapter the best alternative is the failure mode that poses the greatest risk to the system under investigation. Although TOPSIS has many advantages, the rating methodology uses precise values and in effect is incapable of dealing with some real life problems where data may be imprecise or incomplete. To address these challenges the averaging technique for data aggregation detailed in Section

3.3.1.1 has been integrated with TOPSIS for prioritisation of risk in machinery systems. In this case, the mean values of O, S, and D are used as input data for the TOPSIS methodology. The TOPSIS methodology steps applied here are as shown in Çalişkan et al. (2013). Although the TOPSIS model is capable of incorporating more than three risk criteria, the number of risk criteria were was limited to three here for an unbiased comparison with the output of AVRPN. The steps involved in the TOPSIS methodology are as follows:

(1) Formation of decision matrix:

Since the problem is one of dealing with imprecise or incomplete risk criteria rating, a decision matrix is formed using values obtained at the aggregation stage. The decision matrix, X, may be represented as:

$$X = \left(\overline{x}_{ij}\right)_{m.n} \tag{3.5}$$

(2) Normalization of the decision matrix.

Normalization of the decision matrix is carried out as follow:

$$r_{ij} = \frac{\overline{x}_{ij}}{\sqrt{\sum_{i=1}^{m} \overline{x}_{ij}^{2}}}, \quad i = 1, \dots m; \; j = 1, \dots, n \tag{3.6}$$

Where r_{ij} are the normalised criteria ratings.

(3) Calculation of the weighted normalised decision matrix:

The weighted normalised decision matrix can be calculated by multiplying each row of the normalised decision matrix by the weight w_j of each criterion:

$$v_{ij} = w_j r_{ij}, \quad i = 1, \dots, m; \quad j = 1, \dots, n \tag{3.7}$$

Where w_j is the weight of the jth criterion.

(4) Computation of the weights of decision criteria:

In the literature, many methods are reported for assigning the weight of risk criteria such as the entropy method, AHP, ANP etc. (Ölçer and Odabaşi, 2005, Chu et al., 2007b, Çalişkan et al., 2013, Liou and Chuang, 2010). For this particular solution to the risk prioritisation problem, the entropy method was adopted because of its dynamism and objectivity in weighting of risk criteria relative to the decision making process, as opposed to AHP and ANP and other prior weighting methods that assign weight subjectively and independent of the decision making process. The steps are as follows (Çalişkan et al., 2013):

Using the normalised decision matrix, the entropy value e_j of jth criterion is calculated as follow:

$$e_j = -k \sum_{i=1}^{m} r_{ij} \ \ln r_{ij} \tag{3.8}$$

Where $k = \frac{1}{\ln m}$ is a constant which guarantees $0 \leq e_j \leq 1$and m is the number of failure modes.

The objective weight for each risk criterion is then given by

$$w_j = \frac{1 - \mathrm{e}_j}{\sum_{j=1}^{n} 1 - \mathrm{e}_j} \tag{3.9}$$

(5) Determination of the positive-ideal and negative-ideal solutions.

The reference values for risk prioritisation are the positive and negative ideal solutions. The positive ideal solution, A^{+}, is the best value of each weighted criterion and the negative ideal solution, A^{-}, is the worst value of each weighted criterion and are determined as follows:

$$A^{+} = \{v_1^{+}, v_{2,\ldots,}^{+} v_n^{+}\} = \left\{\left(\max_i v_{ij} \middle| j\epsilon I\right), \left(\min_i v_{ij} \middle| j\epsilon I'\right)\right\} \tag{3.10}$$

$$A^{-} = \{v_1^{-}, v_{2,\ldots,}^{-} v_n^{-}\} = \left\{\left(\min_i v_{ij} \middle| j\epsilon I\right), \left(\max_i v_{ij} \middle| j\epsilon I'\right)\right\} \tag{3.11}$$

Where I is associated with the benefit criteria and I' is associated with cost criteria

(6) Determination of the distance from positive-ideal and negative-ideal solutions.

The distance of each failure mode from the positive-ideal solution, D_i^{+}, and from the negative-ideal solution, D_i^{-}, are evaluated, respectively as:

$$D_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+ \right)^2} \qquad i = 1,2 \dots . m; \;\; j = 1, 2, \dots , n \tag{3.12}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^- \right)^2} \;\; i = 1,2, \dots , m; \;\; j = 1,2, \dots , n \tag{3.13}$$

(7) Computation of the relative closeness of failure mode i to the positive ideal solution

The relative closeness RC_i of each failure mode to the positive ideal solution is computed as:

$$RC_i = \frac{D_i^-}{D_i^+ + D_i^-} \;\; , \quad i = 1 , \dots , m \tag{3.14}$$

The RC_i value is the risk index of the failure modes. The higher the value the greater the risk the failure mode poses to the system.

(8) Computation of mean risk of failure modes:

Finally, where data is available from multiple experts, RC_i values from the individuals are averaged to obtain the mean risk of each failure mode.

3.4 Case studies

The applicability of the proposed methods for risk prioritisation of failure modes of marine machinery systems were investigated with three case studies.

3.4.1 Case study 1

To validate the aggregation technique (averaging technique) used in this research a case study in the literature presented by Yang et al. (2011) and Su et al. (2012) was used. The authors used modified Dempster-Shafer evidence theory in aggregating opinions of three experts. The methodologies of Yang et al. (2011) and Su et al. (2012) were designed to aggregate only complete distribution criteria ratings (see Section 3.3.1.1 for a description of complete distribution criteria ratings). In addition to this, their methodologies rely on there being only a marginal difference between the risk criteria ratings from the different experts otherwise the combination of the ratings will be zero. Therefore, in order to validate the proposed averaging technique and allow comparison of the results, it was implemented using the data from three experts in Table 3.2 as presented in Yang et al. (2011) and Su et al. (2012). The methodological steps of the AVRPN technique were applied in solving the problem in table 3.2 and the results obtained have been compared with the results obtained from the modified Dempster-Shafer evidence theory technique as shown in Table 3.3 and Figure 3.2.

Table 3.2: Three experts rating of 17 failure modes (Yang et al., 2011, Su et al., 2012)

Failure modes	Rating of risk factor								
	Expert 1			Expert 2			Expert 3		
	O	S	D	O	S	D	O	S	D
1	3:40% 4:60%	7	2	3:90% 4:10%	7	2	3:80% 4:20%	7	2
2	2	8	4	2	8:70% 9:30%	4	2	8	4
3	1	10	3	1	10	3	1	10	3
4	1	6:80% 7:20%	3	1	6	3:70% 2:30%	1	6	3
5	1	3	2:50% 1:50%	1	3	1:70% 2:30%	1	3:60% 2:40%	1
6	2	6	5	2	6	5	2	6	5
7	1	7	3	1	7	3	1	7	3
8	3	5:60% 6:40%	1	3	5:80% 6:20%	1	3	5:80% 7:20%	1
9	2:90% 1:10%	10:60% 9:40%	4	2:75% 1:25%	10:90% 9:10%	4	2:80% 1:20%	10:90% 9:10%	4
10	1	10	6	1	10	6	1	10	6
11	1	10	5	1	10	5	1	10	5
12	1	10	6:60% 5:40%	1	10	5:80% 4:20%	1	10	6:70% 5:30%
13	1	10	5:80% 4:20%	1	10	5	1	10	5
14	1	10	6	1	10	6:80% 7:20%	1	10	6
15	2	7:95% 6:5%	3	2	7	3	2	7	3:70% 4:30%
16	2:90% 1:10%	4	3	2:75% 1:25%	4	3	2:80% 1:20%	4	3:80% 2:20%
17	2	5:90% 6:10%	3	2	5:90% 6:10%	3	2	5:60% 6:40%	3

Table 3.3: AVRPN v. D-S methods

Failure modes	Proposed method	Yang et al	Su et al
	AVRPN	D-S method	Modified D-S
1	46.2	42.56	42.56
2	64.8	64	64.05
3	30	30	30
4	17.6	18	17.97
5	3.7	4.17	3.14
6	60	60	60
7	21	21	21
8	16	15	15
9	71.8	78.92	79.57
10	60	60	60
11	50	50	50
12	53.7	50	50
13	49.3	60	50
14	60.7	60	60.04
15	43.4	42	42.09
16	21.5	23.88	23.86
17	31.2	50.9	30.05

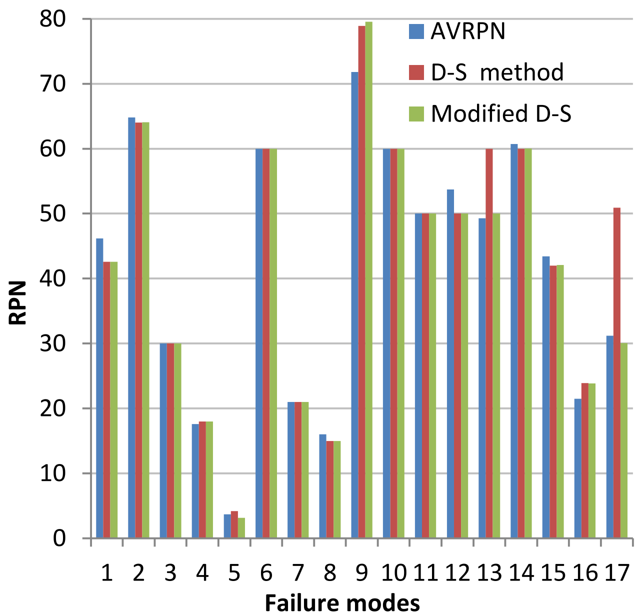


Figure 3.2: Comparison of AVRPN with Dempster – Shafer theory method

From Figure 3.2 it can be seen that the results obtained from AVRPN closely match those from Yang et al. (2011) (D-S method) and Su et al. (2012) (Modified D-S method). For example, for failure modes 3, 6, 7, 10 and 11 the same RPN value was obtained from all three methods and in the cases of failure modes 1, 2, 4, 5, 8, 12 ,14, 15 and 16 the difference in the

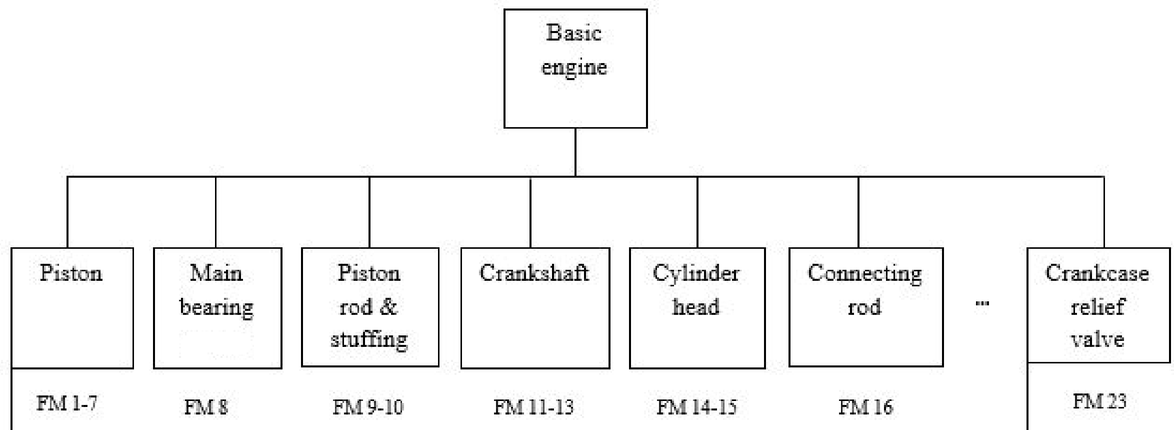
RPN is marginal and results in no change to the ranking of the failure modes. The principal differences occur with failure modes 9, 13 and 17 although there is a high level of similarity between AVRPN and the modified Dempster-Shafer evidence theory method of (Su et al., 2012) other than for failure mode 9. The sharp deviation of the D-S method RPN values for failure modes 13 and 17 is attributed to incorrectly reported values according to Su et al. (2012). It is obvious from the above example that the AVRPN approach is simple and robust but it is also more flexible for real life applications as it is capable of handling not only incomplete distribution risk criteria information but also of dealing with imprecise distribution risk criteria data.

3.4.2 Case study 2: Application to the basic marine diesel engine

The AVRPN technique was also applied to a case study of a marine diesel engine. The marine diesel engine was chosen because it is one of the key marine machinery systems as it provides the power for the propulsion of the entire ship system. In addition, the marine main engine accounts for over 45 percent of the total compensation for fault accident claims of the entire ship system according to the survey carried out by a Swiss shipping insurance Company (Dong et al., 2013). It is then obvious that the marine diesel engine is central to the operation, of not only the machinery systems, but of the entire ship system powered by this type of engine. In this case study only the basic marine diesel engine is considered while in case study 3 the entire marine diesel engine will be considered.

Ten major equipment items of the basic engine were considered including: main bearing, piston, cylinder head and crankshaft. Each equipment item’s failure modes were examined with the causes of failure and the effects of the failures at two levels (local and global effects) for the different failure modes. A total of 23 failure modes were examined; a sample of these are defined in Table 3.4 along with their causes and effects while the full table is in Appendix A1. The risk criteria (O, S and D) values were assigned by three experts for each failure mode through the use of an ordinal ranking scale, as shown in Table 3.1. The three experts that participated in assigning values for criteria reached a consensus and the agreed values are presented in Table 3.5. The three experts have both academic qualifications, with two being PhD holders, and sea going and marine diesel engine maintenance experience over many years.

Table 3.4: Sample of the FMEA for basic engine of a marine diesel engine



Items	Failure modes (FM)	Failure cause	Local effects	Global effects
1	Hole in the piston crown	Dripping of fuel valve	Escape of combustion gas into the crankcase	Reduced engine performance, engine damage and stoppage
2	Piston ring scuffing	Lack of lubrication, liner roundness fault	Oil smoke from exhaust, blow-by	Reduced engine performance
3	Cracked ring	Excessive gap pressure, worn-out ring grooves	Oil smoke from exhaust, loss of power	Reduced engine performance
4	Ring/groove side face wear	Liquid fuel degrading lubricant in ring grooves, solid residue	Loss of power	Reduced engine performance, engine stop
5	Piston ring stuck in grooves	Insufficient clearance during installation, deposits	Excessive clearance, fire blow	Reduced engine output, stop engine
-				
-				
-				
23	Inoperable	Not seated properly	Allow air escape into crankcase	Reduced engine performance, explosion probable

3.4.2.1 AVRPN: AVeraging technique and RPN analysis

The values assigned to failure modes against decision criteria in Table 3.5 were used as the input for the AVRPN models to:

(1) Compute minimum and maximum risk criteria values:

In Table 3.5, for failure mode 1 the expert gave two incomplete rating values for x_{11} i.e. Occurrence (O) to be 7:30% and 8:60%; precise rating for x_{12} i.e. Severity (S) to be 3 and an incomplete rating for x_{13} i.e. Detectability (D) to be 4:70%. Since x_{11} had an incomplete rating it was transformed into minimum x_{ij}^{min} and maximum x_{ij}^{max} risk criteria ratings, using Eq. (3.1) and Eq. (3.2) respectively.

(2) Compute mean risk criteria values:

The mean risk criterion $\overline{x}_{11}$ was computed using Eq. (3.3). Following the same process of evaluation, $\overline{x}_{12}$ and $\overline{x}_{13}$ were calculated.

(3) Compute the risk (RPN) of the failure mode:

The value of RPN for failure mode 1 was obtained using equation (3.4) as follows:

$RPN_1 = 7.5 \; x \; 3 \; x \; 4.5 = 101.25$

The evaluated RPN values for the 23 failure modes and their corresponding rank are presented in Table 3.5 and Figure. 3.3.

Table 3.5: Risk criteria rating, RPN values and rankings

Failure modes (i)	Risk criteria rating (j)			RPN and rank	
	O	S	D	RPN	Rank
1	7:30% 8:60%	3	4:70%	101.25	14
2	7	6:50%	8	324.8	2
3	5	6	5: 90%	153	8
4	7	3	3: 80%	73.5	18
5	7: 80%	6	5: 50%	213.06	5
6	6:85%	6	5:65%	184.08	6
7	8	2: 60%	2	54.4	21
8	8:90%	7	7:70%	360.36	1
9	7	6:70%	8:90%	322.14	3
10	10	4:60%	6	276	4
11	9: 70%	2	2	32	23
12	8	3	3	72	19
13	9	2: 70%	2	55.8	20
14	7	5: 90%	3: 50%	153.51	7
15	8	3: 70%	4: 80%	130.72	11
16	9	3	2	54	22
17	8:70%	3: 65%	2:70%	88.257	17
18	9: 50%	6	2:90%	105.12	13
19	5	5	4	100	15
20	8	6	2:70%	148.8	9
21	7:70%	3	4:70%	89.1	16
22	7	3:60%	5	140	10
23	7:80% 6:20%	2	9:90% 8:10%	121.04	12

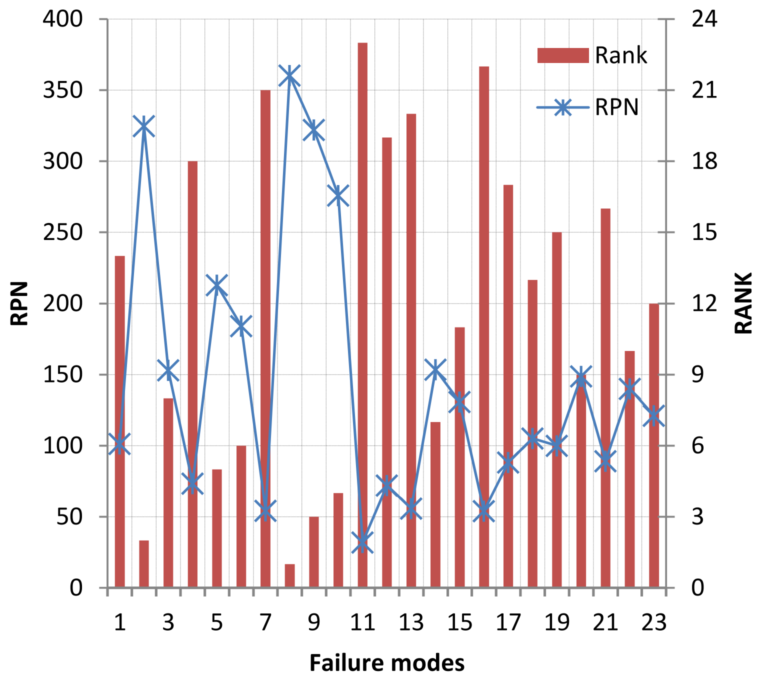


Figure 3.3: Failure modes RPN values and ranking

It is obvious from Figure 3.3 that failure mode 8 has the highest RPN value with a corresponding rank of 1, meaning its poses the greatest risk to the basic marine diesel engine. On the other hand, failure mode 11 with the lowest RPN value and a corresponding rank of 23 poses the least risk to the system. One advantage of this methodology lies in its ability to aggregate imprecise expert rating of risk criteria with simple averages that are very easy to compute unlike the Dempster-Shafer theory method, data envelopment techniques and fuzzy logic theory approaches that are more computationally intensive.

3.4.2.2 AVTOPSIS analysis

In the application of AVTOPSIS to the case study of the marine diesel engine, information obtained from the aggregation stage was used to form the decision matrix shown in Table 3.6. The decision matrix was normalised using Eq. (3.6) and then multiplied by the criteria weights to obtain a weighted normalised matrix. The weighted normalised matrix is also presented in Table 3.6. Note the weights of each criterion were evaluated using Eq. (3.6), (3.8) – (3.9). Eq. (3.10) and (3.11) were then utilised to determine the positive ideal and negative ideal solutions respectively. Finally, applying Eq. (3.12) – (3.14) the distance of each failure mode to the positive-ideal solution D_i^+ and to the negative-ideal solution D_i^- together with relative closeness RC_i of each failure mode to the ideal solution were calculated and the results are shown in Table 3.7. The failure modes were then ranked based on RC_i scores; the ranking order is also presented in Table 3.7 and Figure 3.4.

Table 3.6: Decision matrix with weighted normalised decision matrix expert 1 basic engine

Failure modes	Decision matrix			Weighted normalised decision matrix		
	O	S	D	O	S	D
1	7.5	3	4.5	0.0721	0.0451	0.0625
2	7	5.8	8	0.0673	0.0872	0.1111
3	5	6	5.1	0.0481	0.0902	0.0709
4	7	3	3.5	0.0673	0.0451	0.0486
5	6.7	6	5.3	0.0645	0.0902	0.0736
6	5.9	6	5.2	0.0567	0.0902	0.0722
7	8	3.4	2	0.0770	0.0511	0.0278
8	7.8	7	6.6	0.0751	0.1052	0.0917
9	7	5.9	7.8	0.0673	0.0887	0.1084
10	10	4.6	6	0.0962	0.0691	0.0834
11	8	2	2	0.0770	0.0301	0.0278
12	8	3	3	0.0770	0.0451	0.0417
13	9	3.1	2	0.0866	0.0466	0.0278
14	7	5.1	4.3	0.0673	0.0767	0.0597
15	8	3.8	4.3	0.0770	0.0571	0.0597
16	9	3	2	0.0866	0.0451	0.0278
17	7.3	3.9	3.1	0.0702	0.0586	0.0431
18	7.3	6	2.4	0.0702	0.0902	0.0334
19	5	5	4	0.0481	0.0752	0.0556
20	8	6	3.1	0.0770	0.0902	0.0431
21	6.6	3	4.5	0.0635	0.0451	0.0625
22	7	4	5	0.0673	0.0601	0.0695
23	6.8	2	8.9	0.0654	0.0301	0.1237

Table 3.7: Performance index and rank

Failure modes	D+	D-	RCj	Rank
1	0.0891	0.0448	0.3348	15
2	0.0362	0.1028	0.7394	1
3	0.0730	0.0739	0.5032	8
4	0.1004	0.0321	0.2422	21
5	0.0611	0.0773	0.5584	5
6	0.0666	0.0752	0.5306	7
7	0.1118	0.0357	0.2422	22
8	0.0383	0.1023	0.7273	3
9	0.0366	0.1015	0.7350	2
10	0.0541	0.0832	0.6061	4
11	0.1234	0.0289	0.1897	23
12	0.1035	0.0354	0.2549	20
13	0.1128	0.0419	0.2707	18
14	0.0757	0.0597	0.4406	10
15	0.0823	0.0508	0.3819	13
16	0.1136	0.0413	0.2666	19
17	0.0967	0.0392	0.2885	17
18	0.0952	0.0643	0.4031	12
19	0.0886	0.0529	0.3740	14
20	0.0842	0.0684	0.4481	9
21	0.0918	0.0408	0.3080	16
22	0.0762	0.0549	0.4186	11
23	0.0812	0.0974	0.5454	6

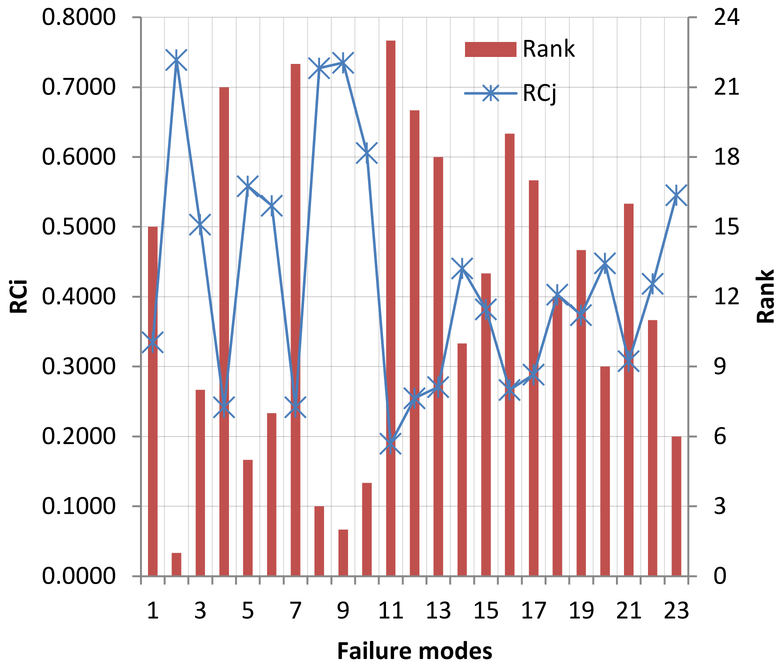


Figure 3.4: RC_i values and rankings of 23 failure modes

From Figure. 3.4 it is clear that the second failure mode i.e. failure to lubricate the main bearing with the highest value of RC_i is the best ranked and as such poses the greatest risk to the basic engine of a marine system while failure mode 11 i.e. cracking of the crankshaft has the lowest value of RC_i meaning it is the least critical failure mode of the system. It can also be observed that failure modes 8 and 9 although ranked third and second have RC_i values almost the same as that of failure mode 2 and as such the same attention should be given to all three failure modes. This is the case because the method is subjective and any slight changes in the input information into the model can make a significant change to the rankings.

3.4.2.3 Comparison of the methods

The failure mode risk ranking generated using the two proposed methods with risk criteria information obtained from experts is shown in Figure 3.5. From Figure 3.5 it is obvious that when AVRPN and AVTOPSIS are performed on the same task, the results generated may not be the same but are very similar. For example failure modes 3, 5, 10, 11, 17 and 21 were all given same ranking in both methods. The majority of other failure modes had a difference of 1 ranking between the methods.

According to Jahan et al. (2010) the degree of agreement between MCDM methods is measured using the Spearman rank correlation which evaluates the sum of the squares of the deviations between the different rankings. When the Spearman rank correlation between the methods was evaluated a result of 0.9585 was obtained showing that the two methods are strongly correlated. The implication of this is that either method can be suitable for use in prioritisation of marine machinery systems and other engineering systems when dealing with data that may be imprecise. However when the risk prioritisation problem involves dealing with more than three risk criteria the AVTOPSIS method should be employed since AVRPN is limited to three risk criteria.

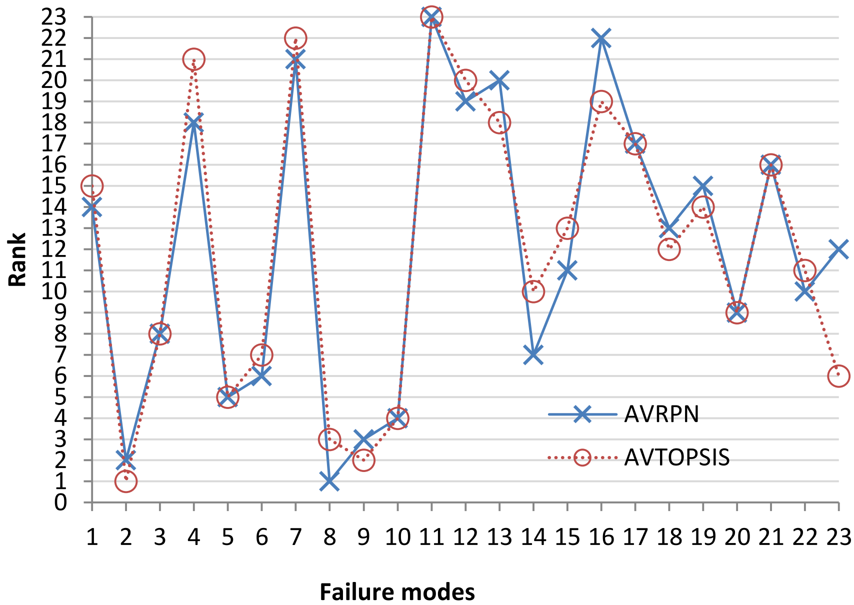


Figure 3.5: Comparison of risk of failure mode ranking obtained with proposed methods.

3.4.3 Case study 3: Application to the marine diesel engine

The second case study that was used to demonstrate the applicability of the proposed methodologies was the basic marine diesel which included components such as the piston, crankshaft and the cam assembly. The third case study is not be limited to the basic engine but includes other sub-systems of the marine diesel engine such as the scavenge air system, exhaust gas system, air starting system, main lube oil system and central cooling systems. The failure modes of the components of the various sub-systems of the marine diesel engine were used to further illustrate the application of the proposed methodologies for risk assessment for use in the marine industry. For the whole system, 74 failure modes were considered for investigation, as presented in Appendix A1, together with their causes and effects. The same experts that were used in assigning ratings for the 23 failure modes in case study 2 were also utilised in rating the 74 failure modes of this case study. A sample of the assigned ratings is shown in Table 3.8 while the full table is presented in Appendix A2. It is worth noting that a consensus was reached among the three experts in rating of the 74 failure modes.

Table 3.8: Sample of assigned criteria rating

Failure modes	O	S	D
1	7:30% 8:60%	3	4:70%
2	7	6:50%	8
3	5	6	5: 90%
4	7	3	3: 80%
5	7: 80%	6	5: 50%
.	.	.	.
.	.	.	.
.	.	.	.
71	3:40%	9:90%	9:60%
72	3	8:85%	9:70%
73	2	9	10
74	2	8:70%	9:70%

3.4.3.1 AVRPN analysis

The assigned ratings against the three decision criteria; O, S and D for the 74 failure modes were then applied as input data into the AVRPN methodology.

Firstly the expert-assigned imprecise ratings for the 74 failure modes in Table 3.8 were aggregated using Eq. 3.1 to 3.3. The aggregated values were then used as input in Eq. 3.4 to evaluate risk of the 74 failure modes and the results are presented in Appendix A4 and Figure 3.6. From the graph, failure mode 8 is the best ranked failure mode having the highest risk priority number (RPN). This shows that based on this particular risk ranking methodology failure mode 8 poses the greatest risk to the marine diesel engine. The least ranked failure mode is failure mode 70 having the lowest value of RPN. Hence failure mode 70 poses the least threat to the marine diesel engine.

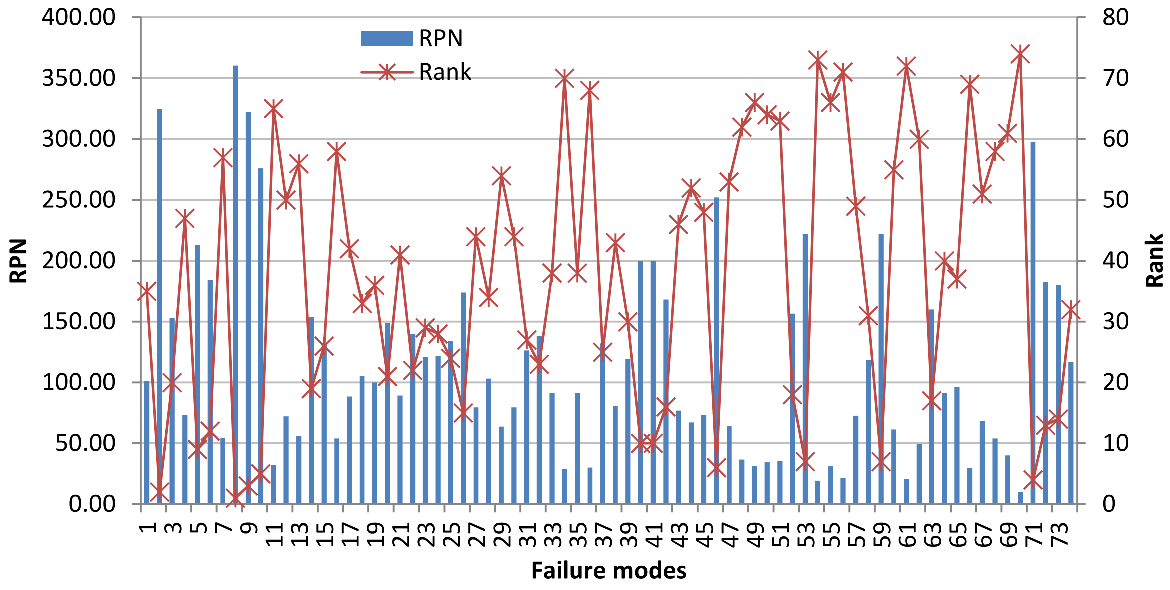


Figure 3.6: Failure modes RPN values and ranking

3.4.3.2 AVTOPSIS analysis

The assigned risk ratings of the 74 failure modes aggregated using Eq. 3.1 to 3.3 were then used to form a decision matrix, a sample of which is presented in Table 3.9 and the full matrix is presented in Appendix A3. Next the decision criteria were normalised using Eq. 3.6. The normalised decision matrix was then multiplied by the decision criteria weight to form the weighted normalised matrix. In this case study the weight of the decision criteria were determined using the entropy method modelled as Eq. (3.6), (3.8) – (3.9). The decision criteria weights obtained were as follows; O =0.3443, S = 0.3326 and D = 0.3231. The positive ideal and negative ideal solutions were determined using Eq. (3.10) and (3.11). The distance of each failure mode to the positive-ideal solution, D_i^+, and negative-ideal solution, D_i^-, together with relative closeness, RC_i, of each failure mode to the ideal solution were evaluated using Eq. (3.12) – (3.14). The graphical representation of the result of the relative closeness of each failure mode to the ideal solution and the corresponding ranking of the 74 failure modes are shown in Figure 3.7.

Table 3.9: Sample of decision matrix

Failure mode	O	S	D
1	7.5	3	4.5
2	7	5.8	8
3	5	6	5.1
4	7	3	3.5
5	6.7	6	5.3
.	.	.	.
.	.	.	.
.	.	.	.
71	4.5	8.7	7.6
72	3	7.6	8
73	2	9	10
74	2	7.3	8

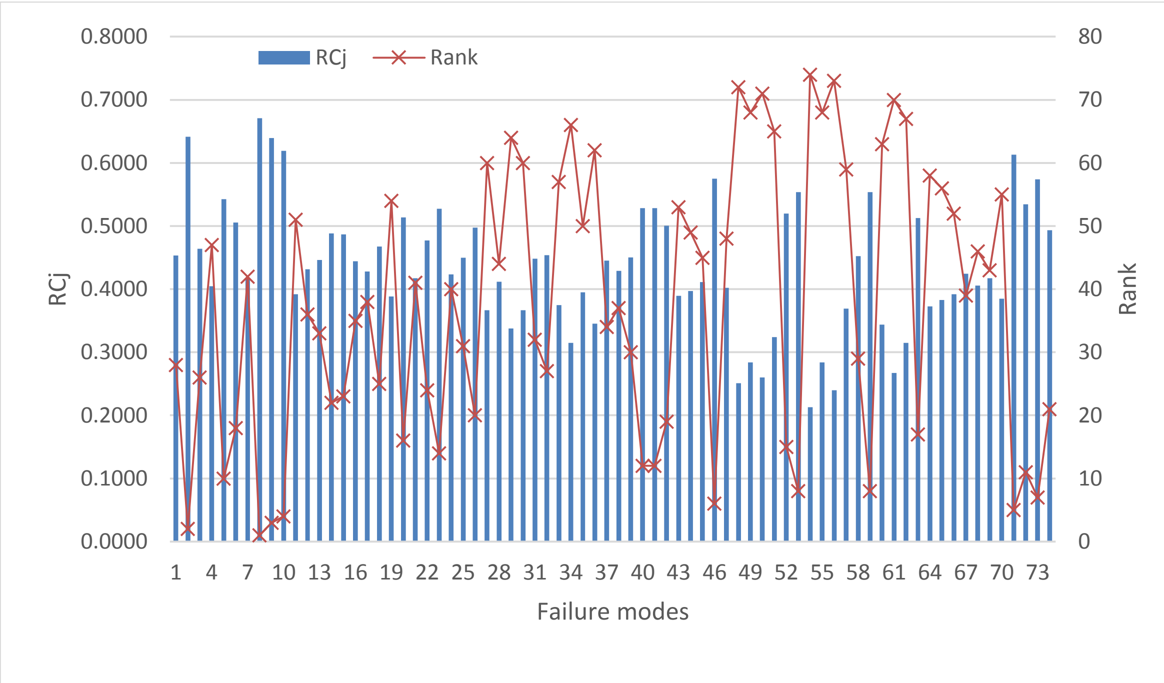


Figure 3.7: RC_i values and rankings of 23 failure modes

From Figure 3.7, failure mode 8 with TOPSIS performance index of 0.6707 is the best ranked failure mode and as such possess the highest risk to the system. In terms of risk contribution to the system this is followed by failure mode 2 ranked second with a TOPSIS performance index (RC_i) of 0.6413 while the least contributor to the system risk is failure mode 54 having the lowest TOPSIS performance index value of 0.2129.

3.4.3.3 Comparison of methods

The failure mode rankings generated from utilising the two techniques; AVRPN and AVTOPSIS are presented in Figure 3.8.

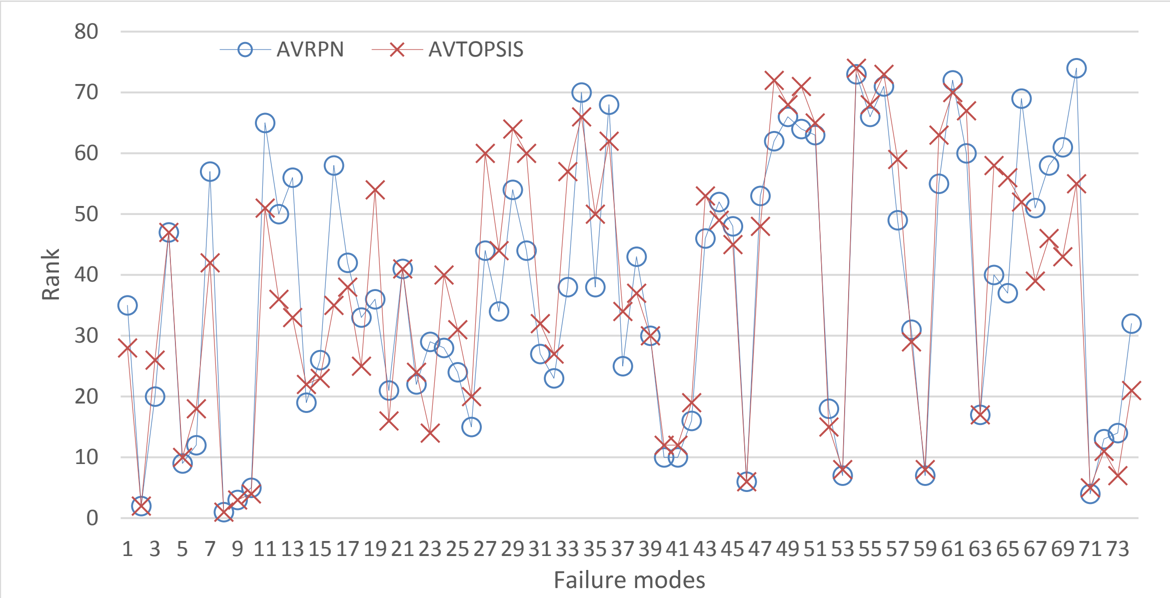


Figure 3.8: Comparison of proposed methods

From Figure 3.8 it can be seen that the majority of failure modes are ranked the same by the two methods while a few others have a rank difference of one between them. The Spearman rank correlation coefficient between AVRPN and AVTOPSIS was evaluated and a value of 0.9000 was obtained. With the strong correlation between the two methods it can be suggested that the two techniques can be used individually or in combination for risk prioritisation.

3.5 Summary

In this Chapter some of the limitations of the conventional FMEA method were addressed using two approaches for risk prioritisation; AVRPN and AVTOPSIS. Both methods utilise a novel approach using averages without resorting to specialised software or the need for the decision maker to have knowledge of specialised programming concepts, in aggregating multiple experts' diverse information that may be imprecise or incomplete. The AVRPN technique was proven to match almost completely with the Yang et al. (2011) and Su et al. (2012) modified Dempster-Shafer method when it was applied to a complete distribution risk criteria problem from the literature. It was also demonstrated that the approach is simple yet robust and capable of dealing with imprecise distribution risk criteria problems which the modified Dempster-Shafer theory technique is incapable of solving. Comparison between the two proposed methods (AVRPN and AVTOPSIS) revealed that both techniques can be suitable for use in risk prioritisation jointly or independently as the results generated by both methods were very similar. However the AVTOPSIS method is capable of incorporating more than three risk criteria unlike AVRPN. Although both techniques have been developed for risk prioritisation, they can easily be modified to address other multi-decision engineering problems such as maintenance strategy selection problems. Finally another novel aspect in the chapter, to the best of the author's knowledge, is the fact that this is the first application of TOPSIS, an MCDM tool, in analysing a problem involving imprecise information from multiple experts.

Chapter 4 Risk Assessment using Compromise Solution Method

4.1 Introduction

In Chapter 3 two techniques were proposed for prioritisation of the risk of failure modes of machinery systems. As stated in Chapter 3, AVRPN addresses only a single limitation of the classical FMEA. AVTOPSIS which is the combination of the averaging technique and TOPSIS has an advantage over AVRPN in that it is capable of addressing more challenges of the classical FMEA. TOPSIS is a compromise solution methodology that is based on the fact that the best alternative is the one closest to the positive ideal solution and farthest from the negative ideal solution, however when compared to other compromise solution methods, more computational effort is required in evaluating the positive and negative ideal solutions (Rao, 2008). Other limitations of the TOPSIS technique are (Opricovic and Tzeng, 2004): (1) the optimum solution is not close to the ideal solution when the ideal solution has value of 1 and (2) the relative distance between positive ideal and negative ideal is not considered in the evaluation process which negatively affects the decision making process.

In order to further eliminate or mitigate the limitations of the classical FMEA, two Multi-Criteria Decision Making (MCDM) tools are proposed as alternatives to the classical FMEA. The proposed MCDM tools are Vlsekriterijumska Optimizacija Ikompromisno Resenje, meaning: Multicriteria Optimization and Compromise Solution (VIKOR) and Compromise Programming (CP).. Utilising these two MCDM techniques, which have successfully been applied in solving problems other than risk prioritisation, will allow more decision criteria and flexible decision criteria weights to be use in prioritising risk of failure modes which will therefore result in the risk of failure mode being more effectively prioritised or ranked. In order to enhance the capability of the two MCDM techniques in addressing the limitations of the classical FMEA, the averaging technique introduced in Chapter 3 has been integrated with the two proposed MCDM techniques. This allows the proposed compromise solution methods to use precise and /or imprecise ratings from experts as input. Thus the use of the averaging technique in the MCDM tools will eliminate the limitation of the classical FMEA of the inability to aggregate imprecise criteria ratings from experts. Furthermore two objective weighting techniques are incorporated into the methodology which is a break away from the use of subjective weighting techniques that may biasedly influence the decision making process. The suitability and applicability of the proposed methodologies in risk ranking of failure modes of the marine diesel engine are investigated through case studies.

The chapter is organised as follows: Section 4.2 presents a review of MCDM tools and Section 4.3 presents the proposed methodology for risk prioritisation. In Section 4.4 three case studies are presented for illustration of the proposed technique. Finally conclusions are presented in Section 4.5.

4.2 Review of MCDM tools and their relevance to the Marine industry

As previously stated in Chapter 3, the classical FMEA technique has limitations and in order to enhance its capability and reduced these flaws, various MCDM techniques have been applied in the literature.

Braglia (2000) proposed the Analytical Hierarchical Process (AHP) technique as an alternative to RPN in the FMEA system. With this method, a three-level hierarchy was formed with the top level representing the main objective of fault cause selection, the intermediate level representing the four risk criteria, O, S, D and economic cost and the lowest level representing the alternative causes of failures. With this, a series of pairwise comparison matrices was formed and evaluated to obtain the weight of risk criteria and local priorities of the possible causes of failure with respect to O, S, D and economic cost. The aggregation technique in AHP was used to synthesize the local priorities of causes of failure into global priorities based on which possible cause of failure was ranked. Carmignani (2009) used a similar approach to that of Braglia (2000) and in the methodology of the former, a new profitability calculation technique was introduced in place of economic cost for risk prioritisation of an electro-injector, a fuel system component. However the use of AHP has been criticised due to its use of an unbalanced scale of judgement and its inadequacy in addressing risk criteria ratings that may be uncertain and imprecise in the pairwise comparison process (Deng, 1999, Ilangkumaran and Kumanan, 2009). Furthermore, the AHP technique is performed on problems with 2 to 15 risk criteria and if a problem with more than 15 decision criteria is to be considered some other technique is required to initially reduce the number of risk criteria (Vidal et al., 2011a).

Maheswaran and Loganathan (2013) proposed a hybrid MCDM technique as an alternative to RPN in the traditional FMEA system. The technique was based on integration of AHP and the

Preference Ranking Organisation METHod for Enrichment Evaluation (PROMETHEE). The authors used AHP to determine the weight of each risk factor and used PROMETHEE for prioritising the failure modes. The methodology was illustrated by applying it to prioritising failure modes of a boiler system in the tyre manufacturing industry. Ayadi et al. (2013) presented a multi-criteria failure mode and effects analysis approach based on PROMETHEE for prioritising potential failure modes applied to manufacturing of a gas treatment plant. Moreira et al. (2009) proposed PROMETHEE in the ranking of equipment failure modes. PROMETHEE results in poor structuring of problems compared to AHP and when more than seven risk criteria are used it becomes difficult to obtain a view of the problem thereby making the evaluation process very complicated (Macharis et al., 2004).

Seyed-Hosseini et al. (2006) proposed a methodology referred to as Decision Making Trial and Evaluation Laboratory (DEMATEL) as alternative to RPN in the classical FMEA for prioritisation of failure modes. With this approach, failure modes are prioritised based on severity of effect and direct/indirect relationships between them. However one of the challenges of DEMATEL is that it requires a lot of computational effort and according to Shaghaghi and Rezaie (2012) it cannot address the limitations of the traditional RPN method especially in a system where each cause of failure is linked to a single failure mode; the results obtained by both methods are the same.

Sachdeva et al. (2009b) proposed an integrated Shannon’s entropy method with TOPSIS which enhanced the FMEA for risk assessment. Six criteria of O, D, maintainability, spare parts availability, economic safety and economic cost were considered for risk prioritisation. An illustration was given with the application to the digester of a paper manufacturing plant in India. Braglia et al. (2003) also used TOPSIS under a FUZZY environment for risk prioritisation of a foaming machine of a refrigerator production line. The use of TOPSIS, especially in the fuzzy environment, is computationally intensive and that may make the proposed technique unattractive to the maintenance practitioner.

From the above review and according to Maheswaran and Loganathan (2013), only limited publications are available using MCDM techniques in enhancing the classical FMEA evaluation methodology. Moreover the few MCDM techniques employed so far all have one limitation or another. Hence there is need for an alternative MCDM technique devoid of the limitations of the MCDM techniques applied by other researchers and which will sufficiently address the challenges of FMEA especially for the marine environment. On this basis, two

MCDM compromise solution methods are proposed; VIKOR and CP as alternatives to the standard RPN calculation of the FMEA system.

4.3 Proposed hybrid MCDM risk analysis tool for use on marine machinery systems

The proposed enhanced FMEA based on the averaging technique integration with VIKOR and CP is presented in Figure 4.1.

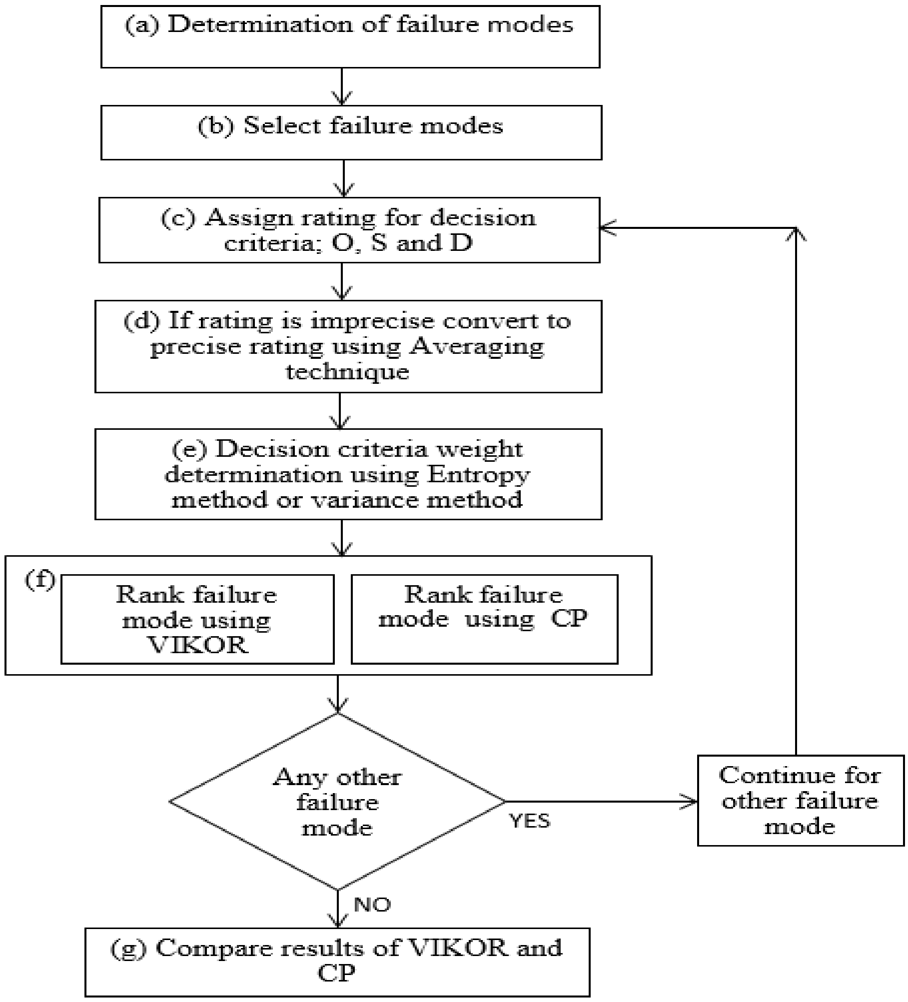


Figure 4.1: Flow chart of proposed hybrid MCDM risk analysis tool

The methodological steps of the enhanced FMEA model are briefly discussed as follows:

Steps (a), (b) and (c): The activities here involve formation of a team of experts who determine the particular system to be investigated. The failure modes of the system are then determined through brainstorming and the use of techniques such as root cause analysis and Fault Tree Analysis (FTA)

Step (d) Aggregation of imprecise rating: If imprecise ratings are assigned by experts to failure modes against decision criteria these are aggregated into precise ratings using the averaging technique discussed in Chapter 3.

Step (e) Determination of criteria weight: The weight of each of the decision criteria is determined objectively by employing two techniques; the entropy method and the variance method. The results from the two techniques are compared in order to ascertain the relationship between both techniques.

Step (f) Ranking of failure modes: VIKOR and CP are both applied individually in place of the RPN of the classical FMEA to determine the risk of the failure modes. This is carried out by using the performance index of both techniques to measure the performance of each failure mode and based on the index, the failure modes are ranked.
Step (g) the ranking obtained from both methods are compared.

4.3.1 Criteria weighting methods

The determination of the weight of risk criteria is a key factor in risk prioritisation because of the impact of the risk criteria in the final ranking of the failure modes of a system. In the literature, many methods are available for assigning weight of attributes; among these techniques is the use of the entropy method (Çalişkan et al., 2013, Jee and Kang, 2000, Shanian and Savadogo, 2006). The statistical variance method has also been used by some authors (Rao and Patel, 2010, Nirmal, 2013). Subjective methods such as AHP, Weighted Evaluation Technique (WET), the Points method and the digital logic method have also been employed (Rao, 2007).

For this chapter, the entropy method and the statistical variance method were adopted because these are objective techniques of weighting criteria there-by reducing personal bias in the overall decision making process which may influence purely subjective methods. Moreover they have been applied individually by previous researchers in dealing with similar problems as detailed above. However one of the objectives of this chapter is to compare both methods in order to determine suitability and applicability for marine machinery systems.

4.3.1.1 Entropy method

The steps of the Entropy method are as follows (Çalişkan et al., 2013):

(1) The decision matrix is formed. The decision matrix is produced using the values of $\overline{x}_{ij}$ obtained in the data aggregation stage as follows:

$$X = \left(\overline{x}_{ij}\right)_{m.n} \tag{4.1}$$

(2) The decision matrix is then normalised:

$$p_{ij} = \frac{\overline{x}_{ij}}{\sum_{i=1}^{m} \overline{x}_{ij}} \ , \qquad i = 1,2,\dots,m; \quad j = 1,2,\dots,n \tag{4.2}$$

Where p_{ij} is the normalised matrix.

(3) The entropy value e_j of each criterion is then determined:

$$e_j = -k \sum_{i=1}^{m} p_{ij} \ln p_{ij} \tag{4.3}$$

Where $k = \frac{1}{\ln m}$ is a constant which guarantees $0 \le e_j \le 1$

(4) Finally the objective weight w_j^e for each attribute is given by:

$$w_j^e = \frac{1 - \mathrm{e}_j}{\sum_{j=1}^{n} 1 - \mathrm{e}_j} \tag{4.4}$$

4.3.1.2 Statistical variance method

In determining the weight of risk criteria, the steps are as follows (Rao and Patel, 2010, Nirmal, 2013):

(1) The first step is the normalisation of the decision matrix in equation (4.1) as follows:

$$r_{ij} = \frac{\overline{x}_{ij}}{\sum_{i=1}^{m} \overline{x}_{ij}} \ , \qquad i = 1,2,\dots,m; \quad j = 1,2,\dots,n \tag{4.5}$$

Where r_{ij} is the normalised matrix.

(2) Next the variance of each risk criterion is evaluated as follows:

$$V_j = \frac{1}{m}\left[\sum_{i}^{m}\left(r_{ij} - \overline{r}_{ij}\right)^2\right] \tag{4.6}$$

Where $\overline{r}_{ij}$ is the mean value of r_{ij}

V_j is the variance of each risk criterion.

(3) Finally the weight of each risk criterion is calculated as follows:

$$w_j^v = \frac{V_j}{\sum_j^n V_j} \tag{4.7}$$

Where w_j^v is the weight of each criterion

4.3.2 Failure mode ranking tools

The two MCDM techniques; VIKOR and CP proposed for the ranking of the failure modes of marine machinery systems are discussed next.

4.3.2.1 VIKOR method

The VIKOR method was developed by S. Opricovic in 1979 (Opricovic, 1998) and is defined as a multi-criteria decision making tool which focuses on ranking and selecting a compromise solution from a set of alternatives with reference to conflicting criteria. The compromise solution is obtained using a ranking index based on a measure of closeness to the positive ideal solution (Opricovic, 1998, Opricovic and Tzeng, 2004). The key concept of the method lies in defining the positive and negative ideal solutions. While the positive and negative ideal solutions are defined as the alternatives with the highest and lowest values respectively with reference to risk criteria (Chu et al., 2007a), the optimum or compromise solution is defined as the alternative closest to the positive ideal solution and farthest from the negative ideal solution. The VIKOR method has been used by many authors in resolving different multi-criteria decision problems in literature; in the selection of industrial robots (Nirmal, 2013), selection of vendors (Hsu et al., 2012), an equipment selection problem for mining operations (Aghajani Bazzazi et al., 2011) and material selection problems (Liu et al., 2013, Chatterjee et al., 2009, Rao, 2008, Çalişkan et al., 2013, Anojkumar et al., 2014).

The use of VIKOR in this context as an alternative to the RPN calculation of the FMEA system is based on the following considerations:

(1) The classical FMEA is limited to use of only three decision criteria; O, S and D for prioritisation of the risk of failure modes of marine machinery systems. However the use of VIKOR in place of the RPN of the classical FMEA allows the inclusion of other important decision criteria such as economic cost and profitability.

(2) Failure modes are better ranked and more clearly distinguished from one another using VIKOR than RPN of the classical FMEA system. This is because with the use of RPN in the classical FMEA, different combinations of O, S and D may result in having the same RPN values for different failure modes but the risks in the practical sense may not be the same. The aggregation technique of VIKOR combines the decision criteria; O, S and D in a systematic manner such that it is almost impossible to have the same value for risk.

(3) VIKOR allows varying decision criteria weights to be applied in evaluating risk as opposed to classical FMEA that assumes equal weight for decision criteria.

(4) The integration of the averaging technique into VIKOR allows both precise and imprecise data to be applied in evaluating risk of failure modes whereas classical FMEA relies only on precise data from experts.

(5) No application of VIKOR techniques is reported in the literature for risk assessment of marine machinery systems and other related systems, so applying this MCDM technique which has successfully been used in solving other multi-criteria decision problems will be a positive step for the marine industry.

(6) Less computational effort is required than for the TOPSIS method (Nirmal, 2013, Rao, 2008, Carpinelli et al., 2014) and other MCDM techniques that have previously been used by other authors in risk prioritisation of failure modes. Moreover the limitation of the TOPSIS methodology is with respect to its inability to consider relative distance from the positive ideal and negative ideal solutions which may be addressed through the VIKOR method (Anojkumar et al., 2014).

The basic steps involved in the VIKOR methodology are as follows (Çalişkan et al., 2013, Sayadi et al., 2009):

(1) Determination of the best and worst values for each criterion.

Using the decision matrix in Eq. (4.1) the best and worst values for each criterion are determined as follows:

$$\overline{x}_j^{\,+} = \max_i \overline{x}_{ij}, \quad \overline{x}_j^{\,-} = \min_i \overline{x}_{ij} \qquad (4.8)$$

Where,

$\overline{x}_j^{\,+}$ is the best value for the jth criterion, and

$\overline{x}_j^{\,-}$ is the worst value for the jth criterion.

(2) Computation of the utility measure and regret measure for each failure mode is as follows:

$$S_i = \sum_{j=1}^{n} w_j \left(\overline{x}_j^{\,+} - \overline{x}_{ij}\right) / \left(\overline{x}_j^{\,+} - \overline{x}_j^{\,-}\right) \qquad (4.9)$$

$$R_i = \max_j \; of \; \left[w_j \left(\overline{x}_j^{\,+} - \overline{x}_{ij}\right) / \left(\overline{x}_j^{\,+} - \overline{x}_j^{\,-}\right)\right] \qquad (4.10)$$

Where

w_j is the weight of jth criterion, which represents the relative importance of the criterion.

S_i is the utility measure

R_i is the regret measure

(3) Computation of the VIKOR index value Q_i,

This is expressed as:

$$Q_i = v\,(S_i - S^+)/(S^- - S^+) + (1 - v)(R_i - R^+)\,/(R^- - R^+) \qquad (4.11)$$

Where

$$S^+ = \max_i[(S_i)\,, \qquad i = 1,2, \dots, m]$$

$$S^- = \min_i[(S_i)\,, \qquad i = 1,2, \dots, m]$$

$$R^+ = \max_i[(R_i)\,, \qquad i = 1,2, \dots, m]$$

$$R^{-} = \min_{i}[(R_i)\,, \qquad i = 1,2,\dots,m]$$

v represents the weight of the decision making strategy of the maximum group utility which is usually set at 0.5 although it can take any value from 0 to 1 (Çalişkan et al., 2013).

However according to (Vahdani et al., 2010, Çalişkan et al., 2013) the compromise can be selected with "voting by the majority" ($v > 0.5$), with "consensus" ($v \approx 0.5$), or with "veto" ($v < 0.5$).

(4) The ranking of failure modes is based on the VIKOR index Q_i value and the smaller the value the higher the rank is and the greater the risk that it poses to the system. The value of Q_i represents the individual expert performance index rating. However if information is available from multiple experts the values of individual experts is averaged.

4.3.2.2 Compromise Programming (CP)

Compromise Programming was proposed by Po-lung Yu and Milan Zeleny in 1973 (Zeleny, 1982) and has since been used by different authors in solving various multi-attribute decision problems. The objective is to produce a solution that is closest to the 'ideal' solution which is measured in terms of comparing distances of various points to a reference point (the ideal point). The optimal solution is the one with the shortest distance to the ideal point. CP has been applied in the following areas: Bilbao-Terol et al. (2006) presented a Fuzzy CP technique for portfolio selection; Diaz-Balteiro et al. (2011) used the CP technique in the ranking of seventeen European countries evaluated in terms of the sustainability of the European paper industry; Tiwari et al. (1999) utilised CP in selecting optimum cropping pattern using several criteria such as land suitability, energy output/input, water requirements and environmental cost and Phua and Minowa (2005) presented a geographical information system (GIS)- based CP technique for forest conservation planning. Having been successfully applied in solving other problems elsewhere this chapter uses the technique to solve the risk prioritisation problem in the marine environment.

The use of CP as an alternative to the RPN calculation of the FMEA system is based on the following consideration:

(1) CP is capable of incorporating more than three risk criteria, unlike RPN, for evaluating risk of failure modes of marine machinery systems.

(2) The relative importance of different risk criteria is taken into consideration in the risk analysis process unlike RPN which assumes equal weight for all risk criteria.

(3) The incorporation of the averaging technique into CP makes it possible for CP to allow the use of imprecise data for risk of failure mode evaluation as opposed to the classical FMEA that is limited to the use of precise data.

(4) The computational effort and time required in evaluating the CP method is far less than that of other MCDM techniques. In support of this claim Marler and Arora (2004) and Carpinelli et al. (2014) postulated that the CP method can effectively be used when reduced computational effort is a strict requirement.

The basic steps involved in this methodology are as follows:

(1) Determination of the positive ideal solution $\overline{x}_j{}^+$ and the negative ideal solution $\overline{x}_j{}^-$ for the jth criterion using Eq. 4.8. These are then used as input values in the risk prioritisation index d_{pi}

(2) Computation of the risk prioritisation index d_{pi}

$$d_{pi} = \left[\sum_{j}^{n} w_j^p \left| \frac{\overline{x}_j{}^+ - \overline{x}_{ij}}{\overline{x}_j{}^+ - \overline{x}_j{}^-} \right|^p \right]^{\frac{1}{P}} \tag{4.12}$$

Subject to $1 \leq p \leq \infty$

Where risk prioritisation index d_{pi} represents the distance of failure mode i (alternative i) from the ideal solution and p is the distance parameter which is used in compensating for deviation from the ideal solution point. In the case of risk prioritisation, the smaller the value of d_{pi} the higher the risk a failure mode possess to the system.

It is worth noting that both methods proposed are compromise solution methods. In fact Eq. (4.9) and (4.10) of the VIKOR method were derived from equation (4.12) when p values are set at 1 and ∞ respectively (Rao, 2008, Sayadi et al., 2009). However the key interest in the CP method in this context is to compare results obtained, with those of VIKOR to identify whether the methods can be used jointly or independently. The value of p was set at 2 for the CP method because this is the standard value used in the literature (Zeleny, 1982, Phua and Minowa, 2005).

4.4 Case studies

4.4.1 Case study 1: Application to the boiler of a tyre manufacturing plant

To validate the two proposed methodologies a boiler failure mode ranking problem that Maheswaran and Loganathan (2013) solved with the PROMETHEE method was considered. The authors identified ten failure modes using "What-if analysis" and generated a failure report of the system. The identified failure modes were assigned precise ratings for each of the four risk criteria Severity(S), Occurrence (O), Detection (D) and Protection (P) by different experts, with each of the expert ratings forming an individual decision matrix. The average of the individual decision matrices is shown in Table 4.1 which was then normalised; the result is shown in Table 4.2.

Table 4.1: Failure modes of a boiler system and corresponding decision matrix (Maheswaran and Loganathan, 2013)

S/N	Failure modes	S	O	D	P
1	Induced Draft fan get tripped	7.0	7.4	4.2	3.4
2	Feed water pump get failed	5.8	4.4	7.4	7.8
3	Safety valve fail to act	8.2	1.8	1.4	3.8
4	Nozzle failure at the fuel supply system	6.2	5.4	2.2	3.4
5	Low temperature of the furnace oil	7.8	5.8	4.6	3.0
6	Safety door fail to act	7.0	1.8	1.4	1.8
7	Electrode rod failure at the ignition system	6.2	6.6	2.2	1.8
8	Failure of water level controller	6.6	3.6	3.4	5.8
9	Failure of water pipe gets ruptured	6.2	1.6	7.8	2.6
10	Failure occurs in the steam separator	6.6	2.0	1.8	1.8

Table 4.2: Normalised Decision matrix (Maheswaran and Loganathan, 2013)

Failure modes	S	O	D	P
1	0.5000	0.0000	0.4370	0.2660
2	1.0000	0.5170	0.9370	1.0000
3	0.0000	0.9650	0.0000	0.3330
4	0.8330	0.3450	0.1250	0.2660
5	0.1660	0.2760	0.5000	0.2000
6	0.5000	0.9650	0.0000	0.0000
7	0.8330	0.1380	0.1250	0.0000
8	0.6660	0.6550	0.3120	0.6660
9	0.8330	1.0000	1.0000	0.1330
10	0.6660	0.9310	0.0620	0.0000

4.4.1.1 VIKOR method analysis

From Table 4.2 the positive ideal and negative ideal solutions of all the risk criteria were determined using Eq. 4.8. The relative weights of criteria are then required. For the purpose of comparison of this proposed methodology with the PROMETHEE method of Maheswaran and Loganathan (2013), criteria weights evaluated by these authors using AHP techniques were used. The criteria weights assigned were 0.4996, 0.2884, 0.0655 and 0.1465 for Severity (S), Occurrence (O), Detection (D) and Protection (P) respectively. Knowing the weight of risk criteria, the distance of each failure mode from the positive ideal solution was then calculated firstly based on utility measure using Eq. (4.9) and secondly based on regret measure using Eq. (4.10). The VIKOR index Q_i was then calculated using Eq. (4.11) and based on the result, the failure modes were ranked. The results of Q_i for each of the failure modes and their corresponding rankings are presented in Table 4.3.

Table 4.3: S_i, R_i and Q_i and corresponding Rank of a boiler system

Failure modes (i)	Value			Rank		
	Si	Ri	Q_i	Si	Ri	Q_i
1	0.6826	0.2884	0.6432	9	8	8
2	0.1434	0.1393	0.0165	1	2	1
3	0.6729	0.4996	0.9189	8	10	10
4	0.4372	0.1889	0.3155	5	5	5
5	0.7754	0.4167	0.8887	10	9	9
6	0.4719	0.2498	0.4247	6	7	6
7	0.5358	0.2486	0.4737	7	6	7
8	0.3604	0.1669	0.2251	3	3	3
9	0.2104	0.1270	0.0530	2	1	2
10	0.3947	0.1669	0.2523	4	3	4

From Table 4.3, failure mode 2 is the most significant failure mode having the lowest Q_i value meaning it poses the highest risk to the boiler system. On the other hand, failure mode 3 having the highest Q_i value is the least significant of the 10 failure modes of the boiler system considered. The implication is that failure mode 3 has the lowest risk contribution to the system and as such it should attract the least attention while the greatest attention should be paid to failure mode 2.

4.4.1.2 Compromise Programming

For the Compromise Programming method, values of the best and worst solutions were obtained by applying Eq. (4.8) to the normalised decision matrix in Table 4.2. The values generated were used as input into Eq. (4.12) to evaluate the risk index of the CP method. The index values of the ten failure modes of the boiler system together with their rankings are presented in Table 4.4.

Table 4.4: dp values and rank

Failure modes(i)	dpi	Rank
1	0.8163	9
2	0.2169	1
3	0.7387	8
4	0.6244	6
5	0.8790	10
6	0.6192	5
7	0.6797	7
8	0.5971	4
9	0.3406	2
10	0.5744	3

From Table 4.4 it obvious that the highest ranked failure mode is number 2 having the lowest dpi values and the lowest ranked is failure mode 5.

4.4.1.3 Comparison of the two methods

Table 4.5 and Figure 4.2 show comparisons of the results obtained by the two proposed compromise solution methods with the results generated by the Maheswaran and Loganathan (2013) PROMETHEE based methodology.

Table 4.5: Comparison of methods

Failure modes	VIKOR	CP	(Maheswaran and Loganathan, 2013)
1	8	9	9
2	1	1	1
3	10	8	8
4	5	6	5
5	9	10	10
6	6	5	6
7	7	7	7
8	3	4	3
9	2	2	2
10	4	3	4

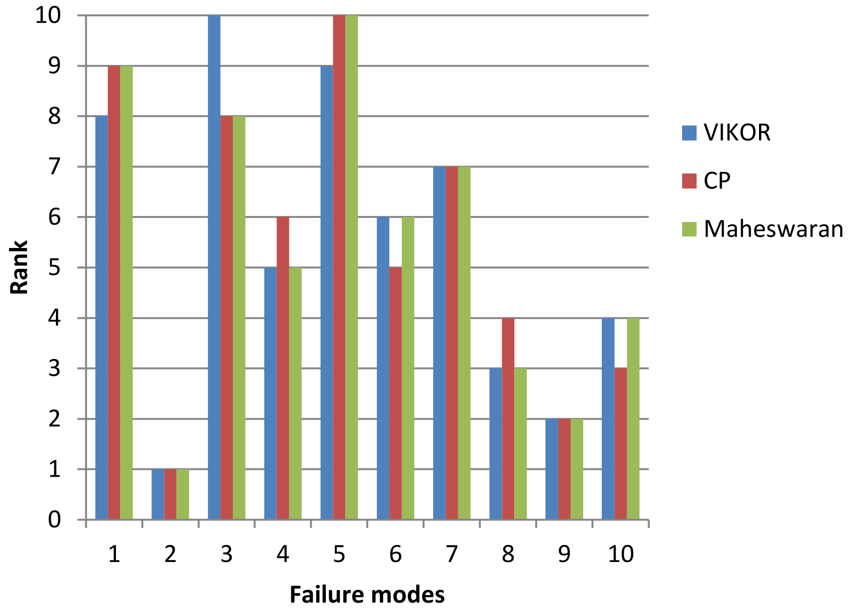


Figure 4.2: Comparison of methods

Table 4.6: Spearman's rank correlation coefficient

Method	VIKOR	CP	Maheswaran
VIKOR	-	0.9394	0.9626
CP	-	-	0.9758
Maheswaran			-

From Figure 4.2 and Table 4.5 it can be seen that all three ranking methods; VIKOR, CP and PROMETHEE assigned the top rank to failure mode 2 (feed water pump failure). There is absolutely no doubt that failure mode 2 is the most critical failure mode of the boiler system. Other failure modes assigned the same ranking by the three methods are failure mode 7 and 9.

From Table 4.6, the high Spearman's rank correlation coefficient between CP and Maheswaran and Loganathan (2013) rankings and between VIKOR and Maheswaran and Loganathan (2013) of 0.9758 and 0.9626 respectively, again validated the proposed methodologies. The compromise solution methods applied in this study demand less computational effort and time compared to the PROMETHEE method and yet produce very similar outputs. Also the Maheswaran and Loganathan (2013) methodology can only be applied to exact or precise data from experts but the methodology proposed in this paper is capable of solving system problems involving both precise and imprecise information from experts.

4.4.2 Case study 2: Application to the basic marine diesel engine

To demonstrate the suitability and applicability of the integrated averaging technique with VIKOR and the CP methods in conjunction with entropy and statistical variance weighting methods within the marine environment, the same case study of the basic marine diesel engine applied to validate the AVRPN and AVTOPSIS in Chapter 3 was considered. Ten major equipment items of the basic engine which include: main bearing, piston, cylinder head and crankshaft and a total of 23 failure modes were identified alongside their causes and effects; a sample of these was presented in Table 3.4 in Chapter 3 while the full table is in Appendix A1. The risk criteria (O, S and D) values assigned by the three expert for each failure mode through the use of the ordinal ranking scales was also presented in Table 3.5 in chapter 3. Eq. (3.1) – (3.3) had already been applied in aggregating the values assigned by the three experts and the aggregated decision matrix formed was also presented in Table 3.5 in Chapter 3.

4.4.2.1 Risk criteria weighting

The entropy method was applied firstly to determine the weight of each criterion. Using the entropy methodology the aggregated risk criteria ratings in Table 3.6 in Chapter 3 were normalised using Eq. 4.2. The weight of each criterion was then computed by applying Eq. (4.3) and (4.4) to the normalised matrix and the results obtained are shown in Table 4.7. Next the weight of the risk criteria were evaluated with the statistical variance models of Eq. (4.5) – (4.7) and the results obtained are also presented in Table 4.7.

Table 4.7: Risk criteria weightings by entropy and statistical variance

	O	S	D
w_j^e	0.0745	0.3526	0.5729
w_j^v	0.0734	0.3423	0.5844

From Table 4.7 it can be seen that the two weighting techniques yielded very similar results. It was decided to implement the VIKOR and CP risk analyses using the entropy method as there was evidence from the literature to support this decision see (Çalişkan et al., 2013).

4.4.2.2 VIKOR method analysis

The positive ideal solution f^+ and the negative ideal solution f^- were determined from the decision matrix in Table 3.6 in Chapter 3 using Eq. (4.8). The distance of each failure mode from the positive ideal solution was then calculated based on utility measure S_i and regret measure R_i using Eq. (4.9) and (4.10) respectively. The VIKOR index values, Q_i , were then evaluated for the various failure modes by subtituting values of S^+, S^-, R^+ , R^- and v into Eq. (4.11). The failure modes were ranked based on the VIKOR index values. The results of the Q_i values of the failure modes together with the rankings are presented in Table 4.8 and Figure 4.3.

Table 4.8: VIKOR index Qi of failure modes and rankings

Failure modes	Qi	Rank
1	0.6073	12
2	0.0000	1
3	0.4071	8
4	0.7525	16
5	0.3622	5
6	0.3842	6
7	0.9343	20
8	0.1220	3
9	0.0132	2
10	0.2970	4
11	1.0000	23
12	0.8128	19
13	0.9385	21
14	0.5417	10
15	0.5929	11
16	0.9431	22
17	0.7634	18
18	0.7631	17
19	0.6084	13
20	0.6579	15
21	0.6162	14
22	0.4952	9
23	0.4050	7

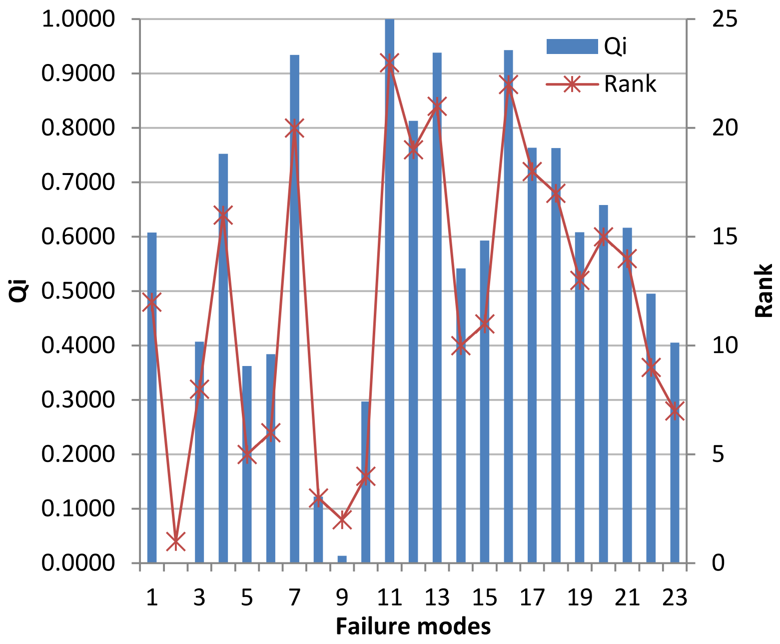


Figure 4.3: Q_i values of 23 failure modes of marine diesel engine and corresponding rankings

From Figure 4.3, it is clear that failure mode 2 is the one with the lowest value of Q_i and thus is ranked number one among the 23 failure modes of the marine diesel engine. In terms of risk impact on the system, its poses the highest risk to the marine diesel engine. On the other hand failure mode 11 which has the highest value of Q_i is ranked number 23 among the 23 failure modes and thus poses the least risk to the system.

4.4.2.3 CP method analysis

Applying Eq. (4.8) to the decision matrix in Table 3.6, the values of $\bar{x}_j^{\,+}$, $\bar{x}_j^{\,-}$ were obtained and used as inputs to Eq. (4.12) to obtain the risk prioritisation index d_p of the CP technique. The risk prioritisation index d_p values of the 23 failure modes together with the rankings are presented in Table 4.9 and Figure 4.4.

Table 4.9: dp of failure modes and ranking

Failure modes	dp	Rank
1	0.2145	13
2	0.0148	1
3	0.1102	7
4	0.2827	17
5	0.0968	5
6	0.1032	6
7	0.3936	20
8	0.0376	3
9	0.0164	2
10	0.0866	4
11	0.4535	23
12	0.3205	19
13	0.4041	21
14	0.1659	10
15	0.1977	12
16	0.408	22
17	0.2814	16
18	0.2979	18
19	0.1911	11
20	0.2378	15
21	0.2157	14
22	0.1517	9
23	0.1267	8

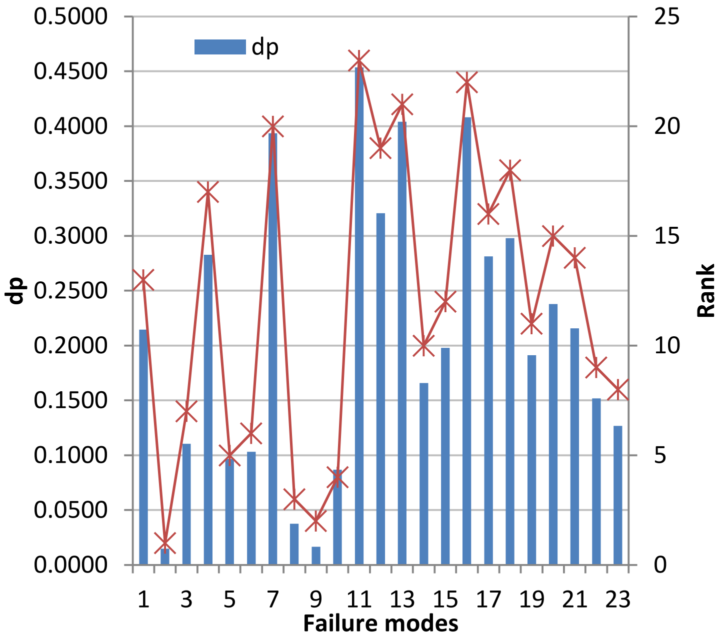


Figure 4.4: dp values of 23 failure modes and corresponding ranking.

It is obvious from Figure 4.4 that failure mode 2 has the lowest value of Q_i, thus it is ranked number one among the 23 failure modes. Based on this methodology, it is the most critical failure mode in the system and, as such, greater attention should be paid to it to mitigate the effect on the system. Failure mode 11 is again the one with the highest value of Q_i, thus the lowest ranked among the 23 failure modes.

4.4.2.4 Comparison of the ranking of the proposed methods with TOPSIS and AVTOPSIS

In order to validate the proposed methodologies, the results obtained from them together with the results obtained by solving the same problem with the standard TOPSIS technique and results obtained by AVTOPSIS in Chapter 3 were compared as shown in Figure 4.5.

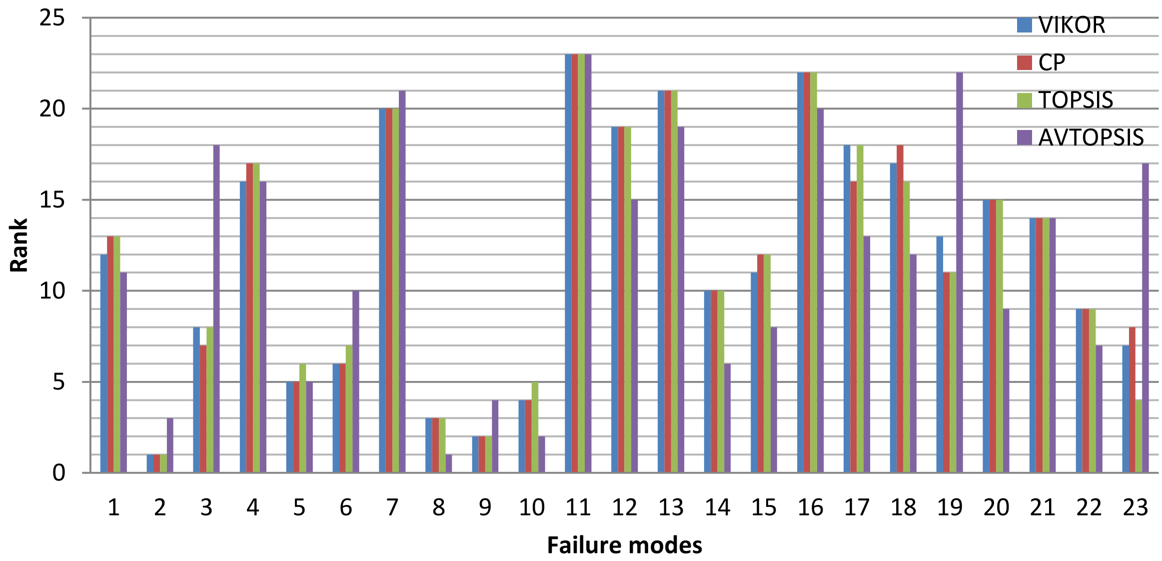


Figure 4.5: Comparison of rankings obtained with MCDM methods

Table 4.10: Spearman's rank correlation between methods

Method	VIKOR	CP	TOPSIS	AVTOPSIS
VIKOR	-	0.9931	0.9901	0.7757
CP		-	0.9862	0.7520
TOPSIS			-	0.7213
AVTOPSIS				-

From Figure 4.5 failure modes 2, 7, 8, 9, 11, 12, 13 14, 16, 20 and 22 representing about 50% of the total failure modes are ranked the same for three methods; VIKOR, CP and TOPSIS while the majority of the others have a difference of one place between failure modes. However the TOPSIS method involves more computational effort. The gap in the results obtained from AVTOPSIS as compared to the other three methods is as a result of the different normalisation technique used in the entropy method in obtaining risk prioritisation criteria weight. While for VIKOR, CP and TOPSIS the summation of the experts' assigned risk criteria values was used in the normalisation process in the entropy method for obtaining criteria weight, the square root of the summation of the square values of risk criteria assigned by experts' was applied in the normalisation technique used in the entropy methodology in obtaining criteria weight for the AVTOPSIS. This resulted in different risk criteria weights used for AVTOPSIS and the deviation in rankings obtained using the technique from the three other techniques. This then shows that criteria weights used as input in the risk prioritisation methodology have a very strong influence in the ranking outcome. This makes the process of evaluating criteria weight a very important and critical subject.

The Spearman rank correlations between VIKOR, CP and TOPSIS and AVTOPSIS were evaluated and the results are shown in Table 4.10. From Table 4.10 the near perfect Spearman rank correlations between VIKOR and CP; VIKOR and TOPSIS; CP and TOPSIS of 0.9931, 0.9901 and 0.9862 respectively, shows the viability and validity of the two proposed methods for prioritising risk of failure mode of a marine machinery system or any other related systems. The Spearman rank correlation coefficient between rankings of VIKOR and AVTOPSIS; CP and AVTOPSIS; and TOPSIS and AVTOPSIS of 0.7757, 0.7520 and 0.7213 respectively show that AVTOPSIS is also strongly related with VIKOR, CP and TOPSIS and this further shows the viability of the proposed methodologies.

4.4.3 Case study 3: Application to a marine diesel engine

The case study of the marine diesel engine which includes all of the systems of the marine diesel engine such as the basic engine, main lube oil system and the scavenge air system was previously described in Section 3.4.3 in Chapter 3. The values assigned by experts using the ordinal scale to the 74 failure modes identified for the systems as well as the resulting aggregated decision matrix have also already been presented in Table 3.8 and 3.9 respectively in Chapter 3. The application of the VIKOR and CP for analysis of this data is discussed next.

4.4.3.1 VIKOR method analysis

Applying Eq.4.8 to Table 3.9, the positive ideal solution f^+ and the negative ideal solution f^- were determined. The distance of each failure mode from the positive ideal solution was then calculated based on utility measure S_i and regret measure R_i using Eq. (4.9) and (4.10) respectively. The VIKOR index values, Q_i , were then evaluated for the various failure modes by subtituting values of S^+, S^-, R^+ , R^- and v into Eq. (4.11). Based on the VIKOR index values the failure modes were ranked. The results of the Q_i values of the failure modes together with the rankings are presented in Figure 4.6. From the result, failure mode 71 is ranked 1 having the lowest performance index i.e. 0.0234 and as such the failure mode contributed the highest risk to the system. The failure mode that poses the least risk to the system is failure mode 54 with a ranking of 74 and having the highest performance index value.

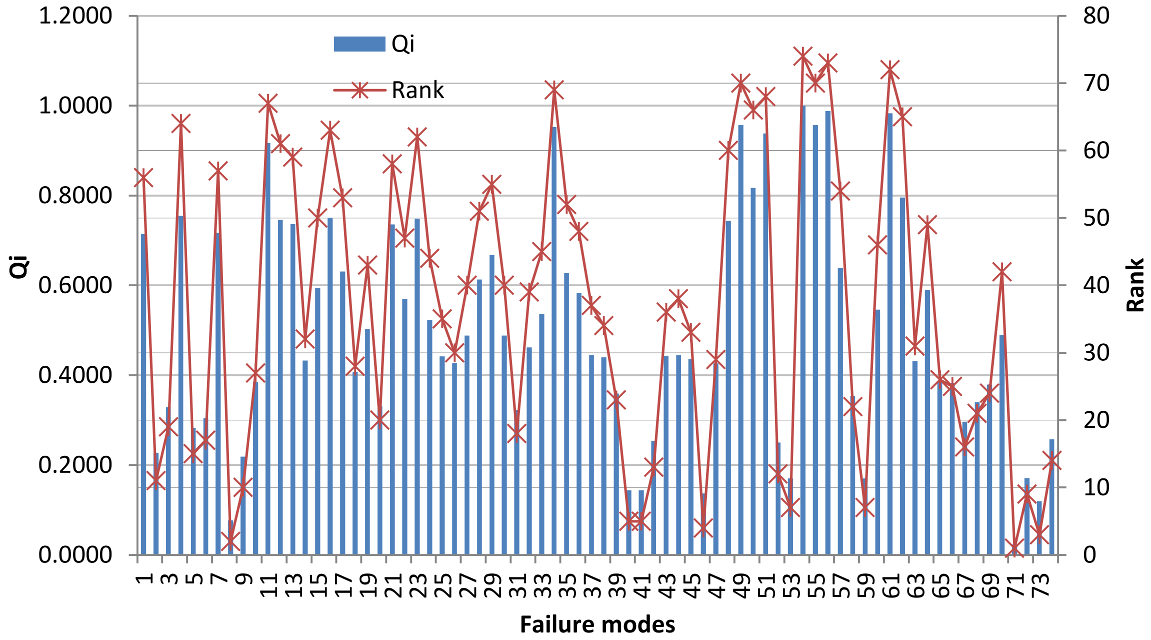


Figure 4.6: Qi values of 78 failure modes and corresponding rankings

4.4.3.2 CP method analysis

The values of $\overline{x}_j^{\,+}$, $\overline{x}_j^{\,-}$ were obtained by applying Eq. (4.8) to the decision matrix in Table 3.9 and then used as inputs to Eq. (4.12) to obtain the risk prioritisation index d_p of the CP technique. The risk prioritisation index d_p values of the 74 failure modes together with the rankings are presented in Figure 4.7.

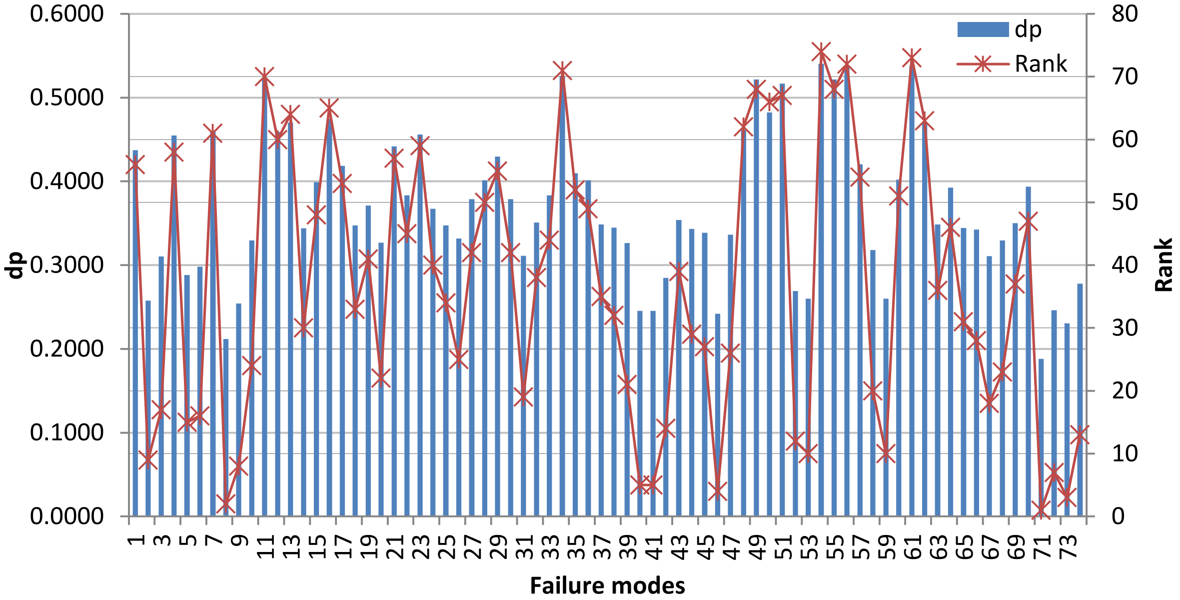


Figure 4.7: dp values of 74 failure modes and corresponding ranking

4.4.3.3 Comparison of the ranking of the proposed MCDM methods with AVRPN, AVTOPSIS and TOPSIS

To further determine the applicability of the two proposed MCDM compromise techniques the results obtained from their analysis were compared with those of ARPN, AVTOPSIS and the standard TOPSIS. The ranking comparison of the two proposed methods with AVTOPSIS, AVRPN and TOPSIS are shown in Figure 4.8 a, b &c.

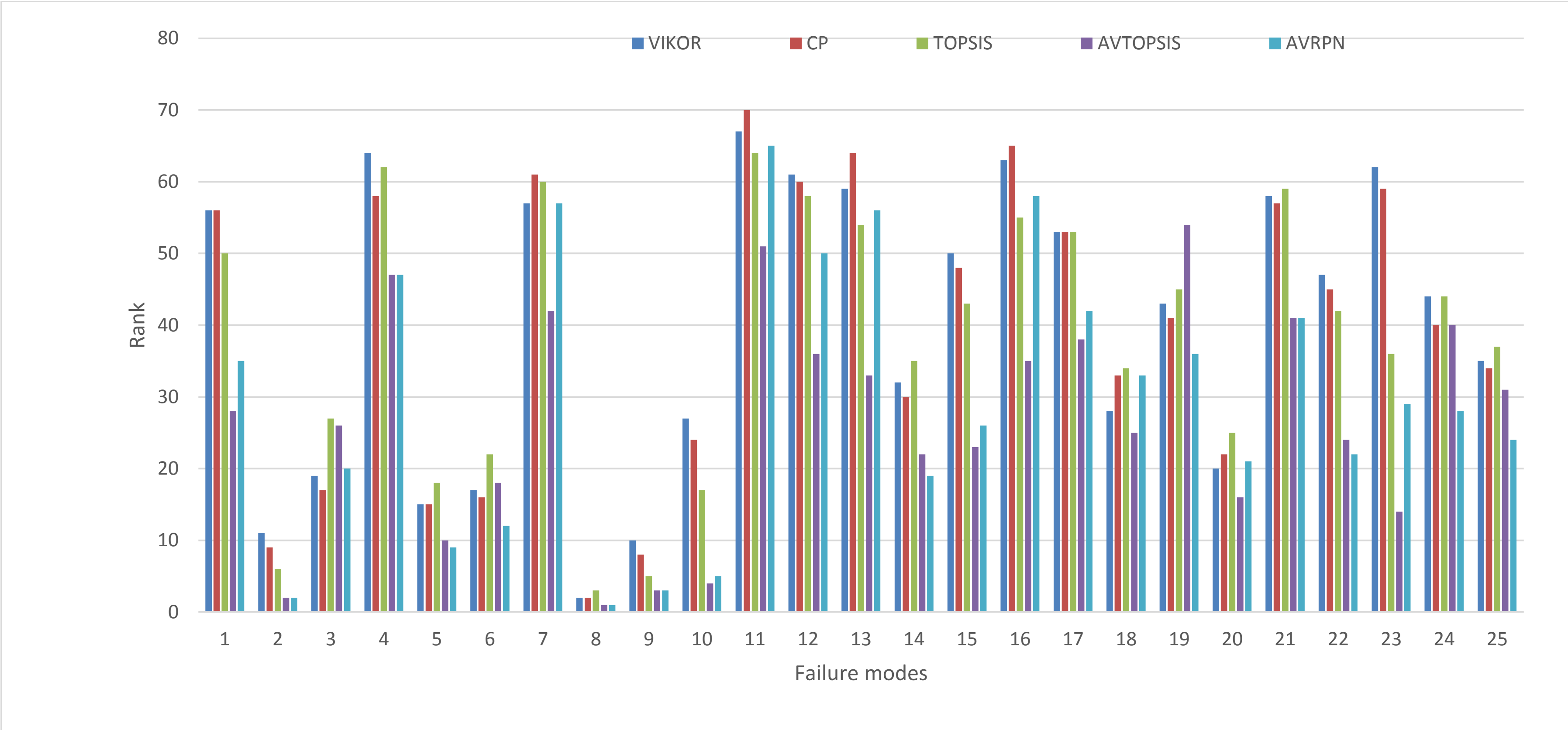


Figure 4.8a: Comparison of proposed methods with AVRPN, AVTOPSIS and TOPSIS

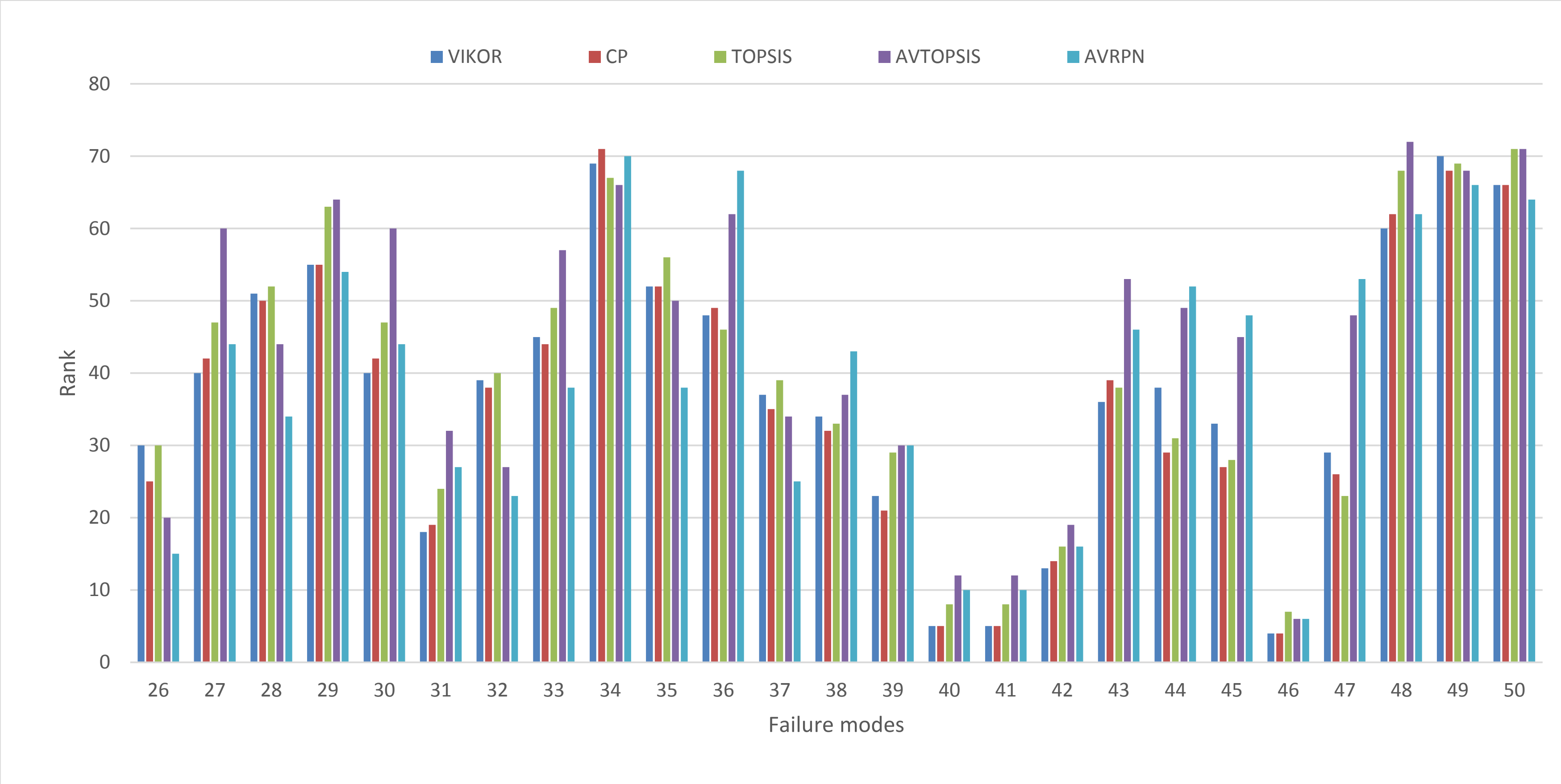


Figure 4.8b: Comparison of proposed methods with AVRPN, AVTOPSIS and TOPSIS

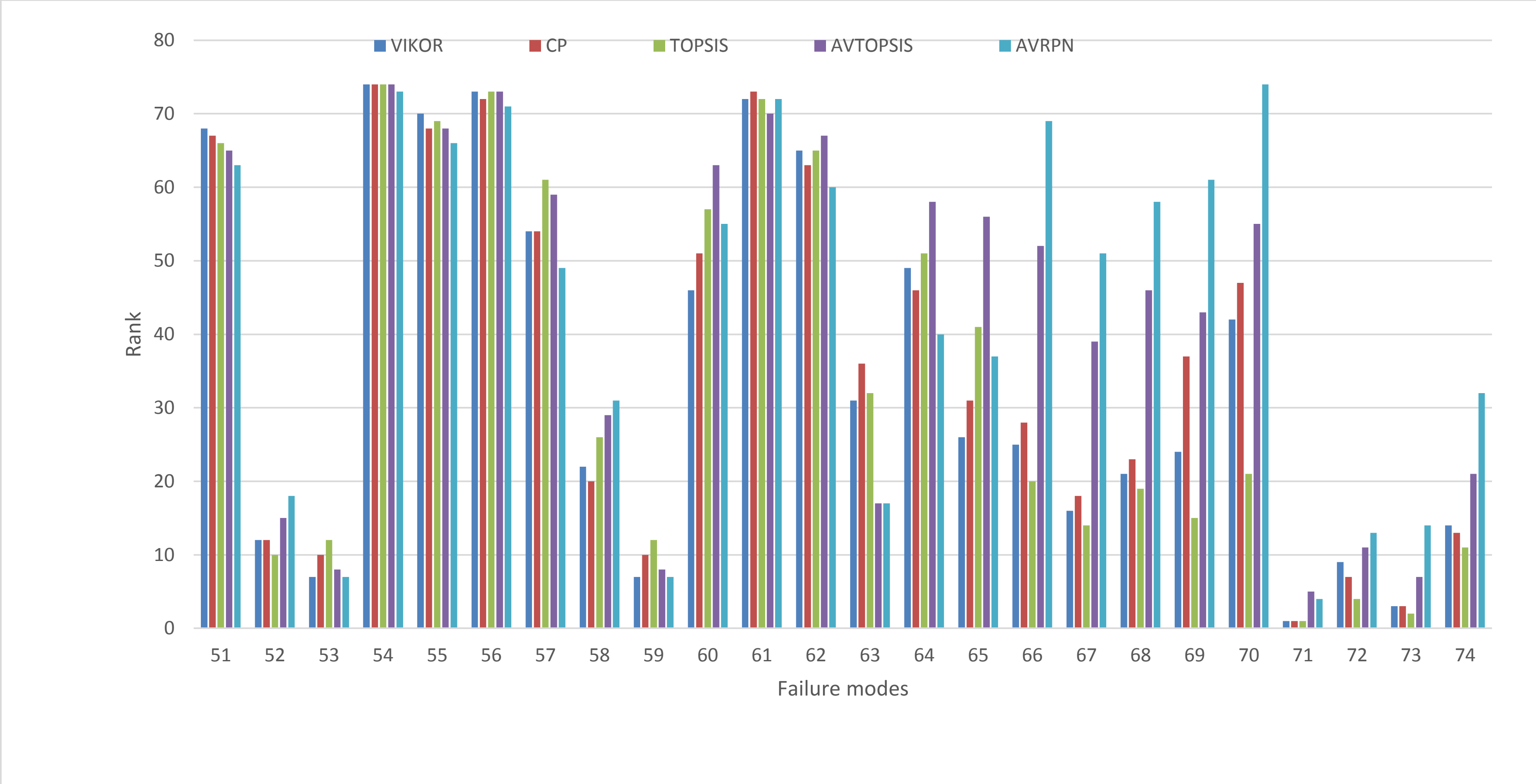


Figure 4.8c: Comparison of proposed methods with AVRPN, AVTOPSIS and TOPSIS

From Figure 4.8 a, b & c it is obvious that there is a very close relationship between the two proposed MCDM methods (VIKOR and CP) and TOPSIS as most of the failure modes are ranked the same for the three methods with the exception of a few failure modes that had a difference of one or two ranking places between them. On the other hand, AVRPN and AVTOPSIS also has most of the failure modes ranked the same with the exception of a few others that have a difference of one or two places between failure modes. The AVRPN and AVTOPSIS closely match because the decision criteria weights utilised for their analysis was almost the same. For AVRPN the weights of the decision criteria were assumed to be equal while for AVTOPSIS the decision criteria; O, S and D were assigned with weights of 0.3443, 0.3326 and 0.3231 respectively.

The gap in the ranking obtained from AVTOPSIS as compared to the standard TOPSIS is as a result of the different normalisation technique used in the entropy method in obtaining risk prioritisation decision criteria weights. The Spearman's correlation coefficients between the different methods were evaluated and are shown in Table 4.11.

Table 4.11: Spearman's rank correlation between methods

Method	VIKOR	CP	TOPSIS	AVTOPSIS	AVRPN
VIKOR	-	0.9890	0.9580	0.7660	0.7640
CP		-	0.9540	0.7790	0.7950
TOPSIS			-	0.8100	0.7250
AVTOPSIS				-	0.9000

From Table 4.11, the very strong Spearman's rank correlation coefficient between the two proposed MCDM methods and TOPSIS and the relatively strong correlation between the proposed methods and AVRPN and AVTOPSIS has further proven the suitability of these techniques for prioritisation of risk of failure modes. From the table, the near perfect Spearman rank correlation between VIKOR and CP =0.9890; VIKOR and TOPSIS = 0.9580 and CP and TOPSIS =0.9540 shows that the three techniques can be used individually or in combination in the prioritisation of risk for marine machinery systems or any other related engineering systems.

4.5 Summary

The place of risk assessment in maintenance strategy selection cannot be overemphasized as the maintenance strategy to be adopted depends upon the assessed risk. In this Chapter two popular compromise solution methods, VIKOR and CP, have been investigated for suitability and applicability for prioritising risk of failure modes of marine machinery systems and other related engineering systems. Three case studies have been investigated in determining the suitability and applicability of the proposed methodologies.

Both techniques use the novel averaging technique in aggregating multiple experts' opinions and with the integration of the averaging technique with VIKOR and CP both precise and imprecise experts opinions can be captured which is generally what is obtainable in a practical situation. In evaluating weight for risk criteria for use as an input into the risk prioritisation methodologies, two objective techniques, entropy and statistical variance methods, have been compared and findings show that the two techniques yield the same result and as such they can individually be used effectively in evaluating criteria weight for marine machinery systems. The beauty of using the objective risk criteria weighting technique is that the decision maker does not biasedly influence the decision making process as the risk criteria weight is the key element that influences the risk ranking. The issue of risk criteria weight greatly influencing the failure mode rankings of different risk prioritisation methodologies has also been demonstrated in this research as in the case of AVTOPSIS having a different trend of failure mode rankings from the three other methodologies; VIKOR, CP and TOPSIS simply because of the different risk criteria weights used for AVTOPSIS. Finally the methodologies, VIKOR and CP, proposed in the research are robust in producing almost completely the same results when compared to more computationally challenging techniques used by previous researchers thereby validating their applicability and suitability for risk prioritisation of the failure modes of machinery and other related engineering systems.

Chapter 5 Maintenance Strategy Selection

5.1 Introduction

The second major stage in the RCM methodology is the selection of the appropriate maintenance strategy for each of the components/failure modes of marine machinery systems. In the RCM methodology the logic decision tree is used in the selection of an appropriate maintenance strategy which is basically based on two major decision criteria; applicability and cost effectiveness (Deshpande and Modak, 2002). Generally decision problems involving more than one criterion, which are usually conflicting, are better modelled using MCDM tools. From this point of view, some MCDM techniques such as TOPSIS and AHP were proposed in the literature as alternative maintenance strategy selection methods (Gandhare and Akarte, 2012, Braglia, 2000). However it was obvious from the literature review in Chapter 2 that there was a need for a more systematic approach that can easily incorporate qualitatively and/or quantitatively the maintenance alternatives' selection criteria for marine system applications. On this basis, three hybrid MCDM techniques are proposed for maintenance strategy selection for ship machinery systems and other related ship systems in this research. The three proposed techniques are: (1) an integrated Delphi-AHP methodology, (2) integrated Delphi-AHP-PROMETHEE and (3) an integrated Delphi-AHP-TOPSIS methodology. The Delphi method was selected to screen decision criteria for determining the optimal maintenance strategy because, if there are too many decisions, the solution may become too complicated. For the first proposed method, AHP is used in the weighting of decision criteria and subsequently in the final ranking of maintenance strategy alternatives. In the second and third proposed methods AHP serves only to determine the decision criteria weights while PROMETHEE and TOPSIS are applied in the ranking of maintenance strategy alternatives. The hybrid approach was applied in order to combine the merits of the different MCDM tools to produce a more efficient maintenance strategy selection tool.

The Chapter is organised as follows: Section 5.2 discusses the various criteria and sub-criteria for Selection of a maintenance strategy; Section 5.3 presents the proposed methodology for selecting maintenance strategies; in Section 5.4 the case of the high pressure fuel oil pump of the marine diesel engine is presented to demonstrate the proposed methodologies. Finally the conclusion is presented in Section 5.5.

5.2 Criteria for selecting maintenance strategy

The selection of maintenance strategies for different components/equipment items of the marine machinery system, taking into consideration their distinct failure modes, is a complex task which usually involves multiple criteria. These multiple criteria were firstly identified through a thorough literature survey and face to face interviews with marine engineering experts both in academia and shipping industries. The identified criteria were then subjected to screening through the use of the Delphi method, which is described in the next section, in order to ascertain the criteria that are most essential for selecting maintenance strategies. The various criteria and sub-criteria considered in this study are as follows:

(1) Cost: Different maintenance approaches have different cost implications. In this case cost is viewed in terms of spare parts inventory cost, maintenance cost, crew training cost and equipment damage.

- (a) Spare parts inventories: The costs of spare parts inventories for each of the maintenance strategies are quantified. When no quantifiable data is available expert opinion is relied upon.
- (b) Maintenance cost: Cost of labour, equipment for performing maintenance tasks and materials for carrying out each type of maintenance strategy are considered. These are then measured for each of the maintenance strategies in order to determine the strategy that will best suit a particular failure scenario.
- (c) Crew training cost: The cost of training required by the crew members in order to acquire the expertise needed for performing each of the maintenance strategies.
- (d) Equipment damage: This criterion considers the level of damage to plant system equipment that may result from implementing a particular maintenance strategy. The maintenance strategy that will eliminate or reduce the chances of equipment damage is preferred.

(2) Safety: The level of safety required is determined by the maritime industry and regulation bodies and is a key factor in selecting the maintenance strategy for the machinery system. Safety is viewed in terms of personnel, equipment and environment.

- (a) Personnel: Failure of some equipment/components of marine machinery systems can result in serious injury or death of personnel on board ship. In such cases the most effective maintenance strategy is applied irrespective of cost.
- (b) Equipment: In the event of failure of a particular component/equipment item of the marine machinery system, the question is how safe is the entire system. Greater

attention is paid to parts that may result in severe damage to the system. The maintenance strategy that will eliminate or reduce failure frequency to the lowest level is advisable.

(c) Environment: Failure of some parts of the marine machinery system can result in serious environmental hazards. The maintenance strategy that will reduce failure of a piece of equipment to the lowest level is generally considered appropriate.

(3) Added value: This criterion considers the degree of improvement to the system that will result in terms of reliability and availability from implementation of each maintenance strategy. The following factors describe the 'added value' category used in this context.

(a) Minimisation of operational loss: The maintenance strategy that will minimise equipment operational loss the most is generally preferred.

(b) System reliability: High reliability is usually required for most high risk component/equipment items of a system. So the maintenance strategy that will yield the highest reliability is generally chosen in such instances.

(4) Applicability: Whether the maintenance strategy can be implemented in mitigating failures of the marine machinery system. The following factors are considered under this criterion:

(a) System failure characteristics**:** The component failure characteristics; wear-in failure, random and wear-out failure, are key factors in selecting the most appropriate maintenance strategy for plant equipment. For example, online condition-based maintenance is suitable for components with random failure patterns, provided there is an identifiable warning sign for measuring the condition of the component.

(b) Available monetary resource: If available finance for maintaining the system cannot incorporate online condition based maintenance, the plant manager is left with no choice other than to exclude it irrespective of the benefits.

(c) Equipment risk level: The level of failure risk of different equipment in the marine machinery system varies. For the very high risk equipment whose failure is usually catastrophic, condition based maintenance is mostly preferred irrespective of the cost implication.

5.3 Proposed Hybrid MCDM Methodology for maintenance strategy selection

As previously stated three hybrid MCDM methods have been proposed for selecting the maintenance strategy for a marine machinery system in this study. The first method combines

Delphi and AHP methods, the second method combines Delphi, AHP and PROMETHEE while the third method combines Delphi, AHP and TOPSIS. The flow chart of the proposed methodology is presented in Figure 5.1. The methodological steps are as follows:

Step (a) Decision making team formation: A team of experts is formed that will perform the selection of the optimum strategy for each equipment item/component of the system.

Step (b) and Step (c): The maintenance strategy alternatives and the decision criteria for selecting the alternatives are identified by the team based on experience and literature.

Step (d): The team use the Delphi method to carry out screening of the decision criteria such that the most significant criteria are identified for maintenance strategy alternatives.

Step (e): Two types of questionnaire are designed: The first questionnaire is designed for experts to carry out pairwise comparison judgment of decision criteria alongside pairwise comparison judgment of maintenance alternatives against decision criteria. The second type of questionnaire is based on a Likert scale; for this study a 5 point Likert scale was used to design the questionnaire for obtaining data for PROMETHEE and TOPSIS.

Step (f) Determination of decision criteria weight: The pairwise comparison judgment obtained from the experts for the decision criteria is used as the input into the AHP evaluation technique to calculate weights of decision criteria.

Step (g) Ranking of alternatives: The maintenance strategy alternatives are ranked using AHP, PROMETHEE and TOPSIS.

Step (h) and step (i) The ranking obtained from the three methods are compared and an optimum strategy is then determined.

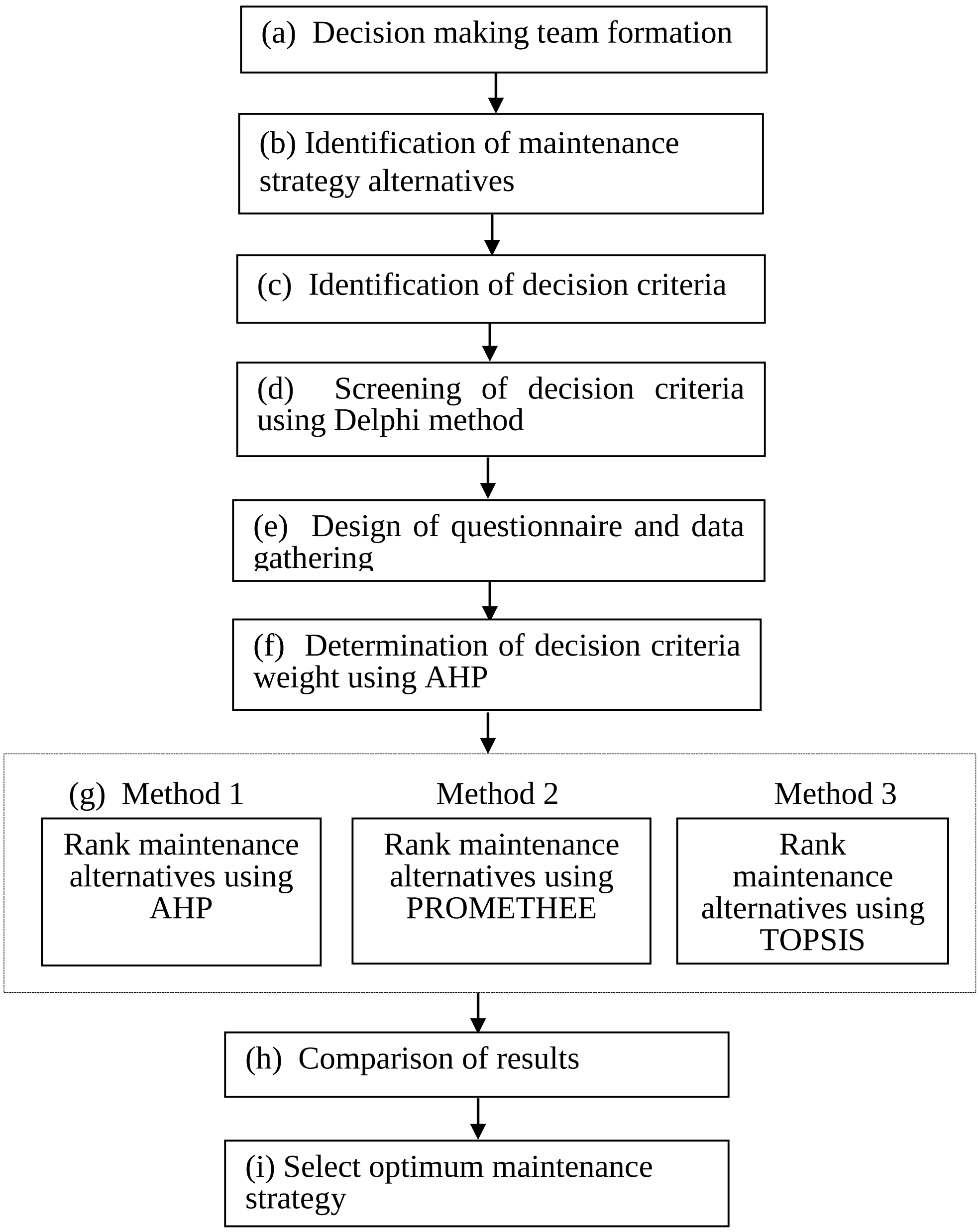


Figure 5.1: Flowchart of proposed methods

5.3.1 Delphi method

The Delphi method can simply be defined as a technique for iteratively processing opinions of experts until a consensus is reach on the subject under investigation (Delbecq et al., 1975). The development of the technique can be dated back to the early part of 1950 as a spinoff of the US Air Force-sponsored Rand Corporation study. It has since gained prominence with various modifications to the conventional Delphi technique emerging (Linstone and Turoff, 1975). In order to obtain quality results from Delphi analysis, some authors have recommended a sample size of between 5 and 15 experts (Kim et al., 2013a, Novakowski and Wellar, 2008, Cavalli-Sforza and Ortolano, 1984) while others recommended between 9 and 18 (Vidal et al., 2011a, Vidal et al., 2011b). Some of the merits of the Delphi technique are: participant experts can freely express their opinions since information is anonymously sourced creating no room for domineering experts to dictate the outcome which is usually the case of the conventional brainstorming technique (Kim et al., 2013b); The process is cheap since through email, surface mail and sometimes face to face contact with individual participant experts, the researcher or investigator can obtain a consensus opinion from participating experts on an issue as compared to the traditional brainstorming technique where experts will need to convene in one place to reach a consensus. The Delphi method has been applied standalone or in combination with other techniques in solving a variety of problems in the literature: Vidal et al. (2011a) applied the Delphi process in conjunction with AHP in evaluating project complexity; Joshi et al. (2011) employed the Delphi technique in identifying, synthesizing and prioritising key performance factors of a cold chain ("temperature-controlled supply chain") of an India company; Kim et al. (2013b) used the Delphi technique to identify objective evaluation criteria for selecting electronic waste to be recycled.

The first step in the Delphi methodology is to select a panel of experts to be used for the investigation. This is followed by developing the questionnaire, which could either be open ended or closed ended questions around the subject of the investigation, and this is sent to the panel of experts (first round Delphi survey). The next step is to analyse the results of the first round survey and resend the results alongside the second round questionnaire which is usually a modification of the first round questionnaire to the participants (second round Delphi survey). The iteration continues until a consensus is reached among experts for all items in the questionnaire and in most cases consensus is reached at the second or third round.

Different authors have advocated various techniques to determine the overall opinions of all experts. Lawshe (1975) proposed a content validity ratio (CVR) with the threshold value defined for removing or retaining a criteria item. This was re-evaluated by Wilson et al. (2012). The model is as follow:

$$\mathrm{CVR} = \frac{\mathrm{N_{PE}} - (\mathrm{N}/2)}{\mathrm{N}/2} \tag{5.1}$$

Where N_{PE} is the number of experts indicating an item is essential and N is the total number of panel experts. The value of CVR varies from +1 (all panel expert indicate an item is essential) to -1 (if all panel experts indicate an item is non-essential). The threshold value is generally set at greater than 0.29 and the implication is that any item with CVR value greater than 0.29 is retained (Kim et al., 2013b). Vidal et al. (2011b) and Vidal et al. (2011a) applied mean values in determining items to remove or retain and with this approach, items with a mean value below 4.5 on a 5 point Likert rating scale were removed.

In this study the criteria for selection of a maintenance strategy for marine machinery systems was screened using the Delphi survey steps described above. The CVR and the mean of all maintenance strategy selection criteria in the first and second round surveys were evaluated. Since there was no significant difference between the opinions of experts for all criteria in the first and second Delphi surveys, the process was terminated at the second round. Finally the criteria items with CVR value greater than 0.29 and mean values equal or greater than 2.7 in the second round survey were retained. It is worth noting that the mean value of all expert ratings in this study was set at 2.7 since a 3 point Likert scale was used in designing the Delphi questionnaire which is equivalent to the 4.5 threshold used by Vidal et al. (2011b) and Vidal et al. (2011a) on 5 point Likert scale.

5.3.2 Analytical Hierarchy Process (AHP)

AHP, first developed by Saaty (1980), is a widely used multi criteria decision making tool which helps decision makers to structure complex decision problems. AHP has been chosen mainly because it provides a framework to manage conflicting multi-criteria problems involving both qualitative and quantitative facets. Additionally the quality of expert opinions involved in the process can be mathematically proven using the consistence index (Zammori and Gabbrielli, 2012, Saaty, 1980). However AHP has limitations and one of the main limitations is the computational complexity in the analysis process when the decision criteria for selecting alternatives is more than 15. This shortcoming of AHP is overcome in this thesis by integrating the Delphi technique into the AHP method. AHP basically involves reducing complex decisions to a series of simple pairwise comparisons and rankings, and then synthesizing the results to obtain an overall ranking. The steps for AHP analysis, as presented in Caputo et al. (2013), with revision are as follows:

(1) Define decision criteria C_i to be used to evaluate and prioritise maintenance alternatives. The criteria were defined using the Delphi study, see section 5.3.1.

(2) Define maintenance alternatives to be prioritised. Three maintenance alternatives have been identified for mitigating effects of equipment failures of marine machinery systems.

(3) Design the AHP questionnaire for k experts to perform pair-wise comparison of the relative importance among the n decision criteria. Each individual expert's judgements are then used to form an n x n pairwise comparison matrix, X^k, represented as follows (Wu et al., 2008):

$$X^k = \left[x_{ij}^k\right]_{nxn} = \begin{bmatrix} x_{11}^k & x_{12}^k & \cdots & x_{1n}^k \\ x_{21}^k & x_{22}^k & \cdots & x_{2n}^k \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1}^k & x_{n2}^k & \cdots & x_{nn}^k \end{bmatrix} \quad (5.2)$$

Where

$x_{ij}^k > 0, x_{ij}^k = 1/\, x_{ji}^k$, $x_{ii}^k = 1$

x_{ij}^k is the k-th expert defined rating of how the importance of criterion *i* compares with that of criterion *j*. For example if criteria *i* and *j* are of equal importance $x_{ij}^k = x_{ji}^k = 1$ and k = 1, 2,…,z. The AHP scale used in the ranking is presented in Table 5.1.

Table 5.1: AHP importance scale (Saaty, 1980)

Score	Relative importance
1	criteria *i* and *j* are of equal importance
3	criteria *i* is slightly more important than criterion *j*
5	criteria *i* is significantly more important than criterion *j*
7	criteria *i* is strongly more important than criterion *j*
9	criteria *i* is extremely more important than criterion *j*
Note: 2, 4, 6 and 8 are intermediate values	

(4) The weight to be assigned to criteria $C_{1,}\, C_{2,} \ldots, C_n$ is evaluated using the pair-wise comparison matrix X^k. The weights of each criterion are evaluated as follows:

$$w_i^k = \frac{1}{n}\sum_j \frac{x_{ij}^k}{\sum_i x_{ij}^k} \quad (5.3)$$

Where w_i^k is the weight of criteria C_i

The weights of the criteria can be represented as weight vector (**W**$^{\mathbf{k}}$).

$$\boldsymbol{W^k} = [w_1^k, \quad w_2^k, \dots, w_n^k]^T \quad (5.4)$$

(5) The consistency of judgement by the experts is then evaluated using the consistency ratio $I_{r,}$. In general a consistency ratio of less than 0.1 is acceptable and if the value is greater than this, experts should be advised to revise their initial judgement (Saaty, 1980). The consistency ratio is calculated as:

$$I_{r,} = \frac{CI}{RI} \quad (5.5)$$

Where RI is the corresponding average random value of CI for an $n \ x \ n$ matrix, the values are shown in Table 5.2, and CI is the consistency index and can be evaluated as

$$CI = \frac{\lambda_{\max} \quad - n}{n \ - \ 1} \quad (5.6)$$

Where $\lambda_{\max}$ is the maximum eigenvalue

$$\lambda_{\max} \quad = \frac{1}{n}\sum_{i=1}^{n} \frac{(X^k w^k \ )_i}{w_i^k} \quad (5.7)$$

Table 5.2: RI values for different matrix order (Saaty, 1980)

n	1	2	3	4	5	6	7
RI	0	0	0.52	0.89	1.11	1.25	1.35

(6) The next step is to evaluate the local weight of each maintenance alternative for each criterion: firstly construct a pairwise comparison matrix between maintenance alternatives for each criterion using Eq. 5.2 (see the sample given in Table 5.7), next the solution models used in evaluating criteria pairwise comparison of individual experts i.e. Eq. 5.3 to 5.7 are also used for the maintenance alternatives' pairwise comparison matrix to obtain local weight of each maintenance alternative.

(7) The overall score of each maintenance alternative is evaluated by multiplying the local weight of a maintenance alternative by criteria local weight and summing over all criteria. Based on the overall score, maintenance alternatives are ranked and the most appropriate selected.

(8) Where pairwise comparison judgements are available from more than one expert, the overall score of each maintenance alternative from individuals is averaged to obtain a group overall score for the maintenance alternative option (Bolloju, 2001).

The Goepel (2014) AHP online calculator was used for the evaluation of Eq. 5.3-5.7

5.3.3 PROMETHEE method

As discussed in Chapter 4, PROMETHEE is an acronym for Preference Ranking Organisation METHod for Enrichment Evaluations, a multi-criteria decision making method developed by Brans, first presented in 1982 (Brans, 1986) and further extended by Brans and Vincke (Brans and Vincke, 1985). There have been 7 versions developed (Behzadian et al., 2010) and the one used here is PROMETHEE II. PROMETTHEE II is the most popular of all the versions and it's fundamental to the implementation of the other versions. The basic principle of PROMETHEE II for solving multi-criteria decision problems is the pairwise comparison of all alternatives for each criterion. The performance of one alternative over another in the pairwise comparison for each criterion is based on a preference function. This preference function (PF) turns the difference between two alternatives for each criterion into real values which range from 0 to 1. This corresponds to the degree of preference a maintenance practitioner has for one alternative over another. If the difference between two alternatives is 0, it simply means no preference and if the value is 1 its means full preference (Mareschal and De Smet, 2009). There are six different types of preference function; usual criterion, U-shape criterion, Gaussian criterion, V-shape criterion V-shape with indifference and level criterion (Brans et al., 1986). For this study the usual criterion was selected as the preference function because there is evidence in the literature that it is most suitable for qualitative data (VPSolution, 2013).

Apart from the preference function that needs to be defined by the maintenance practitioners for the application of PROMETHEE, additional information that needs to be defined are the weights of the criteria. There are different techniques available for determining the weights of criteria such as the AHP method, entropy method and variance technique. The AHP technique was selected for this work as it enables the decision problem to be logically structured, a feature lacking in the PROMETHEE method. However AHP has the disadvantage of trading off assigned criteria "good" ratings for "bad" ratings and vice versa because its information evaluation principle is based on complete aggregation of the additive type which can result in loss of vital information. In PROMETHEE partial aggregation is used which avoids the trade-off associated with the complete aggregation technique (Macharis et al., 2004). Additionally, AHP has a predetermined technique for criteria weight evaluation whereas in the PROMETHEE technique there is no provision for criteria weight determination thereby laying an additional burden on the maintenance practitioners. On this basis, a combination of the two techniques, AHP-PROMETHEE, is proposed for the prioritisation of maintenance alternatives by utilising the areas of strength of each technique. While AHP is used in the structuring of the decision problem and weighting of decision criteria, PROMETHEE is applied in the ranking of the maintenance alternatives.

The basic steps of the PROMETHEE method can be defined as follows:

(1) Definition of the problem: consider a multi-criteria problem of m alternatives (a_1, a_2,…,a_m) and n criteria (c_1,c_2,…c_n).

(2) Determination of deviation based on pairwise comparisons as follows:

$$d_j(a,b) = c_j\,(a) - c_j\,(b) \tag{5.8}$$

Where d is the pairwise difference between evaluations of alternatives a and b for each criterion

(3) Utilisation of preference function:

$$P_j(a,b) = F_j\{d_j(a,b)\} \tag{5.9}$$

Where$P_j(a,b)$ represents the preference of alternative a with respect to alternative b for each criterion, as a function of $d_j(a,b)$.

If the usual criterion is chosen as the preference function then:

$$P_j(a,b) \;=\; \begin{bmatrix} 0 \; if \; d_j(a,b) \le 0 \\ 1 \; if \; d_j(a,b) > 0 \end{bmatrix}$$

(4) Define numerical weight of criteria: This is a measure of the relative importance of each criterion, where w_j^k is the weight of criterion c_j. The normalisation of the weight, if there is need for it, is carried out as follows:

$$\sum_j^n w_j^k = 1 \tag{5.10}$$

(5) Evaluation of the overall preference index of a over b, $\pi(a,b)$: The weighted average of all the preference functions P $_{j\,(}$a, b) for all criteria is mathematically defined as follows:

$$\pi(a,b) = \sum_{j=1}^n w_j^k \; P_j(a,b) \tag{5.11}$$

The net preference flows which are used in the measurement of the performance of each maintenance strategy alternative are then computed. The net flow ϕ is the difference between the positive flow $\emptyset^+$ and the negative flow $\emptyset^-$, evaluated as follows:

$$\emptyset^+(a) = \frac{1}{n-1}\sum_{b \ne a} \pi\,(a,b) \tag{5.12}$$

$$\emptyset^-(a) = \frac{1}{n-1}\sum_{b \ne a} \pi\,(b,a) \tag{5.13}$$

$$\phi(a) = \emptyset^+(a) - \emptyset^-(a) \tag{5.14}$$

The maintenance alternatives are ranked on the basis of the net flow and the higher the value the better the alternative. Having obtained the input information from experts, rather than manually solving the multi-criteria decision problem by applying Eq. 5.8 to 5.14, Visual PROMETHEE, developed by Bertrand Mareschal (VPSolution, 2013) was used in processing the information and in ranking the maintenance alternatives.

5.3.4 TOPSIS method

The TOPSIS methodological steps for choosing an alternative from multiple options have been previously discussed in Chapter 3 Section 3.3.2.2. Although in Chapter 3 it was applied in prioritising risk of failure modes of a marine diesel engine, in this current chapter TOPSIS will be used in the ranking (prioritising) of maintenance strategy alternatives such that the optimum maintenance strategy will be adopted for the system or component under investigation.

5.4 Case study of the marine diesel engine

The prioritisation of risk of failure modes of the marine diesel engine had been carried out in Chapters 3 and 4. From the study, one of the equipment items/components with the greatest failure consequence on the marine diesel engine was found to be the water cooling pump of the central cooling system. The water cooling pump was chosen to demonstrate the applicability of the proposed methodology in the selection of a maintenance strategy.

5.4.1 Delphi evaluation

A panel of ten experts was carefully selected, 5 from academia with 5 to 12 years previous work experience in the shipping industry and 5 from the shipping industry ranging from 2nd Engineer to Chief Engineer. A thorough literature survey was conducted on relevant maintenance strategy selection problems and 22 criteria were initially selected. The 22 criteria were further subjected to two rounds of Delphi survey in order to critically select the most relevant evaluation criteria for selection of the maintenance strategy for maritime applications. The mean of the consensus measurement indices and CVR of all 10 experts' opinions were evaluated in both first and second round Delphi surveys for each of the maintenance strategy selection criteria and their corresponding rankings are presented in Table 5.3 and 5.4. The Delphi iteration process was terminated at the second round because there was no significant difference between results of the first and second rounds.

In Table 5.4, the criteria with the ranking highlighted in pink had mean values below 2.7 and CVR below 0.29. These criteria were removed and the remaining items retained. Some other items were further removed because of their overlapping function with other criteria. The remaining criteria were then re-categorised into main and sub-criteria. For example spare parts inventories cost, minimisation of loss, maintenance cost, crew training cost and plant damage are sub criteria under the main criterion cost.

Table 5.3: Result of first round Delphi survey

S/N	Maintenance strategy selection criteria and description	Mean	CVR
1	Minimisation of operation loss	2.9	0.8
2	Maintenance efficiency	2.9	0.8
3	Spare parts inventories	2.8	0.6
4	Equipment risk level	2.9	0.8
5	Planning flexibility	2.4	-0.2
6	Improved Safety	3	1
7	System reliability	2.9	0.8
8	Compatibility	2.7	0.4
9	Technical expertise requirement	2.9	0.8
10	Acceptance by labour	1.9	-0.8
11	Fault identification	2.9	0.8
12	Availability	2.6	0.2
13	Manufacturer recommendation	2.5	0.2
14	Environmental requirement	2.9	0.8
15	Available monetary resources	2.7	0.4
16	Image damage	2.2	-0.4
17	Plant damage	2.9	0.8
18	Assurance cost	2.4	-0.2
19	Enhanced competitiveness	2.9	0.8
20	System failure characteristics	2.7	0.4
21	Maintenance cost	2.9	0.8
22	Crew training cost	2.7	0.4

Table 5.4: Result of second round Delphi survey questionnaire

S/N	Maintenance strategy selection criteria	Measurement index		Rank	
		Mean	CVR	Mean	CVR
1	Minimisation of operation loss	3.000	1.000	1	1
2	Maintenance efficiency	2.700	0.400	11	11
3	Spare parts inventories	2.800	0.600	6	6
4	Equipment risk level	2.800	0.600	6	6
5	Planning flexibility	2.400	0.000	19	17
6	Improved Safety	3.000	1.000	1	1
7	System reliability	2.800	0.600	6	6
8	Compatibility (Applicability)	2.700	0.400	11	11
9	Technical expertise requirement	2.600	0.400	16	11
10	Acceptance by labour	1.800	-1.000	22	22
11	Fault identification	2.800	0.600	6	6
12	Availability	2.500	0.000	17	17
13	Manufacturer recommendation	2.500	0.000	17	17
14	Environmental requirement	2.900	0.800	3	3
15	Available monetary resources	2.700	0.400	11	11
16	Image damage	2.100	-0.400	20	20
17	Plant damage	2.800	0.600	6	6
18	Assurance cost	2.100	-0.800	20	21
19	Enhanced competitiveness	2.900	0.800	3	3
20	System failure characteristics	2.700	0.400	11	11
21	Maintenance cost	2.900	0.800	3	3
22	Crew training cost	2.700	0.400	11	11

Having defined the decision criteria against which the maintenance strategies will be ranked, the next step is to apply the ranking tools, AHP, PROMETHEE and TOPSIS in evaluating the optimum maintenance strategy. Firstly the case studies that are presented use a single expert information for analysis of the three ranking tools in reaching an optimum solution and then the use of three experts' (group decision making) information in reaching an optimum solution is presented.

5.4.2 AHP analysis using information from a single expert

The maintenance strategy selection criteria categorised into main and sub-criteria were used to form a four level AHP hierarchy decision problem as shown in Figure 5.2. With the first, second, third and fourth levels representing overall goal (Decision problem), main criteria, sub-criteria and the alternative maintenance strategy to be selected with respect to the main and sub criteria, respectively.

To evaluate the problem in figure 5.2, a structured AHP questionnaire was developed and sent to an expert selected from the Delphi survey team to perform the pairwise comparison judgement using the Saaty scale in Table 5.1 firstly for the main criteria with respect to the overall goal, next for the sub-criteria with respect to the main criteria and overall goal and lastly for the maintenance alternatives with respect to the sub-criteria. The comparison matrix developed from the expert's judgement for main criteria is presented in Table 5.5. Samples of the comparison matrices formed from the expert's judgement for the sub-criteria and maintenance alternatives are shown in Tables 5.6 and 5.7. The complete comparison matrices are presented in Appendix B3.1. It is worth noting that in this research, the consistency of this expert's judgement in all scenarios measured using the consistency ratio, I_r , was in the range of 0.00 to 0.084 which is within the acceptable value of less than 0.1.

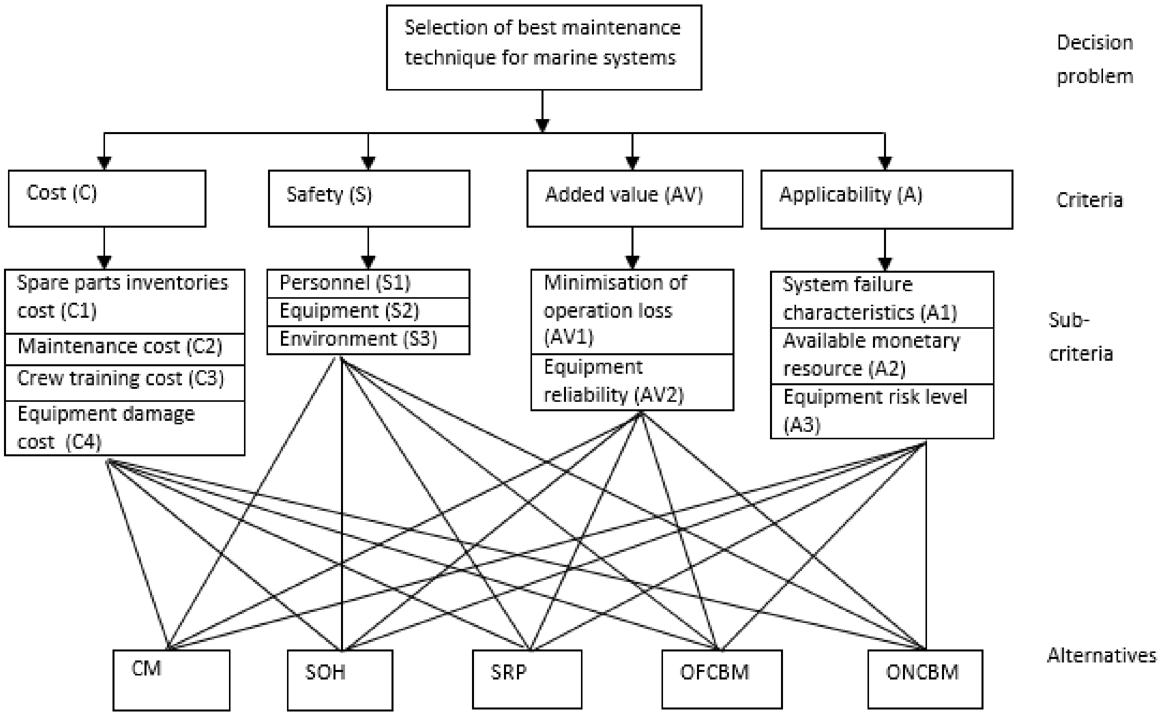


Figure 5.2: AHP hierarchy of multi-criteria decision maintenance strategy selection problem

CM-Corrective maintenance, SOH-Scheduled overhaul, SRP-Scheduled replacement, OFCBM-Offline condition based maintenance, ONCBM-Online condition based maintenance

Next the local weight of the main criteria was evaluated based on Table 5.5 using Eq. 5.3 – 5.7 and the results are presented in Table 5.8. This was followed by applying Eq. 5.3 –5.7 to Table 5.6 (a sample) to obtain local weight of sub-criteria and the result is shown in Table 5.8. The global weight of the criteria was generated by aggregating the local weight of the main criteria and local weight of the sub-criteria and the results are also presented in Table 5.8. Finally the overall score of the maintenance alternatives was obtained by using steps 6 and 7 of Section 5.4.2 and the results are presented in Table 5.9.

Table 5.5: Main criteria comparison matrix with respect to overall goal

	C	S	AV	A
C	1	1/7	1/3	1/3
S	7	1	3	3
AV	3	1/3	1	1
A	3	1/3	1	1

Table 5.6: Sub-criteria comparison matrix with respect to main criterion (cost)

	C1	C2	C3	C4
C1	1	1/3	3	1/5
C2	3	1	3	1/3
C3	1/3	1/3	1	1/7
C4	5	3	7	1

Table 5.7: maintenance alternatives comparison matrix with respect to sub-criterion (spare parts inventories cost)

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1/3	1/3	1/7	1/7
SOH	3	1	1	1/3	1/3
SRP	3	1	1	1/3	1/3
OFCBM	7	3	3	1	1
ONCBM	7	3	3	1	1

Table 5.8: Local and aggregated (global) weight of criteria

Main criteria	Local weight	Sub-criteria	Local weight	Global weight
Cost (C)	0.0690	Spare parts inventories cost(C1)	0.1240	0.0086
		Maintenance cost (C2)	0.2410	0.0166
		Crew training cost (C3)	0.0650	0.0045
		Equipment damage cost (C4)	0.5700	0.0393
Safety (S)	0.5400	Personnel (S1)	0.6000	0.3240
		Equipment (S2)	0.2000	0.1080
		Environment (S3)	0.2000	0.1080
Added value (AV)	0.1930	Minimisation of operation loss (AV1)	0.5000	0.0965
		Equipment reliability (AV2)	0.5000	0.0965
Applicability (A)	0.1930	System failure characteristics (A1)	0.3330	0.0643
		Available monetary resource (A2)	0.3330	0.0643
		Equipment risk level (A3)	0.3330	0.0643

Table 5.9: Maintenance strategies overall score

	CM	SOH	SRP	OFCBM	ONCBM	criteria weight
C1	0.0460	0.1240	0.1240	0.3530	0.3530	0.0086
C2	0.0440	0.1170	0.1170	0.4430	0.2780	0.0166
C3	0.2810	0.2810	0.2810	0.1070	0.0510	0.0045
C4	0.0980	0.1080	0.1080	0.3240	0.3630	0.0393
S1	0.0980	0.1080	0.1080	0.3240	0.3630	0.3240
S2	0.0640	0.1330	0.1330	0.3230	0.3480	0.1080
S3	0.0630	0.1280	0.1190	0.3560	0.3350	0.1080
AV1	0.0540	0.1240	0.1150	0.3760	0.3310	0.0965
AV2	0.0550	0.1290	0.1290	0.3430	0.3430	0.0965
A1	0.2000	0.2000	0.2000	0.2000	0.2000	0.0643
A2	0.2310	0.2310	0.2310	0.2310	0.0770	0.0643
A3	0.0550	0.1290	0.1290	0.3430	0.3430	0.0643
Global score	**0.0935**	**0.1321**	**0.1303**	**0.3210**	**0.3184**	
Rank	5	3	4	1	2	

Comparing the overall scores of the five alternative maintenance strategies in Table 5.9, offline condition based maintenance (OFCBM) with the highest performance index of 0.3210 was the preferred alternative, followed by online condition based maintenance (ONCBM) with a weight of 0.3184 and the least preferred was corrective maintenance (CM) with a priority value of 0.0935. The preferred choice of offline condition based maintenance to online condition based maintenance is probably due to the fact that it is effective and yet is a much cheaper means of monitoring the condition of an asset than the online technique. From this analysis, as it can be seen in Table 5.8, safety criteria have the greatest influence in the selection of the maintenance strategies for the cooling water pump of a marine diesel engine with a weight of 54% when compared to other main criteria such as cost, added value and applicability with weights of 6.9, 19.3 and 19.3% respectively.

5.4.3 TOPSIS and PROMETHEE 2 analysis using a single expert information

For the AHP technique, information was obtained from an expert through a pairwise comparison method in which alternatives were compared in pairs to ascertain which one is more important using the Saaty scale for each criterion. However for the other MCDM techniques such as PROMETHEE and TOPSIS, a 5 point Likert scale was applied in this study in obtaining information from the expert. In order to have an unbiased comparison of

TOPSIS and PROMETHEE with APH that uses the pairwise comparison method, the same expert was used in obtaining information for the three methods. The values assigned by the expert for the five maintenance alternatives with respect to 12 decision criteria using a 5 point Likert scale are shown in Table 5.10.

Table 5.10: Single expert judgement of maintenance alternatives

Criteria	CM	SOH	SRP	OFCBM	ONCBM
C1	1	3	3	5	5
C2	2	3	3	4	2
C3	5	4	3	4	2
C4	1	3	3	5	5
S1	1	3	4	5	5
S2	1	4	3	5	5
S3	1	2	3	5	3
AV1	1	3	3	5	5
AV2	1	2	3	5	5
A1	1	3	2	4	4
A2	4	3	3	5	2
A3	1	4	3	5	4

5.4.3.1 PROMETHEE Analysis using information from a single expert

One of the reasons PROMETHEE is very popular is the availability of software in carrying out the analysis. In this case the 'PROMETHEE software' refers to Visual PROMETHEE which was used in evaluating information obtained from the expert as given in Table 5.10 and the criteria weights generated from the AHP analysis in Table 5.8; the purpose being to determine the optimum maintenance alternative for the water cooling pump.

The decision matrix in Table 5.10 and the decision criteria weights obtained in the AHP analysis were used to populate the PROMETHEE software to obtained the performance index based on which the ranking of the five maintenance alternatives; CM, SOH, SRP, OFCBM and ONCBM was performed. Prior to the PROMETHEE analysis of the data in Table 5.10 a preference function for each criterion was defined. In this study the 'usual' preference function was chosen for each criterion because it is ideally suited for a qualitative scale with a low number of levels such as the 5 point Likert scale (VPSolution, 2013). In the usual preference function, actual values are not important in determining preference of one alternative to another and what is important is the order: best to worst. This characteristic actually makes it ideal for ordinal scale data in contrast to the other preference functions that turn the difference between two alternatives into a real value i.e. from 0 and 1 (De Keyser and Peeters, 1996). After defining the preference function for each criterion, the performance index net flow which is the difference between the positive flow and the negative flow is then evaluated with Visual PROMETHEE. The results of the net flow, ϕ, together with the positive flow, $\emptyset^{+}$, and negative flow, $\emptyset^{-}$, for the five maintenance alternatives are presented in Table 5.11.

Table 5.11: PROMETHEE flow

Maintenance alternatives	$\emptyset^{+}$	$\emptyset^{-}$	ϕ	Rank
CM	0.0530	0.9428	-0.8898	5
SOH	0.3148	0.6113	-0.2966	4
SRP	0.3870	0.5293	-0.1423	3
OFCBM	0.8125	0.0011	0.8114	1
ONCBM	0.6423	0.1250	0.5174	2

The alternative with the highest value of net flow ϕ is considered to be the best alternative while the alternative with the lowest value of net flow is the worst solution. From Table 5.11, OFCBM with the highest value of net flow is the best alternative, followed by ONCBM and the worst alternative is CM. The values of net flow obtained in this case were based on the selection of the preference function referred to as ‘usual criterion’, these values would not be the same if other preference functions were selected for the evaluation. Therefore obtaining a reliable and efficient result using the PROMETHEE technique depends greatly on the maintenance practitioner’s ability to identify the appropriate preference function for each criterion. This creates an additional burden on the maintenance practitioner. Another factor that greatly impacts on the ranking is the weight of the criteria.

Sensitivity Analysis:

In order to test the robustness of the technique, a sensitivity analysis was carried out by changing the weight of different criteria to see the resulting effect with respect to the ranking order of the five maintenance alternatives. The results which are shown in Table 5.12 reveal the lower and upper limit a decision criterion weight can vary between without changing the order of ranking of the five maintenance alternatives. From the result it can be seen that the changes in weight of criteria C2, C3, S2, A1, A2 and A3 beyond 40.75%, 17.44%, 31.88%, 28.52% 47.77% and 22.42% respectively will lead to alteration in the ranking of the five maintenance alternatives while for the other criteria, changes in their weights will not lead to changes in the ranking order. In essence criteria C3 has the greatest impact on the ranking followed by A3. This sensitivity analysis has demonstrated the robustness of the PROMETHEE technique in the prioritisation of the maintenance strategy alternatives.

Table 5.12: Stability interval

Criteria	Weight	Interval	
		Min	Max
Spare parts inventories cost(C1)	0.0086	0.00%	100.0%
Maintenance cost (C2)	0.0166	0.00%	40.75%
Crew training cost (C3)	0.0045	0.00%	17.44%
Equipment damage cost (C4)	0.0393	0.00%	100.0%
Personnel safety (S1)	0.3240	2.47%	100.0%
Equipment safety(S2)	0.1080	0.00%	31.88%
Environment safety(S3)	0.1080	0.00%	100.0%
Minimisation of operation loss (AV1)	0.0965	0.00%	100.0%
Equipment reliability (AV2)	0.0965	0.00%	100.0%
System failure characteristics (A1)	0.0643	0.00%	28.52%
Available monetary resource (A2)	0.0643	0.00%	47.77%
Equipment risk level (A3)	0.0643	0.00%	22.42%

5.4.3.2 TOPSIS Analysis using single expert information

In the application of TOPSIS to the water cooling pump of a marine diesel engine, the decision matrix in Table 5.10 was normalised using Eq. (3.6) and the result is presented in Table 5.13. The normalised matrix was then multiplied by the criteria weights in Table 5.8 to obtain a weighted normalised matrix also shown in Table 5.13. Eq. (3.10) and (3.11) were then utilised to determine the positive ideal and negative ideal solutions respectively as presented in Table 5.14. Finally, applying Eq. (3.12) – (3.14) the distance of each maintenance strategy alternative to the positive-ideal solution D_i^+ and to the negative-ideal solution D_i^- together with relative closeness RC_i of each failure mode to the ideal solution were calculated and the results of RC_i together with their rankings are shown in Table 5.15.

Table 5.13: Normalised decision matrix and weighted normalised decision matrix

	Normalised decision matrix					Weighted normalised decision matrix				
Criteria	CM	SOH	SRP	OFCBM	ONCBM	CM	SOH	SRP	OFCBM	ONCBM
C1	0.1204	0.3612	0.3612	0.6019	0.6019	0.0010	0.0031	0.0031	0.0052	0.0052
C2	0.3086	0.4629	0.4629	0.6172	0.3086	0.0051	0.0077	0.0077	0.0102	0.0051
C3	0.5976	0.4781	0.3586	0.4781	0.2390	0.0027	0.0022	0.0016	0.0022	0.0011
C4	0.1204	0.3612	0.3612	0.6019	0.6019	0.0047	0.0142	0.0142	0.0237	0.0237
S1	0.1147	0.3441	0.4588	0.5735	0.5735	0.0372	0.1115	0.1487	0.1858	0.1858
S2	0.1147	0.4588	0.3441	0.5735	0.5735	0.0124	0.0496	0.0372	0.0619	0.0619
S3	0.1443	0.2887	0.4330	0.7217	0.4330	0.0156	0.0312	0.0468	0.0779	0.0468
AV1	0.1204	0.3612	0.3612	0.6019	0.6019	0.0116	0.0349	0.0349	0.0581	0.0581
AV2	0.1250	0.2500	0.3750	0.6250	0.6250	0.0121	0.0241	0.0362	0.0603	0.0603
A1	0.1474	0.4423	0.2949	0.5898	0.5898	0.0095	0.0284	0.0190	0.0379	0.0379
A2	0.5040	0.3780	0.3780	0.6299	0.2520	0.0324	0.0243	0.0243	0.0405	0.0162
A3	0.1222	0.4887	0.3665	0.6108	0.4887	0.0079	0.0314	0.0236	0.0393	0.0314

Table 5.14: Positive and negative idea solution

Criteria	Positive ideal	Negative ideal
C1	0.0052	0.0010
C2	0.0102	0.0051
C3	0.0027	0.0011
C4	0.0237	0.0047
S1	0.1858	0.0372
S2	0.0619	0.0124
S3	0.0779	0.0156
AV1	0.0581	0.0116
AV2	0.0603	0.0121
A1	0.0379	0.0095
A2	0.0405	0.0162
A3	0.0393	0.0079

Table 5.15: Performance index (RC) and rank

Maintenance alternatives	d+	d-	RC	Rank
CM	0.1876	0.0295	0.1357	5
SOH	0.1011	0.0929	0.4788	4
SRP	0.0711	0.1252	0.6376	3
OFCBM	0.0005	0.1892	0.9972	1
ONCBM	0.0407	0.1768	0.8131	2

From Table 5.15 it is obvious that the optimum maintenance alternative is the OFCBM since it occupies the first position and it has performance index of 0.9972 which is closest to the ideal solution. This is followed by ONCBM and the least preferred maintenance strategy is CM having the lowest performance index of 0.1357 and being in the fifth position.

5.4.4 Comparison of methods

The comparison of the rankings obtained from the three MCDM methods are presented in Table 5.16. From the table, OFCBM appears in first position for all the ranking models and as such is the optimum solution for all of the techniques. Also from the table, last position is occupied by CM for the three ranking models; AHP, PROMETHEE and TOPSIS. The Spearman rank correlation coefficients between the three MCDM techniques are presented in table 5.17.

Table 5.16: Comparison of rankings from methods

Maintenance alternatives	AHP	PROMETHEE	TOPSIS
CM	5	5	5
SOH	3	4	4
SRP	4	3	3
OFCBM	1	1	1
ONCBM	2	2	2

Table 5.17: Spearman's rank correlation between methods

Method	AHP	PROMETHEE	TOPSIS
AHP	-	0.937	0.937
PROMETHEE		-	1
TOPSIS			-

From Table 5.17 the Spearman rank correlation coefficient between PROMETHEE and TOPSIS is 1, between AHP and PROMETHEE is 0.937 and between PROMETHEE and TOPSIS is 0.937. The perfect and near perfect correlation between the three methods shows that the three techniques can be used singly or in combination with one another for the purpose of prioritising maintenance strategy alternatives. This has also validated the applicability of the different MCDM techniques proposed for the selection of the maintenance strategy for the components of marine machinery systems from numerous alternatives.

5.4.5 Group decision making

The case considered above is a situation whereby a single expert is involved in the decision making process. However in many practical situations multiple experts or a group of experts are involved in the decision making process thereby bringing a great deal of complexity into the use of MCDM methods (Raju et al., 2000). Different aggregation methods are available for combining experts' preferences in group decision making. Either rank or score aggregation can be used. In this research the score aggregation technique was chosen because rank aggregation may lead to rank reversal. In aggregating the scores of individual experts a simple arithmetic mean can be applied. The average of the individual experts AHP scores, PROMETHEE and TOPSIS scores for each maintenance alternative are referred to here as group scores. On the basis of the group score, maintenance strategy alternatives were ranked and the highest ranked chosen as the optimum solution.

As previously stated, for AHP the input information is obtained from experts' comparison judgement which is then used in forming comparison matrices. Three of the original ten experts used for the Delphi analysis were used in this group decision making process, the scores obtained for the single expert case studied above will be referred to as expert 1 scores while the expert 2 and 3 scores for the five alternative maintenance strategies were determined based on comparison judgement obtained from experts 2 and 3. The comparison judgements obtained from experts 2 and 3 are presented in Appendix B3.2 and B3.3 respectively.

However PROMETHEE and TOPSIS, require the use of an ordinal scale in the rating of maintenance alternatives against decision criteria. The rating was carried out by the same experts that performed the comparison judgement to ensure unbiased comparison between AHP, TOPSIS and PROMETHEE. The rating obtained from expert 1 was presented in Table 5.10 while the ratings obtained from experts 2 and 3 are presented in Table 5.18. Since AHP, TOPSIS and PROMETHEE had already been applied to the data from expert 1 in Sections 5.4.2 and 5.4.3, only evaluation for experts 2 and 3 will be shown subsequently.

Table 5.18: Experts 2 and 3 judgement of five maintenance alternative

Criteria	Rating of maintenance alternatives									
	Expert 2					Expert 3				
	CM	SOH	SRP	OFCBM	ONCBM	CM	SOH	SRP	OFCBM	ONCBM
C1	2	3	2	4	4	1	2	1	5	4
C2	5	4	3	4	3	2	2	1	5	3
C3	4	3	4	5	3	5	3	1	2	1
C4	1	2	4	5	5	1	4	4	5	5
S1	1	3	2	5	5	1	4	3	5	5
S2	1	3	3	5	5	1	4	3	5	5
S3	2	3	3	5	5	5	2	2	4	2
AV1	2	3	3	4	5	1	4	2	5	5
AV2	2	4	3	5	4	1	4	2	5	5
A1	3	4	2	5	2	1	3	4	4	3
A2	5	3	1	4	1	3	3	1	5	3
A3	2	3	3	5	3	1	3	2	5	5

5.4.5.1 Evaluation of AHP group maintenance strategy alternatives

AHP analysis using expert 2 comparison judgement

The pairwise comparison judgements obtained from expert 2 were firstly used in producing decision matrices which are presented in Appendix B3.2. The comparison matrices were then subjected to AHP analysis to obtain the weightings of the main criteria together with the weightings of sub-criteria and the global weight of sub-criteria. The results are presented in Table 5.19. Finally, overall alternative maintenance strategy scores were obtained as a product of the global weight of sub-criteria and the weight of maintenance alternatives with respect to the decision criteria and the results are shown in Table 5.20.

Table 5.19: Local and aggregated (global) weight of criteria for expert 2

Main criteria	Local weight	Sub criteria	Local weight	Global weight
Cost (C)	0.1180	Spare parts inventories cost(C1)	0.0600	0.0071
		Maintenance cost (C2)	0.3960	0.0467
		Crew training cost (C3)	0.3960	0.0467
		Equipment damage cost (C4)	0.1470	0.0173
Safety (S)	0.4870	Personnel (S1)	0.6000	0.2922
		Equipment (S2)	0.2000	0.0974
		Environment (S3)	0.2000	0.0974
Added value (AV)	0.2760	Minimisation of operation loss (AV1)	0.5000	0.1380
		Equipment reliability (AV2)	0.5000	0.1380
Applicability (A)	0.1180	System failure characteristics (A1)	0.2000	0.0236
		Available monetary resource (A2)	0.6000	0.0708
		Equipment risk level (A3)	0.2000	0.0236

Table 5.20: Maintenance strategies overall score

	CM	SOH	SRP	OFCBM	ONCBM	criteria weight
C1	0.0560	0.1680	0.1680	0.3690	0.2380	0.0071
C2	0.0540	0.1590	0.1490	0.4060	0.2320	0.0467
C3	0.2810	0.2810	0.2810	0.1070	0.0510	0.0467
C4	0.0530	0.1670	0.1190	0.3400	0.3210	0.0173
S1	0.0540	0.1630	0.1180	0.2790	0.3870	0.2922
S2	0.0640	0.1330	0.1330	0.3230	0.3480	0.0974
S3	0.0550	0.1540	0.1420	0.4740	0.1750	0.0974
AV1	0.0540	0.1240	0.1150	0.3310	0.3760	0.1380
AV2	0.0840	0.1320	0.0760	0.3400	0.3690	0.1380
A1	0.1750	0.1750	0.2210	0.3550	0.0740	0.0236
A2	0.1750	0.1750	0.2210	0.3550	0.0740	0.0708
A3	0.0550	0.1290	0.1290	0.3430	0.3430	0.0236
Global score	**0.0812**	**0.1551**	**0.1349**	**0.3258**	**0.3024**	
Rank	5	3	4	1	2	

AHP analysis using expert 3 comparison judgement

Having obtained maintenance alternatives' overall scores from experts' 1 and 2 pairwise comparison judgement, the same AHP procedure was followed in evaluating the overall maintenance alternative scores for expert 3. Firstly the pairwise comparison judgements obtained from expert 3 were converted to comparison matrices which are presented in Appendix B3.3. Applying AHP evaluation techniques to the expert 3 pairwise comparison matrices, the weight of the main criteria together with weight of sub-criteria, the global weight of sub-criteria were evaluated and overall maintenance alternative scores obtained. The results of the weight of the main criteria together with weight of sub-criteria and the global weight of sub-criteria are presented in Table 5.21 while the results of the of the overall maintenance alternative scores are presented in Table 5.22.

Table 5.21: Local and aggregated (global) weight of criteria for expert 3

Main criteria	Local weight	Sub-criteria	Local weight	Global weight
Cost (C)	0.0410	Spare parts inventories cost(C1)	0.5560	0.0228
		Maintenance cost (C2)	0.1840	0.0075
		Crew training cost (C3)	0.2020	0.0083
		Equipment damage cost (C4)	0.0580	0.0024
Safety (S)	0.5880	Personnel (S1)	0.7850	0.4616
		Equipment (S2)	0.1490	0.0876
		Environment (S3)	0.0660	0.0388
Added value (AV)	0.0710	Minimisation of operation loss (AV1)	0.5000	0.0355
		Equipment reliability (AV2)	0.5000	0.0355
Applicability (A)	0.3100	System failure characteristics (A1)	0.0880	0.0273
		Available monetary resource (A2)	0.2430	0.0753
		Equipment risk level (A3)	0.6690	0.2074

Table 5.22: Maintenance strategies overall score

	CM	SOH	SRP	OFCBM	ONCBM	criteria weight
C1	0.0540	0.1150	0.1240	0.3760	0.3310	0.0228
C2	0.0520	0.1080	0.1200	0.4600	0.2600	0.0075
C3	0.3420	0.1140	0.1830	0.2710	0.0900	0.0083
C4	0.0810	0.1500	0.3700	0.4800	0.3510	0.0024
S1	0.0500	0.1260	0.1260	0.3390	0.3590	0.4616
S2	0.0640	0.1330	0.1330	0.3230	0.2480	0.0876
S3	0.0810	0.1500	0.3700	0.3510	0.0480	0.0388
AV1	0.0540	0.1240	0.1150	0.3310	0.3760	0.0355
AV2	0.0530	0.1020	0.1210	0.3620	0.3620	0.0355
A1	0.0200	0.0200	0.0200	0.0200	0.0200	0.0273
A2	0.3420	0.0900	0.1140	0.2710	0.1830	0.0753
A3	0.0450	0.1010	0.1910	0.4550	0.2080	0.2074
Global score	**0.0759**	**0.1167**	**0.1474**	**0.3537**	**0.2841**	
Rank	5	4	3	2	1	

As previously stated, to obtain the group overall rating of maintenance strategy alternatives the individual experts ratings were averaged, as shown in Table 5.23. From the result, it is again obvious that the preferred maintenance strategy alternative is OFCBM, having the highest group overall score of 0.3335. This is followed by ONCBM and the least preferred option is CM having the lowest group overall score of 0.0835. There is no difference between the group rating and the individual expert rating since the same ranking order was obtained. This is as a result of the similarity in the comparison judgement of the five maintenance alternatives against decision criteria obtained from the three experts.

Table 5.23: Group decision making AHP score and ranks

Maintenance alternatives	Expert 1 AHP overall score	Expert 2 AHP overall score	Expert 3 AHP overall score	Group overall scores	Group Ranking
CM	0.0935	0.0812	0.0759	0.0835	5
SOH	0.1321	0.1551	0.1167	0.1346	3
SRP	0. 1303	0.1349	0.1474	0.0941	4
OFCBM	0.3210	0.3258	0.3537	0.3335	1
ONCBM	0.3184	0.3024	0.2841	0.3016	2

5.4.5.2 Evaluation of the PROMETHEE group maintenance strategy alternatives

The decision matrix formed from expert 1's rating of maintenance strategies against decision criteria was firstly subjected to PROMETHEE analysis to obtain the expert 1 PROMETHEE overall score for the maintenance alternatives upon which the maintenance alternatives were ranked. This was carried out in section 5.4.3.1. This was then followed by subjecting data from experts 2 and 3 to PROMETHEE analysis to obtain expert 2 and 3 overall scores (ϕ values) of maintenance strategy alternatives. To obtain the group overall scores for maintenance alternatives, the individual experts' scores were averaged.

PROMETHEE analysis using expert 2 judgement

The expert 2 decision matrix in Table 5.18 and the criteria weights evaluated from the expert 2 AHP analysis of comparison judgement in Table 5.19 were used as input data for the PROMETHEE software to obtain overall scores (ϕ values) of maintenance strategy alternatives. The maintenance strategy alternatives were ranked based on the ϕ values.

As with the analysis for expert 1, the preference function was the "usual" type. The overall scores of maintenance alternatives were then determined using the PROMETHEE software and the result obtained is displayed in Table 5.24.

Table 5.24: PROMETHEE flow for expert 2

Maintenance alternatives	$\emptyset^{+}$	$\emptyset^{-}$	ϕ	Rank
CM	0.1528	0.8337	-0.6809	5
SOH	0.3890	0.4580	-0.0690	4
SRP	0.2289	0.6272	-0.3983	3
OFCBM	0.7964	0.0640	0.7324	1
ONCBM	0.5972	0.1815	0.4157	2

From Table 5.24, the offline condition based maintenance (ONCBM) with the highest value of net flow, ϕ, was the best ranked maintenance alternative while the worst rank was corrective maintenance CM.

Sensitivity Analysis:

A sensitivity analysis was again carried out to test the robustness of the PROMETHEE technique. The results are presented in Table 5.25. From the table, changes in criteria weights

C2, C3, C4, AV1, A1 and A2 beyond a certain level (17.93%, 28.29%, 40.75%, 47.24%, 29.08 and 20.01% respectively) resulted in changes in the ranking order of the five maintenance alternatives. For the other criteria irrespective of the changes in the weights of the criteria, the ranking order remained unchanged. It is obvious that the criteria that cause alteration in the order of ranking have the greatest influence on the ranking of maintenance alternatives.

Table 5.25: Stability intervals for expert 2

Criteria	Weight	Interval	
		Min	Max
spare parts inventories cost(C1)	0.0071	0.00%	100.0%
Maintenance cost (C2)	0.0467	0.00%	17.93%
Crew training cost (C3)	0.0467	0.00%	28.29%
Equipment damage cost (C4)	0.0173	0.00%	40.75%
Personnel safety (S1)	0.2922	0.00%	100.0%
Equipment safety (S2)	0.0974	0.00%	100.0%
Environment safety (S3)	0.0974	0.00%	100.0%
Minimisation of operation loss (AV1)	0.1380	0.00%	47.24%
Equipment reliability (AV2)	0.1380	0.00%	100.0%
System failure characteristics (A1)	0.0236	0.00%	29.08%
Available monetary resource (A2)	0.0708	0.00%	20.01%
Equipment risk level (A3)	0.0236	0.00%	100.0%

PROMETHEE analysis using expert 3 judgement

The expert 3 decision matrix in Table 5.18 and the criteria weights evaluated from the expert 3 AHP analysis of comparison judgements in Table 5.21 were used as input data in the PROMETHEE analysis to obtained overall scores (ϕ values) of maintenance strategy alternatives and the maintenance strategy alternatives were ranked based on the ϕ values. The preference function type 1 was again chosen as in the cases of experts 1 and 2. The overall scores (ϕ values) of the maintenance strategy alternatives were then determined and the five maintenance strategy alternatives ranked. The results obtained are shown in Table 5.26.

Table 5.26: PROMETHEE flow for expert 3

Maintenance alternatives	$\emptyset^+$	$\emptyset^-$	ϕ	Rank
CM	0.0671	0.8881	-0.8210	5
SOH	0.4550	0.4793	-0.0243	3
SRP	0.2257	0.7400	-0.5143	4
OFCBM	0.7741	0.0137	0.7604	1
ONCBM	0.6642	0.0650	0.5992	2

Sensitivity Analysis:

A sensitivity analysis was again carried out and the results are presented in Table 5.27.

Table 5.27: Stability interval for expert 3

Criteria	Weight	Interval	
		Min	Max
spare parts inventories cost(C1)	0.0228	0.00%	100.0%
Maintenance cost (C2)	0.0075	0.00%	29.55%
Crew training cost (C3)	0.0083	0.00%	15.61%
Equipment damage cost (C4)	0.0024	0.00%	100.0%
Personnel safety (S1)	0.4616	0.00%	100.0%
Equipment safety (S2)	0.0876	0.00%	100.0%
Environment safety(S3)	0.0388	0.00%	20.16%
Minimisation of operation loss (AV1)	0.0355	0.00%	100.0%
Equipment reliability (AV2)	0.0355	0.00%	100.0%
System failure characteristics (A1)	0.0273	0.00%	34.70%
Available monetary resource (A2)	0.0753	0.00%	29.17%
Equipment risk level (A3)	0.2074	0.00%	100.0%

From the results in Table 5.27, if criteria C2, C3, S3, A1 and A2 weights are increased by up to 29.55%, 15.61%, 20.16%, 34.70%, and 29.17% respectively, the order of ranking of maintenance alternatives in Table 5.26 will remain unchanged. However if these limits are exceeded the ranking order will be altered while for the other criteria, irrespective of the weight increase, the ranking order will remain unaltered.

To obtain the group overall scores of maintenance strategy alternatives, the individual experts overall scores were averaged, as shown in Table 5.28. From the result it is again obvious that the preferred maintenance strategy alternative is OFCBM, having the highest group overall score of 0.7681. This is followed by ONCBM and the least preferred choice is CM having the lowest group overall score of -0.7972.

Table 5.28: Multiple experts decision making score and rank

Maintenance alternatives	Expert 1 PROMETHEE overall score	Expert 2 PROMETHEE overall score	Expert 3 PROMETHEE overall score	Group overall score	Group Ranking
CM	-0.8898	-0.6809	-0.8210	-0.7972	5
SOH	-0.2966	-0.069	-0.0243	-0.1300	3
SRP	-0.1423	-0.3983	-0.5143	-0.3516	4
OFCBM	0.8114	0.7324	0.7604	0.7681	1
ONCBM	0.5174	0.4157	0.5992	0.5108	2

5.4.5.3 Evaluation of the TOPSIS group maintenance strategy alternatives

TOPSIS was also applied to the maintenance strategy selection using data from the three experts. The expert 1 overall scores (RC_i values) for each of the maintenance strategy alternatives were evaluated in Section 5.4.3.2. The expert 2 and 3 overall scores for each of the maintenance strategy alternatives are evaluated next. The average of the three experts maintenance strategy alternatives scores were then used to obtain the group overall scores of maintenance strategy alternatives.

TOPSIS Analysis using expert 2 judgement

TOPSIS analysis was applied to the expert 2 decision matrix given in Table 5.18. The expert 2 decision matrix in Table 5.18 was first normalised using Eq. (3.6) and then multiplied by the criteria weights in Table 5.19 to obtain a weighted normalised matrix. Both the normalised decision matrix and the weighted normalised decision matrix are shown in Table 5.29. Eq. (3.10) and (3.11) were then utilised to determine the positive ideal and negative ideal solutions respectively as presented in Table 5.30. Finally, applying Eq. (3.12) – (3.14), the distance of each maintenance strategy alternative to the positive-ideal solution D_i^+ and the negative-ideal solution D_i^- together with relative closeness RC_i of alternative maintenance strategy to the ideal solution were calculated and the results are shown in Table 5.31. Based on the relative closeness RC_i of each alternative maintenance strategy to the ideal solution, the maintenance strategy alternatives were ranked as also shown in Table 5.31.

Table 5.29: Expert 2 normalised decision matrix and weighted normalised decision matrix

	Normalised decision matrix					**Weighted normalised decision matrix**				
Criteria	CM	SOH	SRP	OFCBM	ONCBM	CM	SOH	SRP	OFCBM	ONCBM
C1	0.2857	0.4286	0.2857	0.5714	0.5714	0.0020	0.0030	0.0020	0.0041	0.0041
C2	0.5774	0.4619	0.3464	0.4619	0.3464	0.0270	0.0216	0.0162	0.0216	0.0162
C3	0.4619	0.3464	0.4619	0.5774	0.3464	0.0216	0.0162	0.0216	0.0270	0.0162
C4	0.1187	0.2374	0.4747	0.5934	0.5934	0.0021	0.0041	0.0082	0.0103	0.0103
S1	0.1250	0.3750	0.2500	0.6250	0.6250	0.0365	0.1096	0.0731	0.1826	0.1826
S2	0.1204	0.3612	0.3612	0.6019	0.6019	0.0117	0.0352	0.0352	0.0586	0.0586
S3	0.2357	0.3536	0.3536	0.5893	0.5893	0.0230	0.0344	0.0344	0.0574	0.0574
AV1	0.2520	0.3780	0.3780	0.5040	0.6299	0.0348	0.0522	0.0522	0.0695	0.0869
AV2	0.2390	0.4781	0.3586	0.5976	0.4781	0.0330	0.0660	0.0495	0.0825	0.0660
A1	0.3939	0.5252	0.2626	0.6565	0.2626	0.0093	0.0124	0.0062	0.0155	0.0062
A2	0.6934	0.4160	0.1387	0.5547	0.1387	0.0491	0.0295	0.0098	0.0393	0.0098
A3	0.2673	0.4009	0.4009	0.6682	0.4009	0.0063	0.0095	0.0095	0.0158	0.0095

Table 5.30: Expert 2 negative and positive ideal solution

Criteria	A^+	A^-
C1	0.0041	0.0020
C2	0.0270	0.0162
C3	0.0270	0.0162
C4	0.0103	0.0021
S1	0.1826	0.0365
S2	0.0586	0.0117
S3	0.0574	0.0230
AV1	0.0869	0.0348
AV2	0.0825	0.0330
A1	0.0155	0.0062
A2	0.0491	0.0098
A3	0.0158	0.0063

Table 5.31: Performance index and Rank

Alternatives	D^+	D^-	RC	Rank
CM	0.1736	0.0594	0.2549	5
SOH	0.0923	0.0917	0.4984	3
SRP	0.1312	0.0517	0.2826	4
OFCBM	0.0207	0.1751	0.8943	1
ONCBM	0.0466	0.1692	0.7840	2

TOPSIS Analysis using expert 3 judgement

The expert 3 matrix in Table 5.18 was normalised using Eq. (3.6) and then multiplied by the criteria weights given in Table 5.21 to obtain a weighted normalised matrix. The normalised decision matrix and the weighted normalised decision matrix determined are presented in Table 5.32. To obtain the positive ideal and negative ideal solution in Table 5.33 Eq. (3.10) and (3.11) were applied to the weighted normalised matrix. Finally applying Eq. (3.12) – (3.14), the distance of each maintenance strategy alternative to the positive-ideal solution D_i^+ and to the negative-ideal solution D_i^- together with relative closeness RC_i to the ideal solution were evaluated and the results together with the corresponding rankings are shown in Table 5.34.

Table 5.32: Expert 3 normalised decision matrix and weighted normalised decision matrix

	Normalised decision matrix					**Weighted normalised decision matrix**				
Criteria	CM	SOH	SRP	OFCBM	ONCBM	CM	SOH	SRP	OFCBM	ONCBM
C1	0.1459	0.2917	0.1459	0.7293	0.5835	0.0033	0.0067	0.0033	0.0166	0.0133
C2	0.3050	0.3050	0.1525	0.7625	0.4575	0.0023	0.0023	0.0011	0.0057	0.0034
C3	0.7906	0.4743	0.1581	0.3162	0.1581	0.0066	0.0039	0.0013	0.0026	0.0013
C4	0.1098	0.4391	0.4391	0.5488	0.5488	0.0003	0.0011	0.0011	0.0013	0.0013
S1	0.1147	0.4588	0.3441	0.5735	0.5735	0.0529	0.2118	0.1588	0.2647	0.2647
S2	0.1147	0.4588	0.3441	0.5735	0.5735	0.0100	0.0402	0.0301	0.0502	0.0502
S3	0.6868	0.2747	0.2747	0.5494	0.2747	0.0266	0.0107	0.0107	0.0213	0.0107
AV1	0.1187	0.4747	0.2374	0.5934	0.5934	0.0042	0.0169	0.0084	0.0211	0.0211
AV2	0.1187	0.4747	0.2374	0.5934	0.5934	0.0042	0.0169	0.0084	0.0211	0.0211
A1	0.1400	0.4201	0.5601	0.5601	0.4201	0.0038	0.0115	0.0153	0.0153	0.0115
A2	0.4121	0.4121	0.1374	0.6868	0.4121	0.0310	0.0310	0.0103	0.0517	0.0310
A3	0.1250	0.3750	0.2500	0.6250	0.6250	0.0259	0.0778	0.0519	0.1296	0.1296

Table 5.33: Negative and positive idea values

Criteria	A^+	A^-
C1	0.0166	0.0033
C2	0.0057	0.0011
C3	0.0066	0.0013
C4	0.0013	0.0003
S1	0.2647	0.0529
S2	0.0502	0.0100
S3	0.0266	0.0107
AV1	0.0211	0.0042
AV2	0.0211	0.0042
A1	0.0153	0.0038
A2	0.0517	0.0103
A3	0.1296	0.0259

Table 5.34: Performance index and ranks

Alternatives	D^+	D^-	RC	Rank
CM	0.2420	0.0272	0.1010	5
SOH	0.0803	0.1643	0.6718	3
SRP	0.1421	0.1097	0.4357	4
OFCBM	0.0066	0.2233	0.9712	1
ONCBM	0.0272	0.2183	0.8891	2

The group overall scores of maintenance strategy alternatives were evaluated by averaging the individual experts overall scores and the result is shown in Table 5.35. From the table, OFCBM occupies the first position having a group overall score of 0.9542. Hence the preferred maintenance strategy alternative is OFCBM. This is followed by ONCBM and the least preferred choice is CM with the lowest group overall score of 0.1639.

Table 5.35: multiple experts' decision making score and rank

Maintenance alternatives	Expert 1 TOPSIS overall score	Expert 2 TOPSIS overall score	Expert 3 TOPSIS overall score	Group overall score	Group Ranking
CM	0.1357	0.2549	0.1010	0.1639	5
SOH	0.4788	0.4984	0.6718	0.5497	3
SRP	0.6376	0.2826	0.4357	0.4520	4
OFCBM	0.9972	0.8943	0.9712	0.9542	1
ONCBM	0.8131	0.7840	0.8891	0.8287	2

5.4.5.4 Comparison of the proposed hybrid MCDM technique group ranking

The comparison of group ranking of maintenance strategy alternatives obtained from the three MCDM methods is presented in Table 5.36. From the table, OFCBM appears in first position for all of the ranking models and as such is the optimum solution is the OFCBM. Also from the table, last position is occupied by CM for the three ranking models; AHP, PROMETHEE and TOPSIS. The Spearman rank correlation was also used to determine the relationship between group rankings obtained from the three methods and the results are presented in Table 5.37.

Table 5.36: Comparison of group ranking from methods

Maintenance alternatives	AHP	PROMETHEE	TOPSIS
CM	5	5	5
SOH	3	3	3
SRP	4	4	4
OFCBM	1	1	1
ONCBM	2	2	2

Table 5.37: Spear man's rank correlation between methods

Method	AHP	PROMETHEE	TOPSIS
AHP	-	1	1
PROMETHEE		-	1
TOPSIS			-

5.5 Summary

In this chapter, three hybrid MCDM techniques; (1) Delphi-AHP and (2) Delphi-AHP-PROMETHEE and (3) Delphi-AHP-TOPSIS have been presented for the selection of a maintenance strategy for marine machinery systems. In the three proposed hybrid MCDM techniques, Delphi was applied to reduce the number of criteria such that only the most significant criteria were used in the maintenance alternative decision problem. The aim was to make the evaluation process as simple as possible such that it could easily be adopted by shipping system maintenance practitioners. AHP, which has the capability of incorporating quantitative and qualitative information, was used in the first proposed MCDM technique (Delphi-AHP) as a tool for determining the decision criteria weight and for the final ranking of the maintenance strategy alternatives with respect to decision criteria. In the second proposed MCDM technique (Delphi-AHP-PROMETHEE) AHP was applied as a tool for evaluating weights of decision criteria while PROMETHEE was used in the ranking of the maintenance strategy alternatives. In the third proposed MCDM technique (Delphi-AHP-TOPSIS) AHP was used for the weighting of decision criteria while TOPSIS was applied for the prioritisation of the maintenance strategy alternatives. The three hybrid methods were used in addressing a maintenance strategy selection problem involving a single expert firstly in the decision making process and this was followed by involving three experts (group) in the decision making process. For both the single expert and group decision making process the Spearman rank correlation between the three hybrid MCDM techniques was very strong and, as such a conclusion can be drawn that the three MCDM hybrid techniques can be used individually or in combination with one another in selecting the maintenance strategy for a marine machinery system or other related engineering system. Also from the analysis, there was no significant difference between the group rating and the single expert rating as a result of the similarity in the judgement of the five maintenance alternatives against decision criteria obtained from the three experts otherwise the ranking order would have altered significantly. Another reason is that since only five maintenance strategy alternatives were available, the degree of freedom was limited. If more alternatives were available there would be more chance of alteration in the ranking order of maintenance alternatives. Furthermore, from the analysis, the driving force for the selection of maintenance alternatives for critical marine machinery equipment is safety which was assigned half of the total weight of decision criteria.

For the two scenarios, single expert and group decision making, the selected maintenance alternative for the water cooling pump of the marine diesel engine was offline condition based maintenance (OFCBM). This is in line with current best practice. The proposed MCDM methodologies are simple and yet robust and effectively incorporate the RCM methodology decision criteria of cost and applicability in addition to other important decision criteria such as safety and added value which are not usually part of the RCM. Although AHP, PROMETHEE and TOPSIS produced almost completely the same ranking result for the five maintenance strategy alternatives for the single expert and group decision making process, PROMETHEE and TOPSIS would be recommended for those maintenance practitioners who may find generating numerous pairwise comparison judgments too laborious compared to the use of a Likert scale that can be applied in generating data for PROMETHEE and TOPSIS analysis.

Although the proposed methods have been validated for marine machinery systems they can also be applied to other related engineering systems and, depending on the preference of the maintenance practitioners, the decision criteria can further be reduced to make the evaluation process easier.

Chapter 6 Scheduled Replacement Interval Determination

6.1 Introduction

The task of determining the maintenance strategy was performed in Chapter 5. Marine machinery systems are made up of many components/equipment items that require different maintenance approaches. Hence there is a need to define the optimum maintenance strategy for each of the critical components/equipment items. After the determination of the of the appropriate maintenance strategy for each component of the system the next task is to determine the optimum interval for performing the maintenance task. This is the third stage of the Reliability Centered Maintenance approach in the optimisation of maintenance (Rausand and Vatn, 1998).

As stated in the literature review, there are three major maintenance strategies in the RCM methodology for eliminating or mitigating failure of machinery equipment; corrective maintenance, Preventive maintenance and condition based maintenance. Time based preventive maintenance can further be divided into scheduled overhaul and scheduled replacement while condition based maintenance is sub-divided into on-line condition based maintenance and off-line condition based maintenance. This chapter presents a technique for determining the optimal maintenance interval for scheduled replacement while the technique for determining the optimum interval for off-line condition based maintenance (inspection) is presented in Chapter 7.

The chapter is organised as follows: in Section 6.2 the proposed scheduled replacement interval determination methodology is presented. In Section 6.3 the case of the marine diesel engine cooling water pump is presented. Finally conclusions are presented in Section 6.4.

6.2 Proposed scheduled replacement interval determination methodology

In this research, after analysis of the literature in Chapter 2, a need was identified to introduce a multi-criteria decision making (MCDM) methodology as a decision support tool in determining the optimum interval for carrying out scheduled replacement tasks for marine machinery systems. The basis was the following few land-based applications found literature; (Cavalcante et al., 2010, Cavalcante and De Almeida, 2007, Chareonsuk et al., 1997). However the proposed MCDM approach for marine system maintenance is intended to be devoid of the limitations of the approaches used for land-based systems in the literature. To achieve this objective, firstly a multi-criteria decision making approach based on systematic application of TOPSIS was applied for marine systems as opposed to the PROMETHEE technique used for land based applications. Secondly, since the key factors that influence the selection of intervals are the decision criteria, an efficient framework which integrates subjective and objective criteria weighting techniques is introduced for evaluating weights of criteria as opposed to the use of only subjective techniques identified for land based system applications in the literature. The weighting framework is flexible and it allows maintenance practitioners to either use subjective criteria weighting techniques or objective weighting techniques or a combination of the two.

The first step in this methodology is the identification of possible scheduled replacement intervals for implementing maintenance replacement activities. The experience of the maintenance team is vital with respect to determining feasible scheduled replacement intervals. In addition, the manufacturer's manual for an equipment item can also be of help. The optimum interval is then selected based on preferred criteria. The criteria that may be considered are cost, reliability, availability, maintainability, spare parts inventory, quality issues and maintenance downtime (Chareonsuk et al., 1997). In this research, maintenance cost, reliability and maintenance downtime were considered. The maintenance cost criterion was chosen because it constitutes a major portion of the operating cost of ship systems. As previously stated, for a shipping company to remain in business in a deregulated and competitive environment, the cost of operation must be optimised and one way to achieved this is to minimise the cost of ship system maintenance. However in minimising cost, adequate care must be taken not to compromise the reliability of the system. This is because if the reliability of the system is compromised, it can result in catastrophic failure that may have irreversible damage on personnel, equipment and the environment. This makes reliability an important criterion that must not be ignored in selecting the optimum replacement interval for ship machinery systems. The downtime criterion was also chosen because downtime of equipment can produce detrimental penalties. For example, for a ship carrying perishable goods, the goods can be spoilt and this can result in the ship operator compensating the owners of the goods. Furthermore the image of the company can also be badly damaged.

Data availability is central to the successful selection of the optimum interval for scheduled replacement activities and as such data should be collected for the system being investigated. However for equipment which deteriorates with time such as marine machinery systems a Weibull distribution is generally applicable to fit the collected failure data (O'Connor, 1985). On this basis, the Weibull distribution function is assumed in this study. The Weibull distribution was applied to the component life data in evaluating the scale parameter $\emptyset$, shape parameter β and location parameter γ. This was followed by calculation of the criteria values using criteria models for the different alternative intervals. The decision criteria were modelled in this research using the Age Replacement Model (ARM). Another possible technique that can be used in modelling the decision criteria is the Block Replacement Model (BRM) (Wang, 2002). However ARM has been chosen as the tool for modelling the decision criteria because the BRM, in most scenarios, results in unnecessary replacement of equipment/components which makes the ARM technique more cost effective (Ahmad et al., 2011b). Criteria weights were then evaluated and finally a multi-criteria decision tool based on TOPSIS was used to aggregate values of criteria with the weights of criteria in order to determine the optimum preventive interval. The flowchart of this methodology is shown in Figure 6.1.

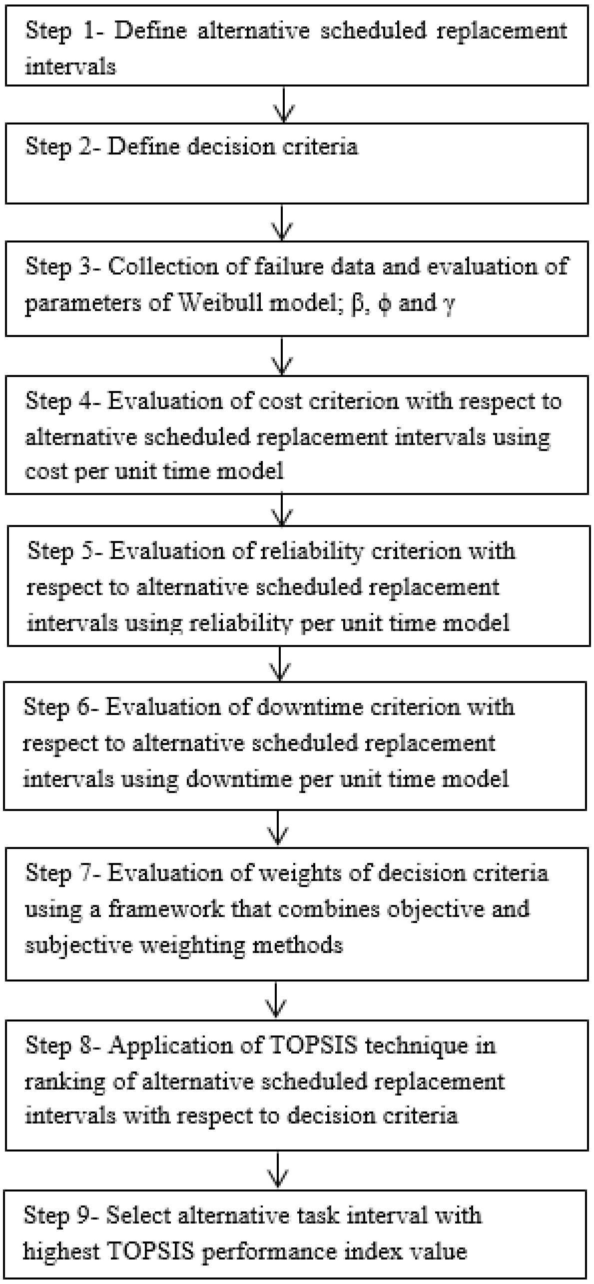


Figure 6.1: Flowchart of methodology

6.2.1 Weibull distribution

The Weibull distribution is one of the most popular probability distributions for modelling the failure behaviour of practical systems, especially equipment that deteriorates with time (Ebeling, 2004). The hazard function rate of the distribution is not constant with time unlike the exponential distribution (Ebeling, 2004). The Weibull distribution comes in different forms; one, two and three parameters versions. The key advantage of this type of distribution is its versatility as it may be applicable in modelling systems or components with increasing or decreasing failure rates. However its use is limited by availability of adequate data for defining the Weibull parameters and this data may be very difficult to access, especially in the marine industry. The three parameter Weibull distribution probability density function is represented as:

$$f(t) = \frac{\beta}{\emptyset}\left[\left(\frac{t-\gamma}{\emptyset}\right)\right]^{\beta-1} \exp -\left(\frac{t-\gamma}{\emptyset}\right)^{\beta} \tag{6.1}$$

Where t ≥ 0, ∅, β and γ > 0

β is the shape parameter which expresses the form of the distribution, γ is the location parameter which describe the location of the distribution and ∅ is the scale parameter which influences the spread of the distribution.

While the cumulative density function is:

$$F(t) = 1 - exp\left[-\left(\frac{t-\gamma}{\emptyset}\right)^{\beta}\right] \tag{6.2}$$

For the two parameter Weibull the probability density function is as follows:

$$f(t) = \frac{\beta}{\emptyset}\left(\frac{t}{\emptyset}\right)^{\beta-1}\ exp\left[-\left(\frac{t}{\emptyset}\right)^{\beta}\right] \tag{6.3}$$

Where t ≥ 0, ∅ > 0 and β > 0

While the cumulative density function is as follows:

$$F(t) = 1 - exp\left[-\left(\frac{t}{\emptyset}\right)^{\beta}\right] \tag{6.4}$$

6.2.1.1 Data types

Failure data is generally classified as: complete data or censored data.

Complete data: Failure data is said to be complete when time of failure of all units investigated are known. For example if failure data of a marine diesel engine is collected for a period of say 5 years and within the period, time to failure of all the components are known and recorded.

Censored data: Censoring occurs when the exact time to failure of an item is unknown and either failure occurred before the assumed time or after. Censored data is further categorised into three groups; right censored data, interval censored data and left censored data. Right censored data arises when there is doubt about the exact times of failure of some units but it is known that it happened after some specified time. Left censored data arises when there is doubt about the exact times of failure of some units but it is known to have happened before some specified times. Interval censored data is when there is doubt as to the precise times of failure of some units within an interval.

6.2.1.2 Parameter estimation

Several techniques such as probability plotting, regression analysis, method of moment and maximum likelihood estimation have been developed for determining parameters $\emptyset$, β and γ that will fit a distribution to a particular data set. The choice of method is a dependent on the data type collected and in some scenarios the type of distribution selected. When a complete set of data for machinery is available, regression analysis is generally more appropriate. However in most real life situations that may not be realistic as data is subjected to censoring. The maximum likelihood technique is usually the most suitable for analysing a data set with a relatively large amount of censoring (Cohen, 1965).

Maximum likelihood estimation

The maximum likelihood estimation technique can be used to obtain parameters for any life distribution such as a Weibull distribution that will best describe the given failure data. The beauty of this technique is that it is capable of handling problems with varying degrees of censored data.

Considering T as a continuous random variable with probability density function $f(t_i,\ \theta_{1,}\theta_{2,} \dots, \theta_k)$, where θ are the parameters of the distribution which are candidates for evaluation and $t_{1,}t_{2,} \dots, t_n$ are failure time data collected for the machinery system. The likelihood function is determined as follows (Al-Fawzan, 2000, Cohen, 1965):

$$L = \prod_{i=1}^{n} f\left(t_i; \theta_{1,}\theta_{2,} \dots, \theta_k\ \right) \tag{6.5}$$

L or the natural logarithm of it is then partially differentiated with respect to $\theta_{1,}\theta_{2,} \dots, \theta_k$ which will then result in equations for obtaining the estimated values of $\theta_{1,}\theta_{2,} \dots, \theta_k$. The partial derivative of natural log of L is as follows:

$$\frac{\partial \ln L}{\partial \theta_j} = 0 \qquad j = 1,2, \dots, k. \tag{6.6}$$

This technique may be illustrated through application to the probability density function of a 2 parameter Weibull distribution function given in Eq. (6.3) to estimate the Weibull parameters; $\emptyset$ and β as presented in the work of (Al-Fawzan, 2000, Cohen, 1965). This is as follows:

$$L\left(t_{1,}t_{2,} \dots, t_k\, ; \beta, \emptyset\ \right) = \prod_{i=1}^{n} \frac{\beta}{\emptyset}\left(\frac{t_i}{\emptyset}\right)^{\beta-1}\ exp\left[-\left(\frac{t_i}{\emptyset}\right)^{\beta}\right] \tag{6.7}$$

The logarithm of Eq. (6.7) was taken and partially differentiated with respect to ϕ and β respectively and equated to zero which resulted in Eq. (6.8) and (6.9).

$$\frac{\partial \ln L}{\partial \beta} = -\frac{\emptyset}{\beta} + \sum_{i=1}^{n} \ln t_i - \frac{1}{\emptyset}\sum_{i=1}^{n} t_i^{\beta} \ln t_i\ = 0 \tag{6.8}$$

$$\frac{\partial \ln L}{\partial \emptyset} = \frac{n}{\emptyset} + \frac{1}{\emptyset^2}\sum_{i=1}^{n} t_i^{\beta}\ = 0 \tag{6.9}$$

Equation (6.8) and (6.9) were reduced to:

$$\frac{\sum_{i=1}^{n} t_i^{\beta} \ln t_i}{\sum_{i=1}^{n} t_i^{\beta}} - \frac{1}{\beta} - \frac{1}{n}\sum_{i=1}^{n} \ln t_i\ = 0 \tag{6.10}$$

From here the first step is to evaluate β using a standard iterative procedure such as the Newton-Raphson method. Finally $\emptyset$ may be determined using Eq. (6.10) which produces

$$\emptyset = \sqrt[\beta]{\frac{\sum_{i=1}^{n} t_i}{n}} \tag{6.11}$$

6.2.2 Criteria function

The scheduled replacement interval selection decision making is based on decision criteria generally defined by the maintenance managers. In this study as previously stated, cost, reliability and maintenance down time are the criteria upon which the optimum interval will be selected. Two factors that influence the selection process are the weights and values of the criteria. In assigning values to criteria, experts' opinion is relied on in the face of a lack of or limited reliable failure data and that approach is qualitative. However the concern here is the quantitative approach that relies heavily on data availability. Quantitative mathematical functions are used in evaluating values of decision criteria (reliability, cost and down time) which are illustrated as follows.

Reliability function: The probability that a system will survive to a particular time *t*, is referred to as reliability (Jardine and Tsang, 2013). The Reliability function is thus represented as follows:

$$R(t_p) = \int_{t_p}^{\infty} f(t)dt \tag{6.12}$$

The two parameter Weibull form of the reliability function is defined as

$$R(t_p) = exp\left[-\left(\frac{t_p}{\emptyset}\right)^{\beta}\right] \tag{6.13}$$

However when the parameter β is 1, the Weibull model becomes an exponential model and is then represented as follows:

$$R(t_p) = e^{-\lambda t_p} \tag{6.14}$$

Cost function: Several cost models have been developed for defining cost with respect to scheduled replacement intervals. The cost per unit time is given as follows (Jardine, 1973):

$$C(t_p) = \frac{C_a\left(1 - R(t_p)\right) + C_b R(t_p)}{\int_0^{t_p} tf(t)dt + T_b\left(1 - R(t_p)\right) + \{(T_a + t_p)R(t_p)\}} \quad (6.15)$$

Where:

The numerator is the expected cost per cycle and the denominator is the expected cycle time;

C_a is the cost of unit failure maintenance

C_b is the cost of unit preventive maintenance

t_p is the given scheduled replacement interval

Downtime function: Downtime is given by (Jardine, 1973)

$$D(t_p) = \frac{T_b\left(1 - R(t_p)\right) + T_a R(t_p)}{\int_0^{t_p} tf(t)dt + T_b\left(1 - R(t_p)\right) + \{(T_a + t_p)R(t_p)\}} \quad (6.16)$$

Where:

T_b is the time taken for unit failure maintenance

T_a is the time taken for unit preventive maintenance

R, *C* and *D*, together with the alternatives' preventive maintenance interval (t_p) are then used to form a decision table. The decision table formed is presented in Table 6.1 where *R*, *C* and *D* are represented as B_j $(j = R, C \,\&\, D)$ and the alternative replacement intervals are represented as A_i $(i = 1, 2 \ldots, m)$ while the measure of performance of the alternatives' preventive maintenance interval is represented as X_{ij}. Having formed the decision table, the next task is to explore different multi-criteria decision making (MCDM) techniques for determining the optimum alternative maintenance task interval. In this research the use of the TOPSIS technique is proposed using the detailed methodology discussed in Section 3.3.2.1 of Chapter 3.

Table 6.1: Decision matrix

Alternatives (A_i)	Decision criteria (B_j)		
	R	C	D
A_1	x_{11}	x_{12}	x_{13}
A_2	x_{21}	x_{22}	x_{23}
A_3	x_{31}	x_{32}	x_{33}
-	-	-	-
-	-	-	-
A_m	x_{m1}	x_{m2}	x_{m3}

6.2.3 Criteria weighting model

6.2.3.1 Compromised weighting method:

After the formation of the decision table or matrix, the next step in the application of the MCDM technique in selecting an alternative from different options is to determine the weight of the decision criteria (R, C and D). Previous authors that have used the MCDM approach in determining the most appropriate time interval for scheduled replacement tasks have only assumed weight for decision criteria in their analysis (for example, see the work of Cavalcante et al. (2010) and Chareonsuk et al. (1997)), forgetting the fact that the weight of decision criteria is a critical factor in arriving at the appropriate scheduled replacement time interval. On the basis of the criticality of this factor, two different decision criteria weighting techniques; the variance method and the AHP method were considered. While the variance method is an objective weighting technique, the AHP method is a subjective weighting technique. The methodological steps for the statistical variance and AHP techniques were discussed in Section 5.3.2 and Section 4.3.2.2 respectively. However in order to have a balanced weighting technique, the two methods were integrated to give a compromise weighting technique. The integrated weighting technique produced by combining the variance method and AHP method is presented as follows:

$$wc_j = \frac{\emptyset A_j . we_j}{\sum_{j=1}^{n} \emptyset A_j . we_j} \quad j = 1, \dots, n \qquad 6.17$$

Where $\emptyset A_j$ is the weight of criteria obtained by AHP method,

we_j is the weight of criteria obtained by variance method.

wc_j is the compromised decision criteria weighting method.

6.2.4 TOPSIS: Preventive maintenance interval alternatives ranking tool

The steps in evaluating alternatives with respect to decision criteria in the TOPSIS methodology were discussed in Section 3.3.2.1. The basis of the TOPSIS methodology is the determination of relative closeness to different scheduled replacement interval alternatives with respect to an ideal solution. The alternatives are ranked based on this relative closeness to the ideal solution. The scheduled replacement alternative interval with the highest value is regarded as the optimum solution.

6.3 Case study: Marine diesel engine

From the risk assessment performed on the marine diesel engine the most critical components of the system were identified. For the basic engine which is one of the systems of the marine diesel engine, components such as the connecting rod, piston and turbocharger were identified as the critical. Scheduled replacement was identified as the optimum maintenance strategy for mitigating critical failure modes of the connecting rod (Liang et al., 2012). The maintenance strategy selection methodology proposed in this research in Chapter 5 has not been applied in validating their claim nevertheless, the connecting rod was used to demonstrate the applicability of the proposed scheduled replacement interval determination model.

6.3.1 Data collection

When applying a life-time distribution such as the Weibull distribution or exponential distribution in curve fitting individual units' failure data or group failure data, reasonable accuracy can be obtained with only four or five data points (Alexander, 2003). Rausand and Vatn (1998) reported that lack of reliability data will always be a challenge because of difficulty in accessing operational data with adequate quality and because transforming operational data into reliability data is challenging. The authors further postulated that in spite of these challenges, useful maintenance decisions can still be made from the little or no data situation as there are other sources of data such as experts' opinions and reliability databanks for making useful reliability decisions. In response to the challenges of obtaining failure data from the shipping industry, in this research values for Weibull parameters β and $\emptyset$ for some of the components of the marine diesel engine were obtained from the work of (Perakis and Inözü, 1991) and they are presented in Table 6.2. The Weibull parameters are the key data required for the implementation of this methodology. However if time to failure data were to be available, the data could have been used as input into eq. (6.3), (6.5) to (6.11) to obtain Weibull parameters β and Ø.

Table 6.2: Reliability data

System	Sub-system	Component	Number of failure observed	No. of censored data point	β (hrs)	Ø (hrs)	Environment
Marine diesel engine	Basic engine	Connecting rod	10	330	3.432	31699	Maritime
Marine diesel engine	Basic engine	Cylinder head	18	304	1.544	69764	Maritime
Marine diesel engine	Basic engine	Cylinder jacket	5	290	2.195	74802	Maritime
Marine diesel engine	Basic engine	Cylinder liner and o-ring	16	321	1.424	83769	Maritime
Marine diesel engine	Basic engine	Piston	8	350	1.221	211070	Maritime
Marine diesel engine	Basic engine	Fuel cam	52	90	0.710	60358	Maritime
Marine diesel engine	Basic engine	Turbocharger	6	59	1.520	31756	Maritime

6.3.2 Data analysis and discussion

Given the values of the Weibull parameters, the next step is to obtained the cost parameters; C_a, C_b, T_a and T_b. However because cost data was also not available, values used by previous researchers were used which were in the form of ratios. For example Wong et al. (2010) used a cost ratio of 1 to 5 ($5000 assumed as the replacement cost when performed under preventive mode and $25000 assumed as the replacement cost when performed under failure mode) as the cost of preventive replacement to the cost of failure replacement. Furthermore Mobley, (2001) stated that the cost of maintenance implemented under reactive mode is generally about three times the cost if executed in preventative mode. In this research, a cost ratio of 1 to 4 was assumed as the cost of preventive replacement to the cost failure replacement. Also, since the downtime as result of failure replacement is usually higher than that resulting from preventative replacement, it was considered appropriate that a ratio of 1 to 5 was assumed as the ratio of downtime for preventive replacement to downtime for failure replacement.

The connecting rod parameters which were used as input data in the reliability function, cost function and downtime function are; β =3.432 and $\emptyset$ = 31699, C_a= £8000, C_b= £2000, T_a = 3 and T_b = 15.

Having obtained the Weibull parameters β and $\emptyset$ and cost parameters; C_a, C_b, T_a and T_b the next step was to evaluate the *R*, *C* and *D* for all possible alternative preventive maintenance intervals which may then be used to form a decision table or matrix. In deciding on the possible scheduled replacement time interval alternatives reference was made to literature (Perakis and Inözü, 1991) in consultation with the experts previously used for the strategy selection stage in Chapter 5. The possible preventive maintenance time intervals arrived at are presented in Table 6.3. The evaluation of *R*, *C* and *D* was carried out with a simple program executed in Matlab® which is given in Appendix C1 and the results obtained are presented in Figures 6.2 to 6.4.

Table 6.3: Alternative scheduled replacement intervals

S/N	Replacement intervals (Hrs)
A1	5000
A2	6000
A3	7000
A4	8000
A5	9000
A6	10000
A7	11000
A8	12000
A9	13000
A10	14000
A11	15000
A12	16000
A13	17000
A14	18000
A15	19000
A16	20000
A17	21000
A18	22000
A19	23000
A20	24000
A21	25000
A22	26000
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A25	29000
A26	30000
A27	31000
A28	32000
A29	33000
A30	34000

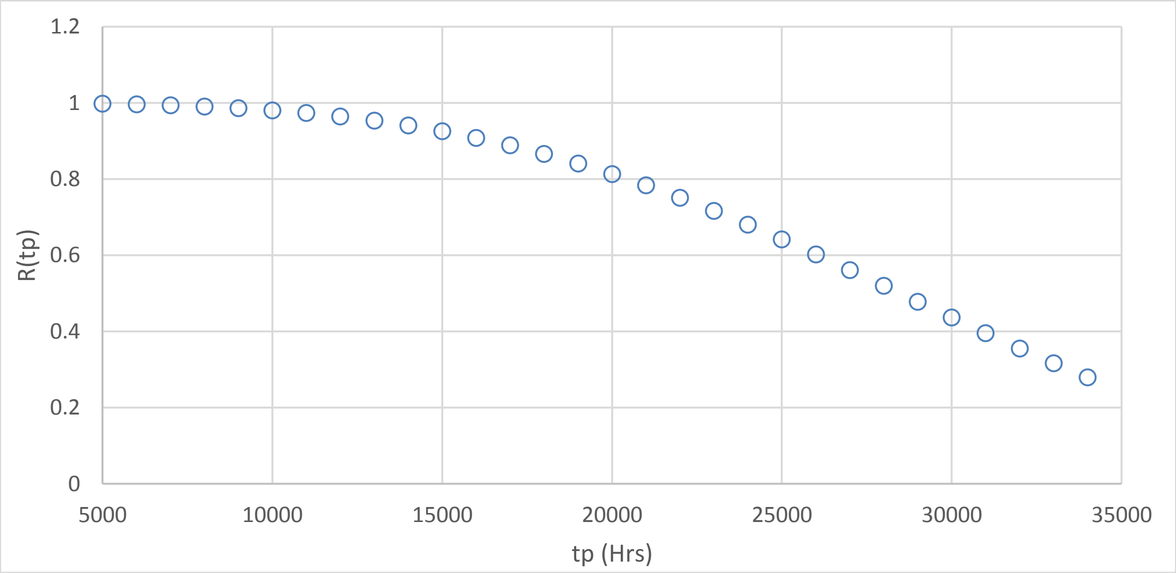

Figure 6.2: Reliability function against scheduled replacement interval t_p

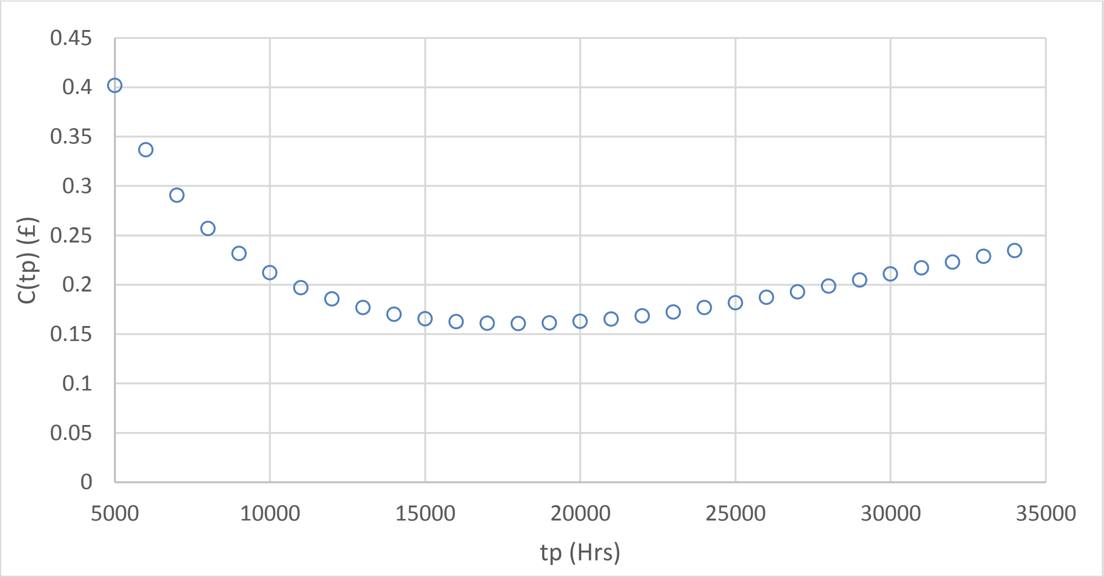

Figure 6.3: Cost function against scheduled replacement interval t_p

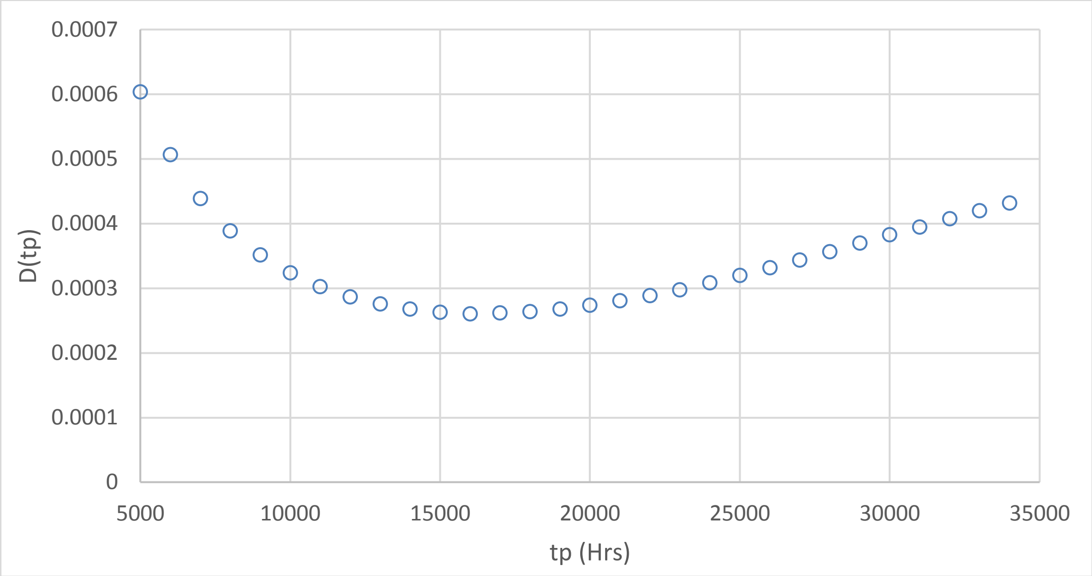

Figure 6.4: Downtime function against scheduled replacement interval t_p

From the results in Figures 6.2, 6.3 and 6.4 it is obvious that the three decision criteria are in conflict with one another making it difficult to select the optimum preventive replacement interval. For example: the maintenance practitioner would prefer to maintain the plant with the highest possible reliability and, as such for the reliability function in Figure 6.2 the optimum preventive maintenance interval is 5000hrs; however considering the cost function in Figure 6.3, the optimum replacement interval will occur at the least possible cost and in this case the preferred maintenance interval is 18,000hrs and finally for the downtime function in Figure 6.4 the maintenance practitioner would prefer to operate the plant with the least possible plant downtime and from this analysis the optimum solution would be to carry out replacement at an interval of 16,000hrs. In such a conflicting scenario, the use of an MCDM method becomes crucial in order to arrive at a compromise solution. As previously stated, the use of the TOPSIS method is proposed in this research in selecting the most appropriate preventive replacement alternative interval. In the TOPSIS technique the first step is to form the decision matrix which is achieved from the results generated for *R*, *C* and *D* for scheduled replacement intervals A1 to A30 as presented in Table 6.4.

Table 6.4: decision matrix for connecting rod

Replacement intervals (tp)	tp(hrs)	Rtp	Ctp(£)	Dtp(hrs)
A1	5000	0.998234	0.402036	0.000604
A2	6000	0.996702	0.336712	0.000507
A3	7000	0.994408	0.290747	0.000439
A4	8000	0.991171	0.257035	0.000389
A5	9000	0.986803	0.231631	0.000352
A6	10000	0.981108	0.212175	0.000324
A7	11000	0.973894	0.197167	0.000303
A8	12000	0.964970	0.185607	0.000287
A9	13000	0.954153	0.176806	0.000276
A10	14000	0.941272	0.170267	0.000268
A11	15000	0.926174	0.165626	0.000263
A12	16000	0.908729	0.162604	0.000261
A13	17000	0.888834	0.160983	0.000262
A14	18000	0.866420	0.160589	0.000264
A15	19000	0.841456	0.161276	0.000268
A16	20000	0.813957	0.162918	0.000274
A17	21000	0.783981	0.165407	0.000281
A18	22000	0.751638	0.168643	0.000289
A19	23000	0.717090	0.172532	0.000298
A20	24000	0.680550	0.176986	0.000309
A21	25000	0.642279	0.181920	0.000320
A22	26000	0.602586	0.187251	0.000332
A23	27000	0.561822	0.192896	0.000344
A24	28000	0.520369	0.198773	0.000357
A25	29000	0.478633	0.204805	0.000370
A26	30000	0.437038	0.210912	0.000383
A27	31000	0.396005	0.217019	0.000395
A28	32000	0.355949	0.223053	0.000408
A29	33000	0.317263	0.228948	0.000420
A30	34000	0.280303	0.234641	0.000432

After the formation of the decision matrix, the next step was to use the MCDM tool in ranking of the alternative maintenance intervals. However prior to the use of the MCDM tool, the weight of each decision criterion had to be determined. As previously explained, a combination of AHP and the variance weighting method was used in this research. The results of R, C and D obtained from the AHP and the variance technique together with the combination of the two techniques (compromise weighting technique) are presented in Table 6.5 and Figure 6.5.

Table 6.5: Combined weight technique comparison with others

	R	C	D
AHP	0.6000	0.2000	0.2000
variance	0.4362	0.3132	0.2506
Compromise	0.6989	0.1673	0.1338

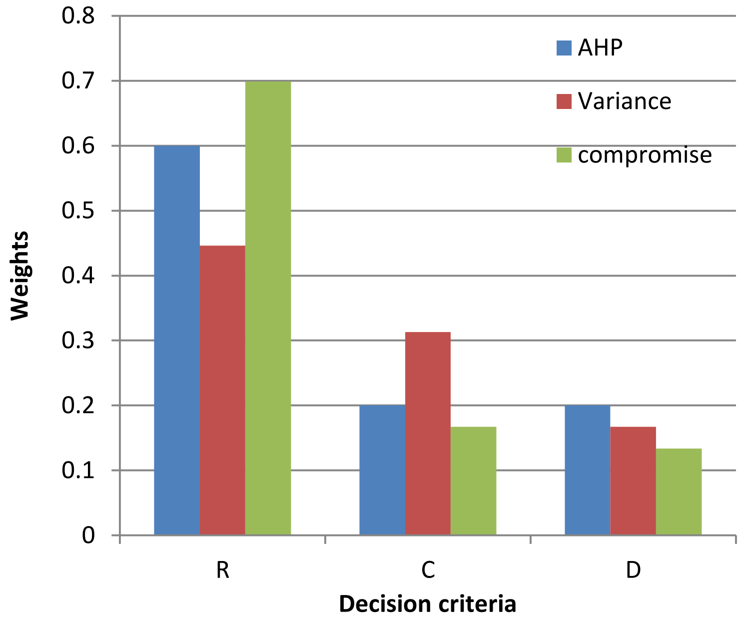

Figure 6.5: combine weight technique comparison with others

The evaluated compromise weights of *R*, *C* and *D* together with data in the decision matrix in Table 6.4 were then used as input data for the TOPSIS analysis. The first step in the TOPSIS analysis was the normalisation of the decision matrix in Table 6.4 using Eq. (3.6). The weighted normalised matrix was then obtained by multiplying the normalised decision matrix by the decision criteria weights. Applying Eq. (3.10) and (3.11), positive and negative ideal solutions were obtained and the results are presented in Table 6.6. Using Eq. (3.12) and (3.13) the separation of each of the alternative replacement interval from the positive and negative ideal solutions were then evaluated. Finally, the relative closeness of each alternative replacement interval to the positive ideal solution was evaluated using Eq. (3.14) and the results together with their corresponding rankings are presented in Table 6.7 and Figure 6.6.

Table 6.6: Positive and negative ideal solution

Criteria	Negative ideal	Positive ideal
Reliability	0.2083	0.9982
Cost	0.4011	0.1605
Downtime	0.0006	0.0003

Table 6.7: Relative closeness to positive solution and ranking

Replacement alternatives	dp	Rank
A1	0.7352	16
A2	0.7932	14
A3	0.8401	11
A4	0.8777	9
A5	0.9073	6
A6	0.9293	4
A7	0.9427	2
A8	0.9458	1
A9	0.9387	3
A10	0.9245	5
A11	0.9058	7
A12	0.8835	8
A13	0.8580	10
A14	0.8293	12
A15	0.7973	13
A16	0.7622	15
A17	0.7240	17
A18	0.6828	18
A19	0.6391	19
A20	0.5930	20
A21	0.5452	21
A22	0.4962	22
A23	0.4469	23
A24	0.3979	24
A25	0.3504	25
A26	0.3056	26
A27	0.2652	27
A28	0.2306	28
A29	0.2036	29
A30	0.1854	30

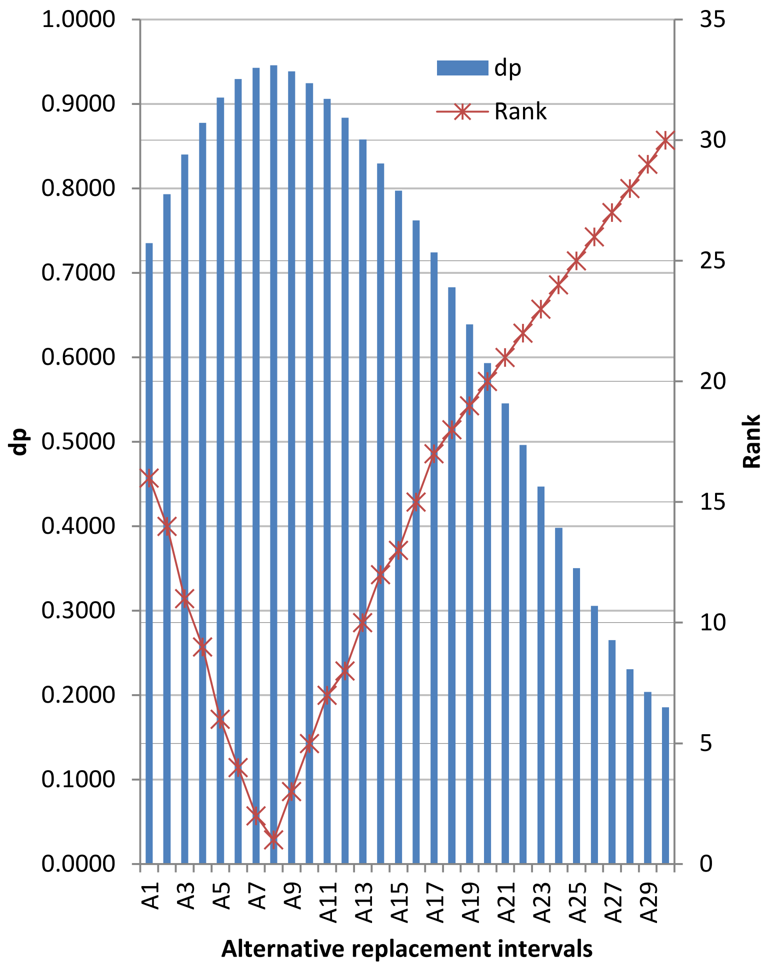

Figure 6.6: Relative closeness to positive ideal and ranking

From Table 6.7 and Figure 6.6 it is obvious that the optimum solution is A8 (12000hrs) having the highest TOPSIS performance index of 0.9452. The implication is that for this system, at every interval of 12000hrs, an equivalent of 500 days, the maintenance practitioner should replace the connecting rod in the marine diesel engine at a cost of 0.18543 per unit time, reliability of 0.96497 and resulting downtime per unit time of 0.00029. However this interval can vary from system to system depending on the input parameters into the model which is controlled by the system age, system failure distribution (such as Weibull, normal and exponential distribution) demand, prevailing cost factor, maintenance practitioner opinion and the environment of the operation of the system. This leads to a sensitivity study carried out to see how the various factors affect the optimum choice.

6.3.3 Sensitivity study

The sensitivity analysis was performed by varying parameters that were used as inputs into the reliability, cost and downtime cost functions. This was firstly to ascertain the impact of the input variables on the individual functions; *R* (*tp*), *C* (*tp*) and *D* (*tp*). Secondly it was to ascertain the impact of the individual input variables in selecting the optimum replacement interval based on the combination of the three decision criteria, *R* (*tp*), *C* (*tp*) and *D* (*tp*) by the MCDM technique (TOPSIS). In performing the analysis, the input variables β and ∅ were increased and decreased by 5%, 10%, 15% and 20% respectively while other variables such as C_a, C_b, T_a and T_b ratios used were increased and decreased by integer increment.

6.3.3.1 *R(tp)* sensitivity analysis

The two variables that influence *R(tp)* are β and ∅ and these factors were increased and decreased by 5% , 10%, 15% and 20% from the nominal. The results of the sensitivity analysis based on β and ∅ are presented in Figures 6.7 and 6.8 respectively.

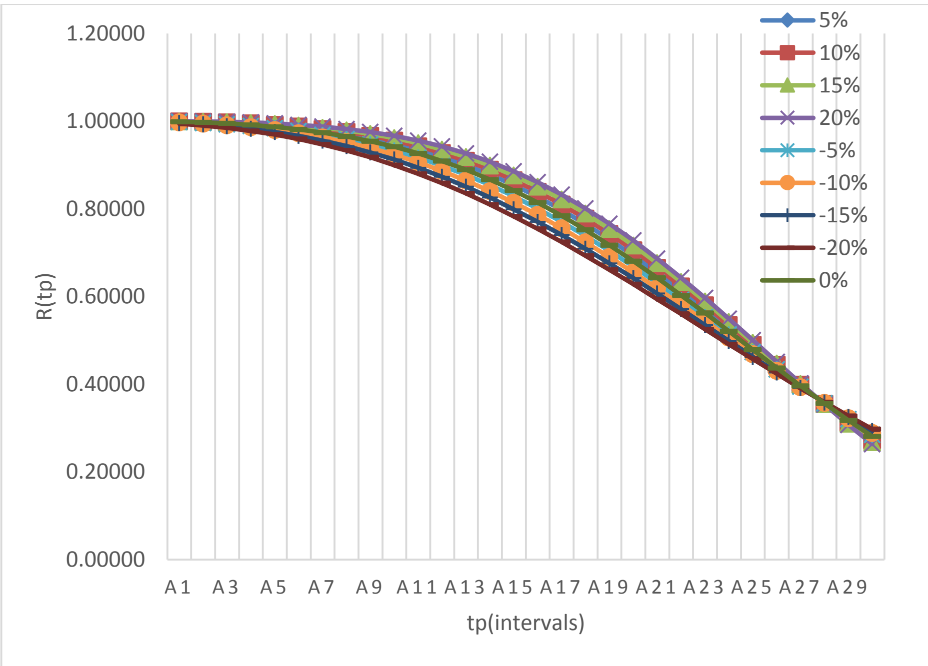

Figure 6.7: Reliability (R(tp)) for sensitivity analysis of β

From Figure 6.7 it can be seen that if only the reliability function was the deciding factor for selecting the optimum replacement interval, then the optimum solution is unchanged for the nine cases because the maintenance practitioner will always prefer the highest possible reliability for the operation of the system. For the nine cases, the highest reliability is approximately one at a time interval for carrying out maintenance of A1 (5000hrs). It is also worth mentioning from the graph that the lowest possible reliability for the nine cases is almost the same. One can then conclude that the rate of decrease of reliability of this system with age or time for any value of the factor β is almost constant.

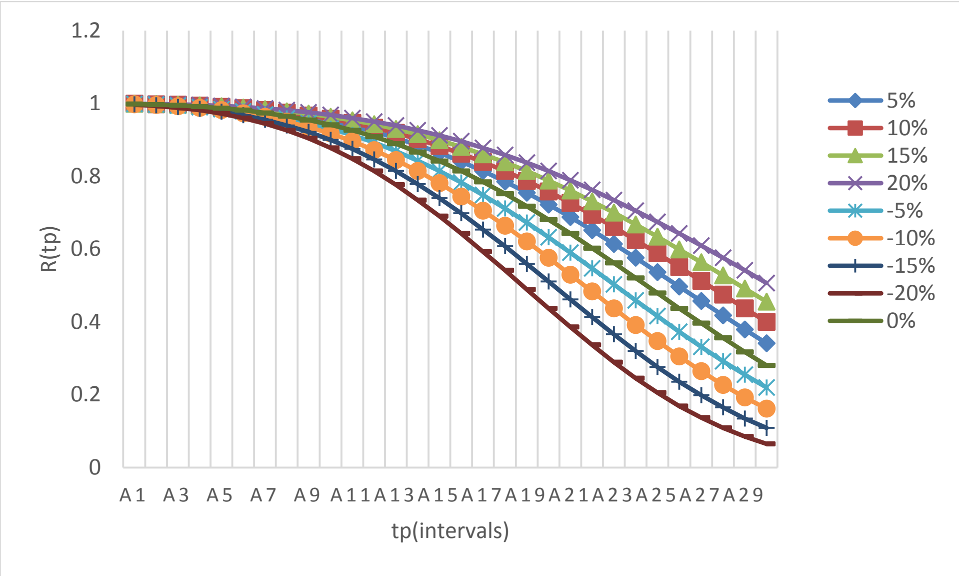

Figure 6.8: Reliability (R(tp)) for sensitivity analysis of ∅

Again increasing or decreasing the value of ∅ as shown in Figure 6.8, does not change the optimum interval (A1) for performing replacement maintenance as the maintenance practitioner would prefer to maintain the highest possible reliability. Although from the graph, the highest possible reliability i.e. approximately one for the nine cases is the same, the lowest possible varies greatly for the nine cases, ranging from 0.064859 when ∅ was decreased by 20% to 0.34103 when ∅ was increased by 20%. It can be concluded that reliability decreases with age i.e. A1 to A30 and the rate of decrease depends greatly on the value of ∅. In terms of the overall ranking of the scheduled replacement interval alternatives using MCDM based on the three decision criteria; *R(tp)*, *C(tp)* and *D(tp)*, the impact of ∅ will be greater than β since reliability is more sensitive to ∅ than β when Figures 6.7 and 6.8 are compared.

6.3.3.2 *C (tp)* sensitivity analysis

For the cost model *C(tp)*, the optimum preventive maintenance interval (*tp*) is the interval with the least possible cost. The input parameters that influence the output of this cost model are Ø, β, C_a, C_b, T_a and T_b and as such a sensitivity analysis was performed on these input variable.

For the sensitivity analysis performed on β, the original value was increased and decreased by 5%, 10%, 15% and 20% and the results are presented in Figure 6.9.

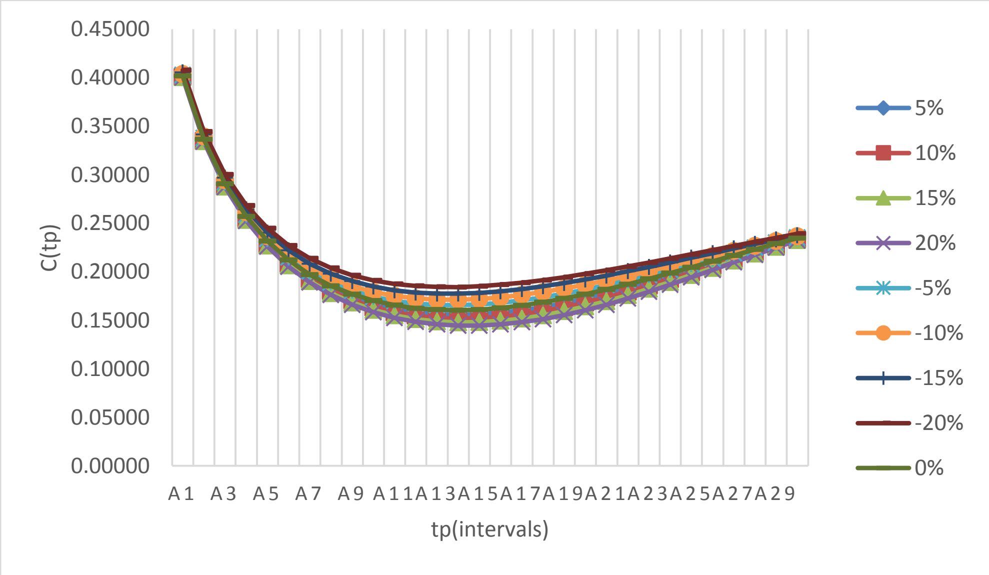

Figure 6.9: Cost per unit time for sensitivity analysis of β

From Figure 6.9, the optimum replacement interval (*tp*) A14 (18,000hrs) remained unchanged when β was increased by up to 20% and decreased by up to 20%. However there was a small decrease in cost when β was increased from the original value by up to 20% and a small increase in cost when β was decreased by up to 20%.

In order to examine the effect of the variation of Ø on the cost model, the variable was again increased and decreased by 5%, 10%, 15% and 20%. The result of the sensitivity analysis is presented in Figure 6.10. From the figure it is obvious that Ø has a greater impact on cost than β, and unlike the analysis of β with respect to cost where the optimal replacement interval remained unchanged, the optimum interval for Ø changes as the parameter is increased or decreased. As the variable Ø was increased from the original value (0%) by 5%, 10%, 15%, the optimal interval changed from A14 to A15, A16, and A17 respectively with a corresponding decrease in the cost for performing preventive maintenance. However when the variable was increased from 15% to 20% the optimum interval was unchanged. On the other hand, when the variable Ø was decreased by 5%, 10%, 15% and 20% there was a corresponding decrease in the optimum replacement interval by a factor of one with a marginal increase in the cost of carrying out scheduled replacement maintenance. For example when the original value of Ø was decreased by 5% the alternative replacement interval changed from A14 (18,000hrs) to A13 (17,000hrs) and when Ø decreased by 10% it changes to A12 (16,0000hrs).

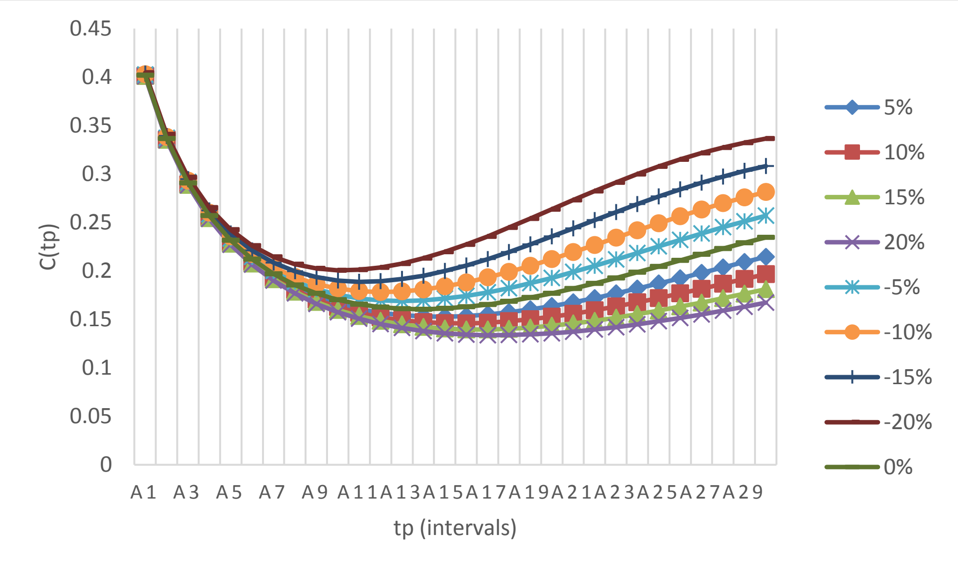

Figure 6.10: Cost per unit time ($C(t_p)$) for sensitivity analysis of Ø

Another input parameter whose impact on the output of the cost model was tested is the cost ratio i.e. the ratio of the cost of maintenance as result of breakdown (C_a) to the cost of preventive maintenance (C_b). The ratio was varied ranging from 2 to 8 in order to measure the effect on the output of the cost model as shown in Figure 6.11. It can be seen from Figure 6.11 that as the ratio increased the optimum replacement interval decreased with an increase in the cost of performing the maintenance task. For example the optimum interval when the ratio of C_a to C_b is set at 2 is A21 (25,000hrs) at a cost per unit time of £0.12; when the ratio is set at 3 the optimum interval (t_p) changes to A16 (20000hrs) at a cost per unit time of £0.14. From this analysis it is obvious that the cost model is more sensitive to the ratio of C_a to C_b than the variable Ø as the decrease in the optimum interval (t_p) is more sudden.

Finally, the impact of changes in the ratio of T_b to T_a on the cost model was determined and in the scenario the ratios were varied from 2 to 9 as presented in Figure 6.12. The figure shows that changes in the ratio did not result in any change in the optimal replacement interval as in all the cases the interval remained at A14 (12,000hrs) with a very marginal increase in cost per unit time.

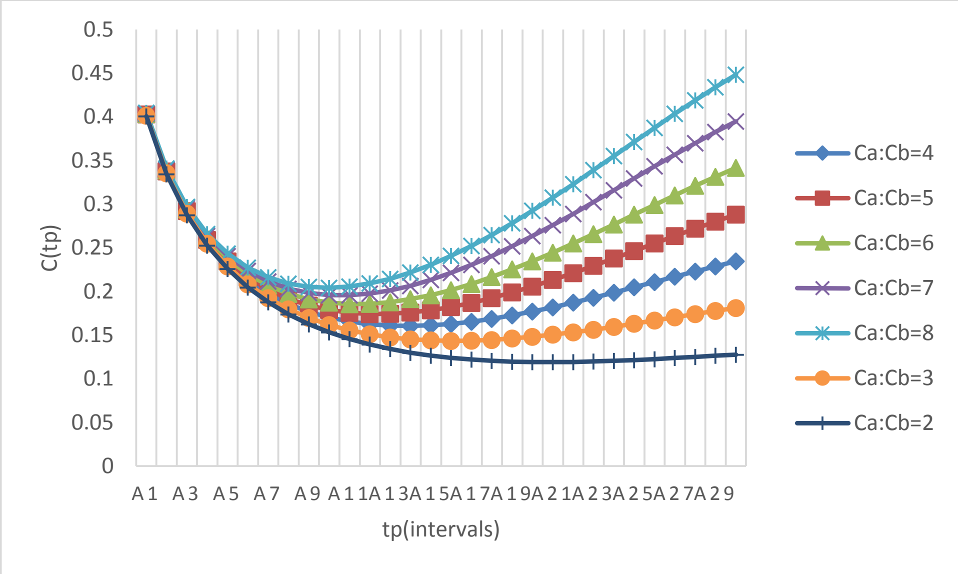

Figure 6.11: Cost per unit (C(tp)) for sensitivity analysis of Cost ratio

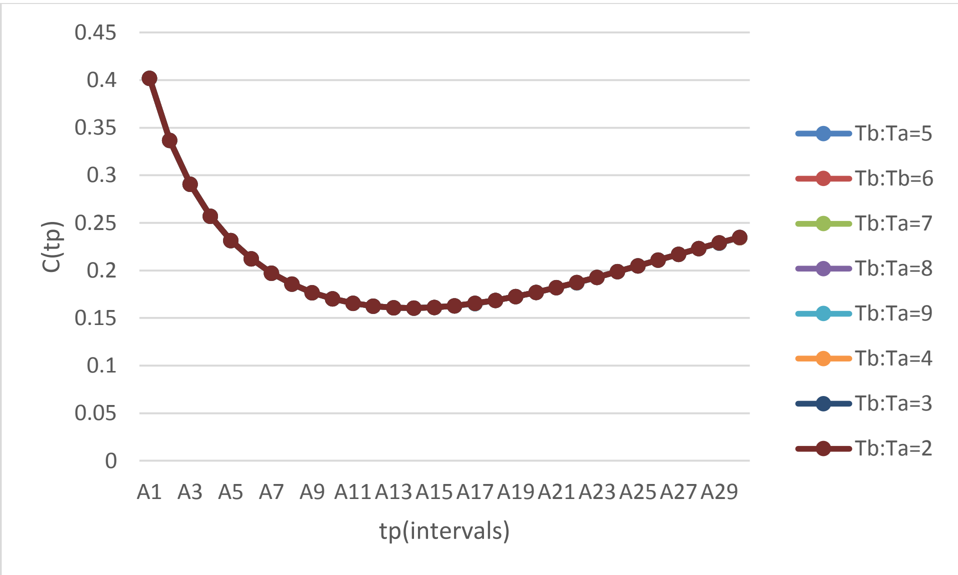

Figure 6.12: Cost per unit time (C(tp)) for sensitivity analysis of ratio of Tb to Ta

6.3.3.3 $D(t_p)$ sensitivity analysis

In order to ascertain the influences of the of the input variables such as β, ∅, C_a, C_b, T_b and T_a on the $D(t_p)$ model a sensitivity analysis was performed by changing these variables by a certain quantity.

For the sensitivity investigation performed on β, the original value was increased and decreased by 5%, 10%, 15% and 20% and the results are presented in Figure 6.13. The results show that the optimum replacement interval (t_p) remains the same in the nine scenarios however with a gradual increase in cost per unit time when β varied from -5% up to -20% and gradual decrease in cost per unit time when β varied from 5% up to +20%. In a similar fashion, a sensitivity analysis was performed by decreasing and increasing ∅ over the range of 5% to 20%. The result of the sensitivity analysis is as shown in Figure 6.14. The result of this investigation shows that an increase in the variable ∅ resulted in a small increase in the replacement interval and a decrease in the value of ∅ produced a decrease in the replacement interval.

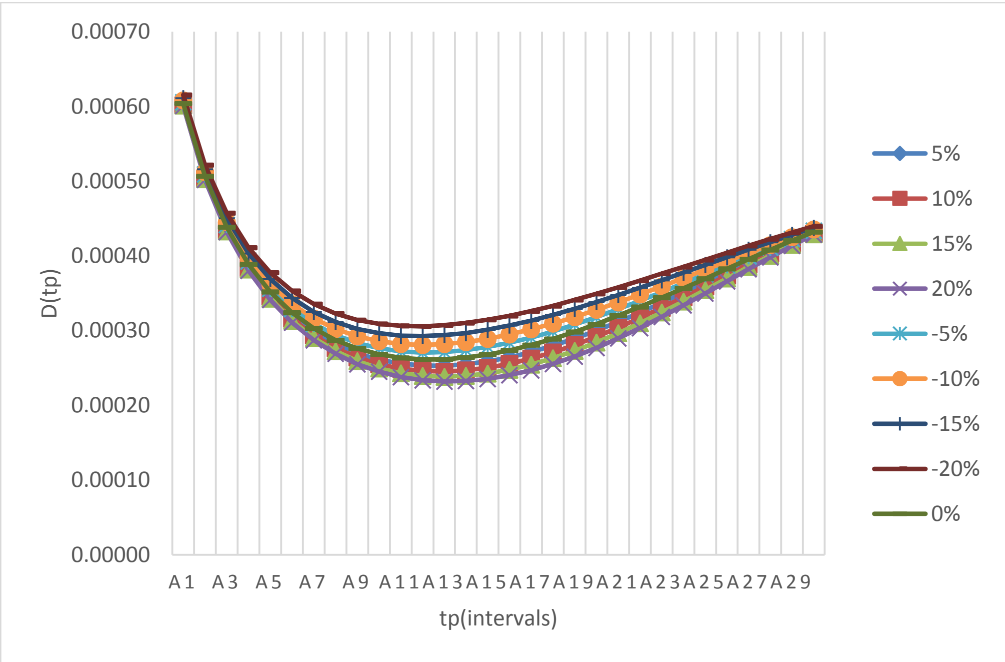

Figure 6.13: Downtime per unit time for sensitivity analysis of β

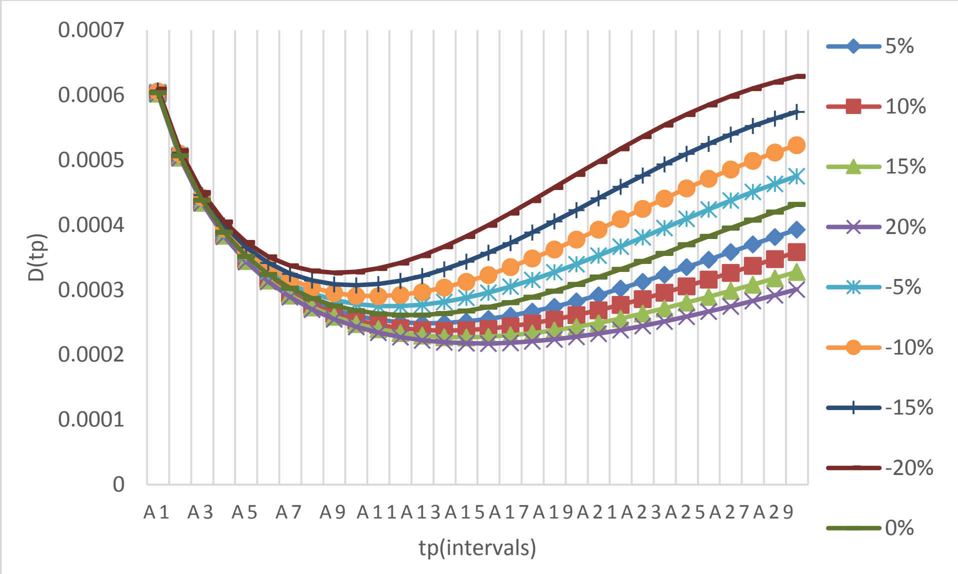

Figure 6.14: Downtime per unit time (C(tp)) for sensitivity analysis of ϕ

Finally, the $D(t_p)$ model sensitivity analysis was performed by varying the ratio of T_b to T_a over the range of 2 to 9. From the result shown in Figure 6.15 it can be seen that when the ratio increased there was a reduction in the optimum replacement interval, however with an increase in cost per unit time of performing the maintenance task.

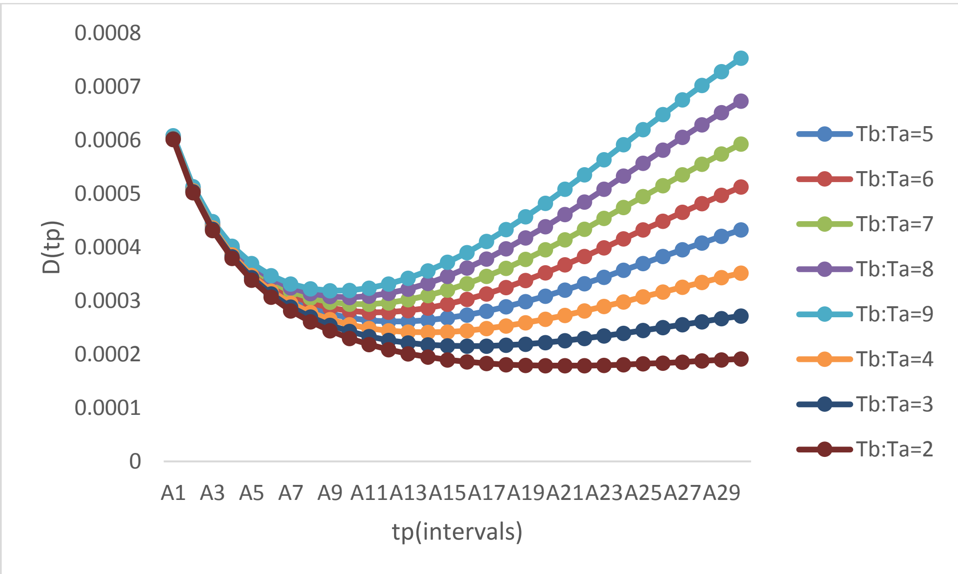

Figure 6.15: Downtime per unit (D(tp)) for sensitivity analysis of ratio of Tb to Ta

6.3.4 Impact of input parameters variations on the overall ranking of replacement interval alternatives

Having established the impact of changes to the individual input parameters on the three decision criteria $R(t_p)$, $C(t_p)$ and $D(t_p)$, the next step was to determine the impact of the variations of input parameters on the overall ranking of the replacement alternative intervals. As previously explained, when $R(t_p)$, C(t_p) and $D(t_p)$ are used simultaneously as decision criteria to determine the optimum replacement intervals, an MCDM technique is appropriate for selecting the optimal alternative interval and in this research TOPSIS was used. The TOPSIS performance index for all replacement alternative intervals was generated as the individual input parameters were varied and based on the TOPSIS performance index, replacement alternative intervals were ranked.

6.3.4.1 Impact of β variations on the overall ranking of replacement interval alternatives

Firstly the impact of the variation of β on the overall ranking of the alternative replacement intervals was considered. The TOPSIS performance index was obtained for all replacement interval alternatives as input parameter β was increased and decreased by 5%, 10%, 15% and 20%. The result obtained is presented in Table C1 in Appendix C2 and based on these, the TOPSIS performance index and scheduled replacement interval alternatives were ranked as shown in Figure 6.16 a &b and Table C2 in appendix C2. Note Figure 6.16b is only a section of Figure 6.16a and it's presented to clearly shown how replacement (maintenance) alternative intervals vary with increase or decrease of parameter β.

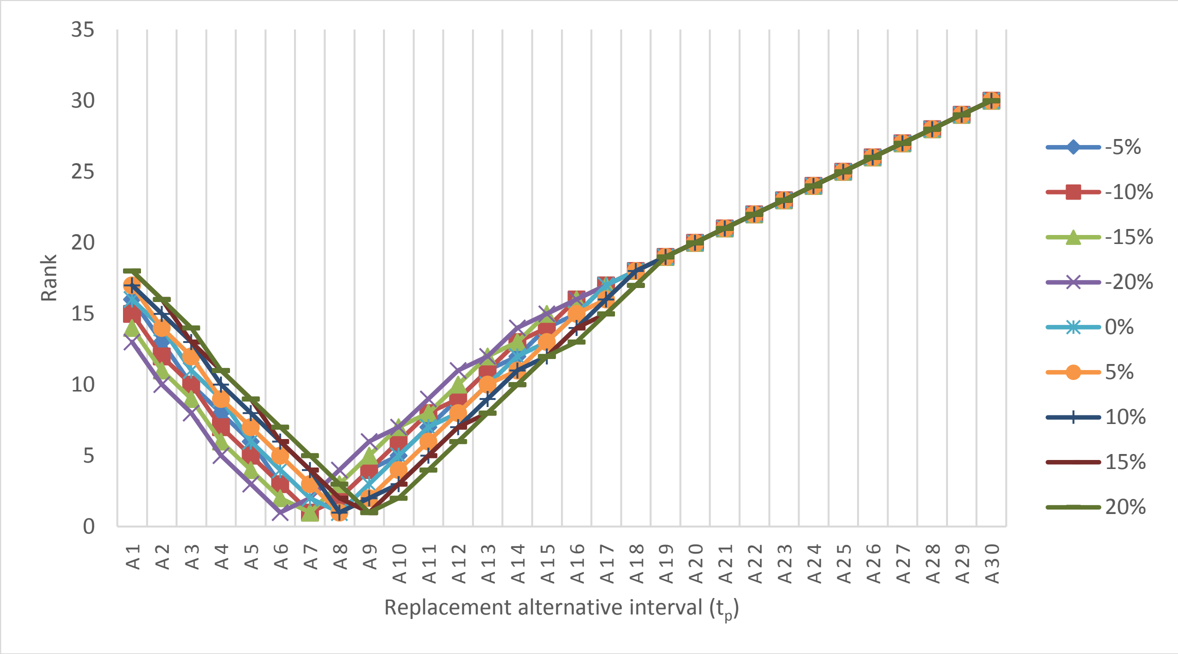

Figure 6.16 a: Ranking of sensitivity analysis of β

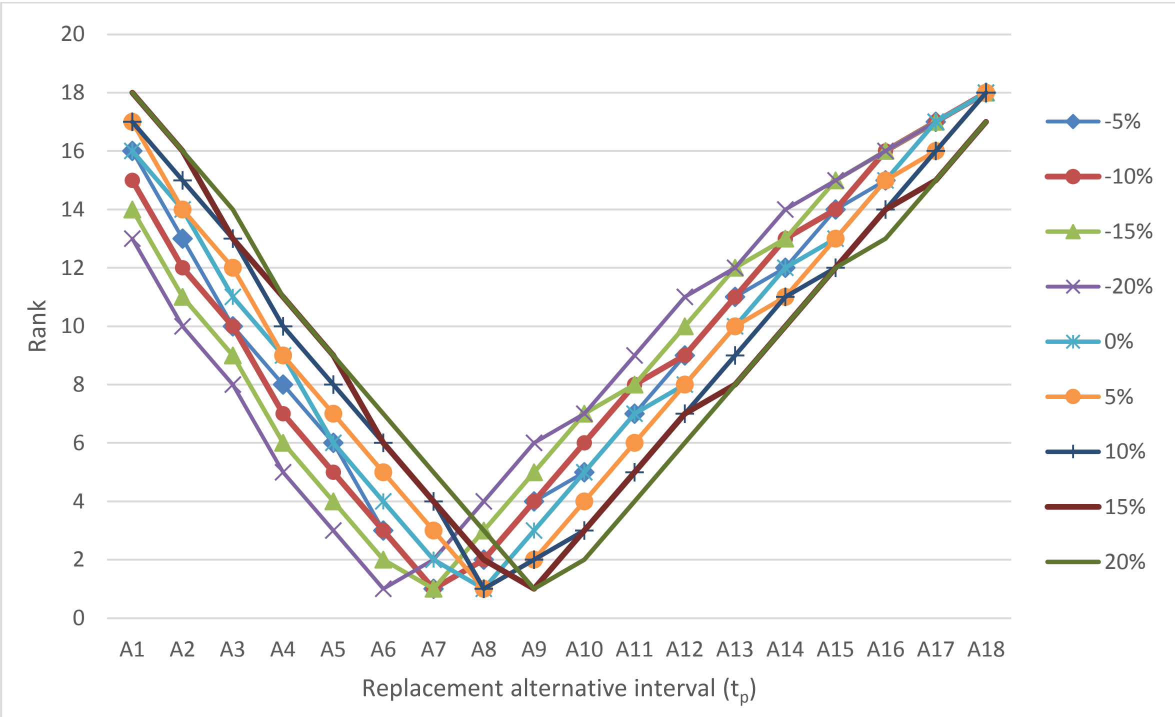

Figure 6.16b: Ranking of sensitivity analysis of β

From Figure 6.16a and Table C2 it can be seen that the optimal replacement interval for the original value of β (0%) was A8 (12,000hrs) having rank of 1. However as the value of β was increased by 10% the optimal replacement interval remained unchanged. It was not until β was increased by 15% and 20% that the optimal interval became A9 (13,000hrs). On the other hand, as the value of β was decreased by 5% the optimal replacement interval changed to A7 (11,000hrs) and it further changed to A6 (10,000) when the value of β was decreased by 20%. To summarise, the higher the value of β the higher the replacement interval and the lower the value of β the lower the replacement interval. An additional conclusion is that in all the scenarios, whether increasing or decreasing the value of β, the optimal replacement interval varied by relatively small amount as the change was over the range A6 - A9.

6.3.4.2 Impact of ∅ variations on the overall ranking of replacement interval alternatives

The impact of ∅ on the overall ranking of alternative replacement intervals was performed by decreasing and increasing the values of ∅ by 5%, 10%, 15% and 20% and using the results obtained in each scenario as input to the TOPSIS methodology which was evaluated using TOPSIS. The TOPSIS performance indices generated in the nine scenarios are presented in Table C3 in Appendix C2. On the basis of the TOPSIS performance indices, the replacement alternative intervals were ranked and the results are presented in Table C4 in Appendix C2 and Figure 6.17.

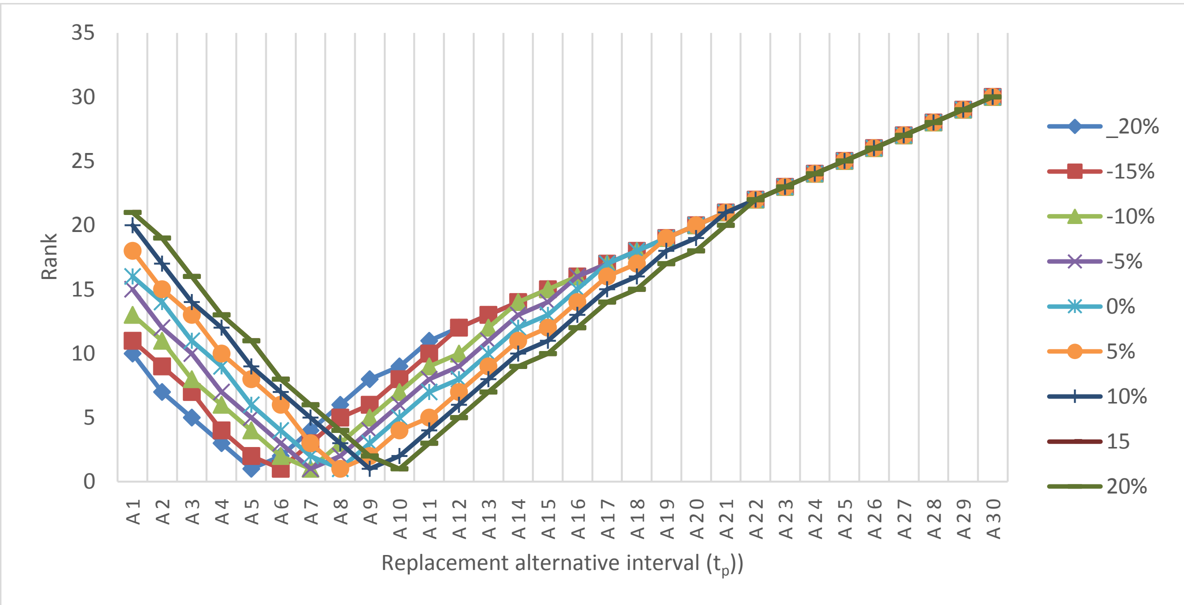

Figure 6.17: Ranking of sensitivity analysis of ϕ

From Table C4 in Appendix C2 and Figure 6.17, it can be seen that the sensitivity analysis results obtained for ∅ are very similar to the results generated for β since as the value of ∅ increased the replacement interval increases and as the value decreases the replacement interval decreased just as in the case of β. However, the corresponding changes in the replacement interval to the changes in Ø are larger than the response to the changes in β. In other words, the ranking model is more sensitive to changes in Ø than β.

6.3.4.3 Impact of cost ratio variations on the overall ranking of replacement interval alternatives

The sensitivity analysis was perform on cost ratio to determine the effect that changes of the ratio of C_a to C_b would have on the overall ranking of replacement interval alternatives. The ratio of C_a to C_b ranging from 2 to 8 was applied in carrying out the investigation. The TOPSIS performance index obtained for all the replacement interval alternatives for all eight scenarios and their corresponding rankings are presented in Tables C5 and C6 in Appendix C2. The graphical representation of the ranking of all alternatives are shown in Figure 6.18a & b. Note Figure 6.18b is only a section of Figure 6.18a and it's presented to clearly shown how replacement (maintenance) alternative intervals vary with increase or decrease of cost ratio.

From Table C6 in Appendix C2 and Figure 6.18a it can be seen that as the ratio of C_a to C_b increased up to 5 there was a reduction in the replacement interval. Increases beyond 5 resulted in no further change across the range of scenarios i.e. the ratio of C_a to C_b ranging from 2 to 8, only three replacement interval choices were obtained (A9, the optimal replacement interval obtained for C_a:C_b =2, A8 the optimal replacement interval obtained for C_a:C_b=3 to 4 and A7 the optimal replacement interval obtained for C_a:C_b=5 to 8). It can be concluded that as the ratio increases, the replacement interval decreases up to a point and then remains constant. When compared to β and Ø the cost ratio has a smaller impact on the ranking of replacement interval alternatives.

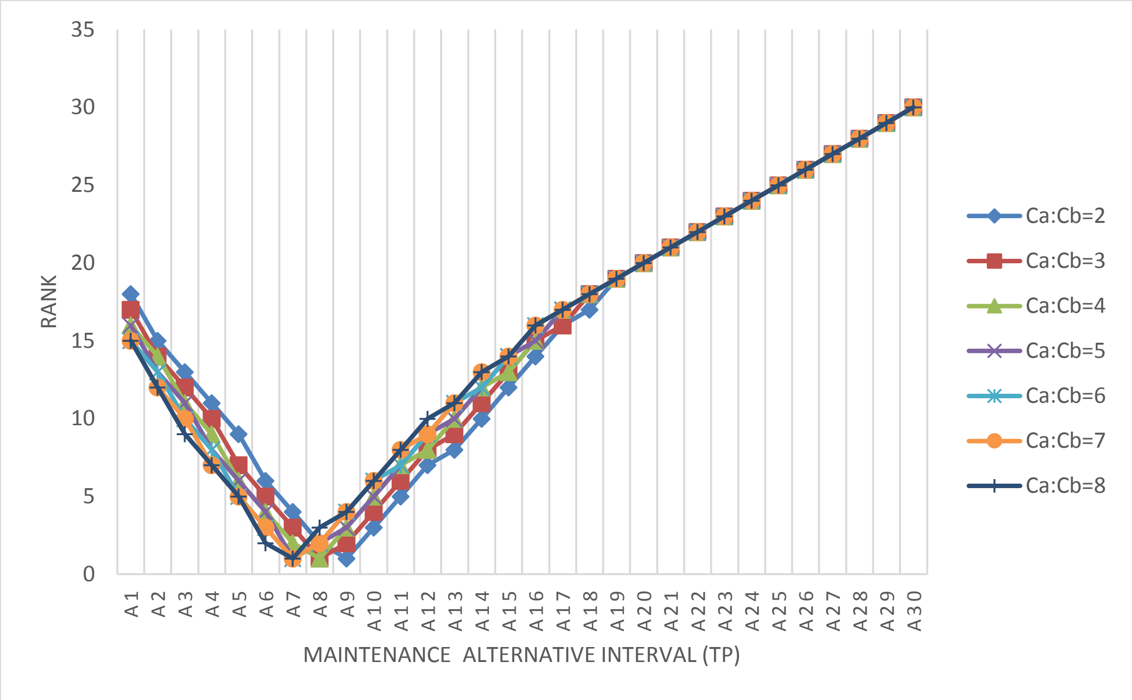

Figure 6.18a: Ranking of sensitivity analysis of cost ratio

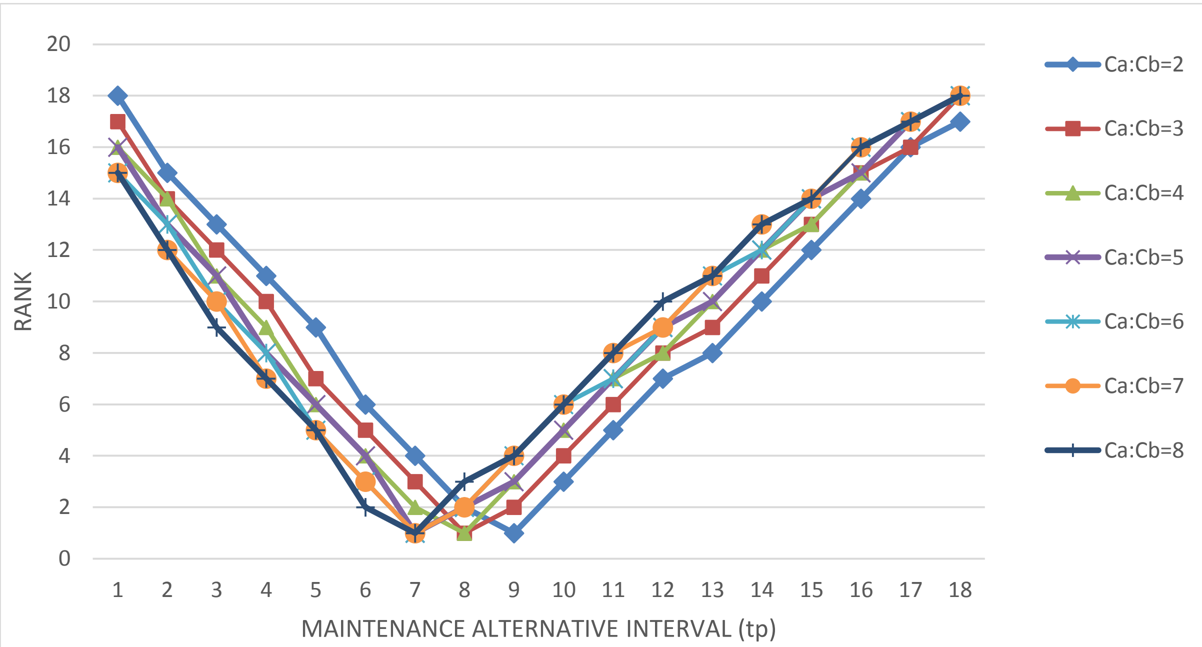

Figure 6.18b: Ranking of sensitivity analysis of cost ratio

6.3.4.4 Impact of ratio T_b to T_a variations on the overall ranking of replacement interval alternatives

In order to determine the impact that variation of the ratio T_b to T_a would have on the overall ranking of replacement interval alternatives, the ratio of Tb to Ta was varied from 2 to 9 and the TOPSIS performance index generated for the replacement interval alternatives for the eight scenarios. The results are presented in Table C7 in Appendix C2. The performance index for the replacement interval alternatives in the nine scenarios were ranked and the results are presented in Table C8 in Appendix C2 and Figure 6.19. It is obvious from the table and graph that the optimal replacement interval for the scenarios remained unchanged with the exception of the first scenario (T_b to T_a equal to 2). When compared to the other input parameters the T_b to T_a ratio has less impact on the overall ranking of replacement interval alternatives.

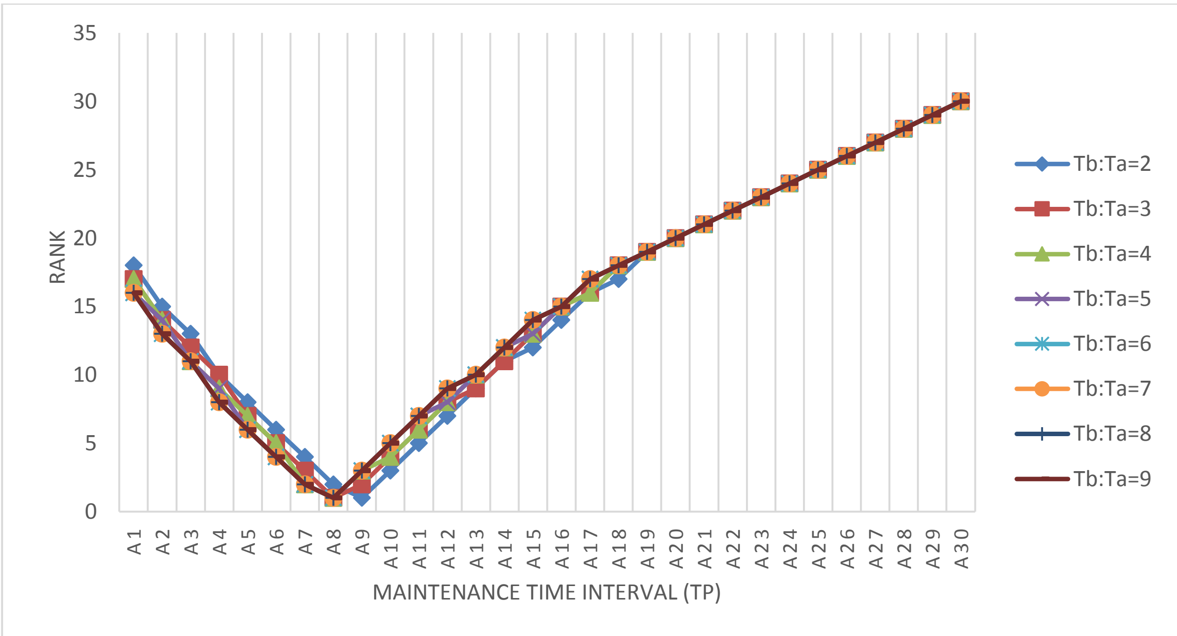

Figure 6.19: Ranking of sensitivity analysis of ratio of Tb to Ta

6.4 Summary

For safe and reliable operation of marine machinery systems at reasonable cost there needs to be in place an efficient maintenance system. However in making maintenance decisions, different parties are involved and the decisions are usually based on certain criteria which are always in conflict with one another. In resolving such conflicts the multi-criteria decision making technique is usually suitable. In this research, decision criteria such as reliability, cost and downtime were considered as the basis for selecting the optimum preventive replacement interval for marine machinery systems. Since the three decision models are in conflict with one another, the outputs were aggregated with the aid of MCDM techniques. In order to demonstrate the applicability of the methodology, failure data obtained from secondary sources and estimated cost data for the connecting rod of a marine diesel engine were used as input data. The result of the investigation revealed the following:

(1) For the data considered, the optimum replacement interval for performing maintenance tasks on the connecting rod of the marine diesel engine is 12,000hrs. However this is not fixed as the interval could vary depending on the operating environment of the system, the age of the system, cost of replacement at breakdown, cost of preventive replacement and type of failure distribution.

(2) If the Weibull distribution is the failure distribution for the system, the scale parameter, $\emptyset$, has a greater impact on the three models than the shape parameter, β. However for the cost model the ratio of C_a to C_b has the greatest impact. For the downtime model, the ratio of T_b to T_a has the greatest impact followed by $\emptyset$ while β has the least impact.

(3) $\emptyset$ has the greatest influence on the overall ranking of replacement interval alternative. The ratio of T_b to T_a has the least impact on the overall ranking of replacement intervals.

(4) Increasing the values of parameters such as $\emptyset$ and β will result in a corresponding increase in the replacement interval and reducing the value will result in a reduction in the replacement interval.

From the result of this analysis the proposed methodology is simple and robust. The approach in this research has an advantage over the technique applied by some authors for land based systems as the criteria weight evaluation model is flexible with both objective and subjective components. The proposed methodology is not limited to application to marine machinery systems as it capable of solving other engineering system problems if provided with the appropriate input data.

Chapter 7 Inspection Interval Determination

7.1 Introduction

One of the maintenance strategy options for maintaining components of a marine system is scheduled on-condition task which was referred to as Offline-Condition Based Maintenance (OFCBM) in Chapter 5. As previously stated, scheduled on-condition task is the inspection carried out on plant systems to monitor their performance degradation. Once it has been established that the optimum maintenance strategy for mitigating failure of a particular equipment item of the system is scheduled on-condition task, the next task is to determine the interval for performing the maintenance task.

Based on the literature review in Chapter 2, the most promising technique for determining the optimum interval for carrying out inspection is the delay time model. However most of the delay-time model applications for inspection interval determination discussed in the literature are based on a single model such as the use of cost or downtime in optimising inspection. However a few cases considered a combination of two models in deciding the inspection plan for either a single unit or multi-unit system. In these few cases, the optimum inspection intervals obtained from the individual models were close and, as such, reaching a compromise solution was straightforward without resorting to special MCDM tools. Nevertheless in most real life applications the decision criteria results may not be close and in such a scenario reaching a compromise solution becomes challenging. For cases of this nature, the use of multi-criteria tools such as PROMETHEE, TOPSIS, Elimination Et Choix Traduisant La REalite (ELECTRE) and Multi-Attribute Utility Theory (MAUT) becomes imperative. Additionally the use of such tools make it possible to include the opinion of maintenance practitioners in the decision making process. The use of the MAUT method specifically has an additional benefit of integrating the risk perception of the maintenance practitioners into the decision making process. Considering the benefits of both delay model and MAUT techniques, a combination of the two methods is proposed for determining the inspection interval for marine machinery systems.

The Chapter is organised as follows: In Section 7.2 a background study of the delay time model is discussed; Section 7.3 presents the proposed methodology for determining the optimum inspection interval; in Section 7.4 the case of the water cooling pump is presented to demonstrate the proposed methodology. Finally the conclusion is presented in Section 7.5

7.2 Delay time model background

In determining the maintenance strategy of marine systems using the RCM methodology, some equipment items are more effectively maintained by scheduled inspection or scheduled inspection in combination with other maintenance tasks. The essence of inspection is to ascertain the true condition of an item and as such it's similar to online condition based maintenance. The difference is that while inspection is carried out by maintenance personnel, online condition based monitoring is carried out through the use of diagnostic tools which continually monitor the condition of the equipment. In the course of performing inspection activities, if a defect is found, a repair or replacement task is schedule and if possible executed immediately to prevent the equipment from further deterioration. If inspections are not carried out, defects may go unnoticed which can result in catastrophic system failure with severe economic loss for the company. However even if inspection tasks are performed, if they are not properly timed, defects can still occur between successive intervals. It is obvious then that the determination of the optimal inspection interval is central to the effective operation of any marine machinery system. Conventionally the inspection interval is determine by maintenance practitioners relying on experience and/ or on the equipment manufacturers' recommendation, the result being far from optimal and also conservative (Christer et al., 1997).

An inspection task as an alternative maintenance approach can only be beneficial if there is a sufficient period between the time that the defect is observed and the actual time of failure of the equipment. The time interval between when a defect becomes identifiable and the actual time of failure is referred to as the delay time (h_f). Based on this concept, Christer proposed the Delay Time model (Christer et al., 1997) for determining the inspection interval of an equipment item. The delay time is the most appropriate time to carry out an inspection on a marine machinery system. Figure 7.1 is used to illustrate the delay time concept.

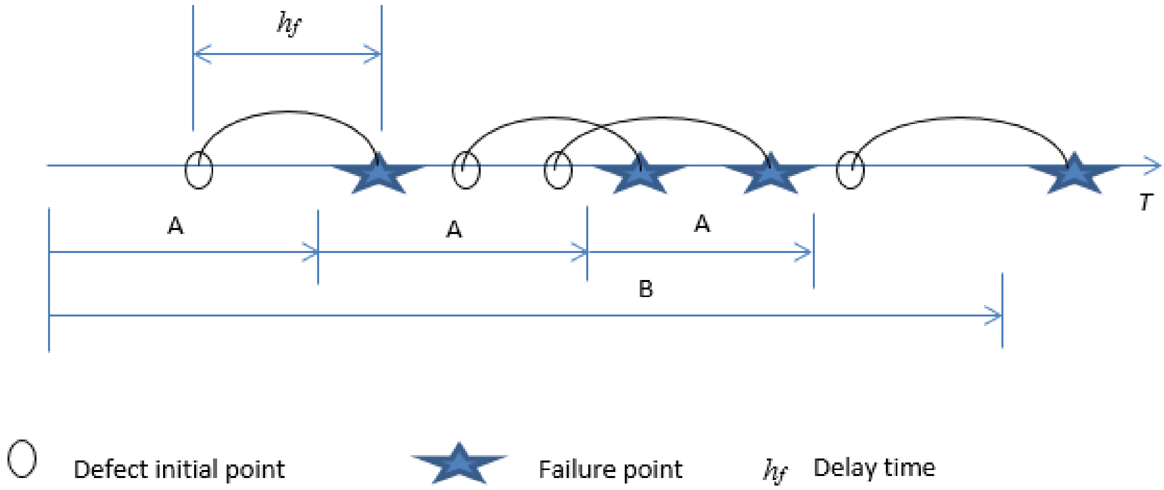

Figure 7.1: Delay time concept showing a defect's initial points and failure points

Figure 7.1 shows multiple points of failure, both initial and actual points where failure occurs and also two different inspection plans for the marine machinery system in question. It is obvious from the figure that if the inspection of the system is performed at an interval of B a lot of failures will happen in the system since most of the defects would have resulted in actual failure. Alternatively inspection plan A would result in detecting virtually all of the defects before the actual failure of the system could occur. The key to achieving maximum success in mitigating catastrophic failure of a marine machinery system is to have a proper understanding of the delay time (h_f) of the system such that maintenance can be performed within this period.

Based on Christer and Waller (1984a), a defect occurring within a period of (0, T) in a marine machinery system has a delay time, h_f and h_f has a probability density function of $f(h_f)$. If failure of the machinery system occurs at a period (0, T-h_f) the maintenance (repair or replacement) carried out is referred to as breakdown maintenance otherwise the maintenance is inspection maintenance. For the marine machinery system, if all possible values of h_f are added up, according to Christer and Waller (1984a), the probability of a defect occurring as a breakdown failure is:

$$B(T) = \int_0^T \frac{T - h_f}{T} f(h_f) h_f \tag{7.1}$$

The above Equation was established based on the following assumptions:

(1) Inspection is performed at regular intervals

(2) Defects discovered during inspection are repaired

(3) Perfect inspection meaning all defects are discovered during inspection

(4) Arrival rate of defects is constant

However it is worth noting that some of these assumptions may not be realistic in practical situations. For example, it may not be possible to identify all defects during inspection as some defects could be hidden although the system performance degradation may have started during inspection. Some of these assumptions are made to ease the modelling of the system and for ease of computation of the models.

Detailed information on the delay time concept and its application in marine and other related industries for the purpose of optimising maintenance, was discussed in the literature section.

7.3 Proposed inspection interval determination methodology

In this research, the delay time model was used in conjunction with MCDM techniques in order to determine the optimum inspection interval for marine machinery equipment. The MCDM techniques are used in aggregating the expected cost, expected downtime and reputation models. The weights of the decision criteria were evaluated with respect to maintenance practitioners' preference. Hence a flexible weighting technique has been developed for this purpose. The decision criteria considered simultaneously in deciding the optimum inspection interval using the delay time technique are; Downtime per unit time D(T) and Cost per unit time C(T) and expected Reputation per unit time R(T). The flowchart of the proposed methodology for selecting appropriate inspection intervals for the marine machinery system is presented in Figure 7.2.

The methodological steps are as follows:

Step (a) the system to be investigated is determined and is usually broken down into sub-systems and components. Next the system is thoroughly studied to identify dominant failures and corresponding consequences. Various techniques such as, group brainstorming, FMEA and FTA can be applied to determine dominant failures, causes and the chances of the failures occurring. In this research, the FMEA technique was chosen for this purpose. Once the dominate failures have been identified, data is gathered to be applied as input into a mathematical model for optimising the inspection interval such that system failure can be eliminated or minimised. The data that can be applied for delay time model analysis may be subjective /and or objective. Objective data is generally preferable however, if it is lacking in quality and quantity, subjective data can be applied. Objective data is obtained from maintenance and failure data records from the marine industry. In most cases, this data is not available because of the nature of the environment and sometimes due to commercial sensitivity. Subjective data on the other hand is obtained by developing questionnaires which are used in gathering information relating to maintenance and equipment failures from marine maintenance personnel, vessel crews and management.

Step (b) The three mathematical models based on the delay time concept; D(T), C(T) and R(T) are evaluated by using data collected in step (a). Common to the three Delay Time Analysis (DTA) models are variables such as B(T), downtime as a result of inspection, ∂ , and arrival rate of defects per unit time, k_r. To determine B(T), a failure mode is chosen and from failure records, the initial point of failure is determined. This is followed by the determination of the distribution of the delay time of failure which may be a normal, exponential or Weibull distribution. Once the distribution has been estimated, the parameters of the distributions may be determined. These parameters are then used as input into the B(T) model to calculate its value. Having known values of B(T), ∂ and k_r, D(T) is evaluated. To evaluate C(T) other variables such as costs of breakdown, inspection repairs and inspection are needed in addition to B(T), ∂ and k_r and finally to evaluate R(T) parameters such as *Rbr* and *Rii* are needed in addition to B(T), ∂ and k_r.

Step (c) C(T), D(T) and R(T) are evaluated for every value of T and used to form a decision matrix, x_{ij} (m x n), as presented in Table 7.1, where m is the number of alternative inspection T_i , and n is the number of decision criteria. In this case, the decision criteria are C(T), D(T) and R(T).

Step (d) Determination of decision criteria weight: The pairwise comparison judgment obtained from the experts for the decision criteria is used as the input into the AHP evaluation technique to calculate weights of decision criteria.

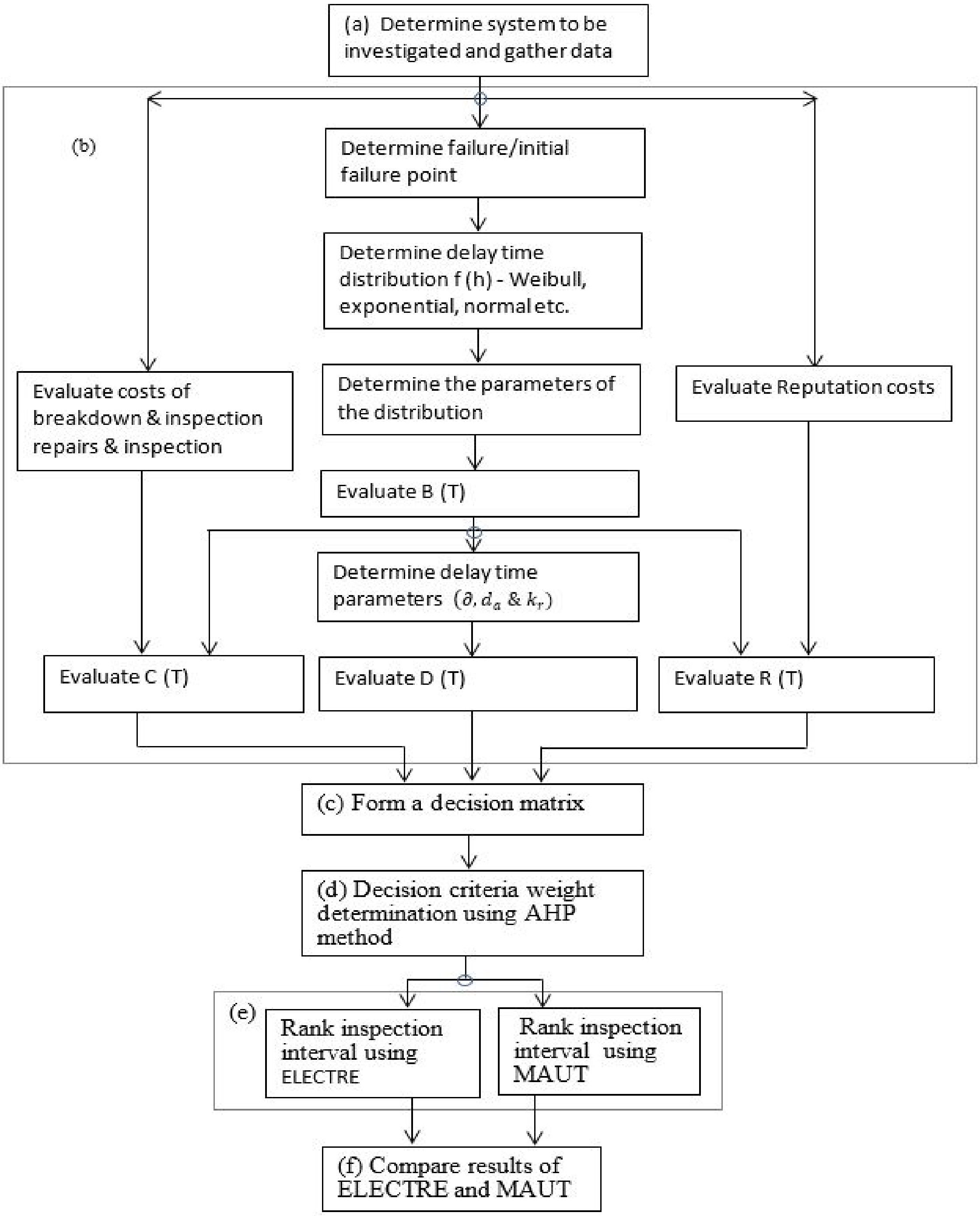

Figure 7.2: Flow of the integrated MCDM and Delay time model for inspection selection

Table 7.1: Inspection interval alternatives decision table

Alternatives (Aj)	Decision criteria (Bi)		
	D(T)	C(T)	R(T)
A_1	x_{11}	x_{12}	x_{13}
A_2	x_{21}	x_{22}	x_{23}
A_3	x_{31}	x_{32}	x_{33}
-	-	-	-
-	-	-	-
A_m	x_{m1}	x_{m2}	x_{m3}

Step (e) Ranking of inspection alternatives: The maintenance strategy alternatives are ranked using Elimination Et Choix Traduisant La REalite (ELECTRE) and Multi-Attribute Utility Theory (MAUT).

Step (f) the ranking obtained from both methods are compared and an optimum strategy is then determined

7.3.1 Develop delay time concepts models

The assumption in this research is that the delay times of failure for the marine machinery systems components follow a Weibull distribution, therefore $f(h_f)$ is represented as follows:

$$f(h_f) = \frac{\beta}{\emptyset}\left(\frac{h_f}{\emptyset}\right)^{\beta-1} exp\left[-\left(\frac{h_f}{\emptyset}\right)^{\beta}\right] \tag{7.2}$$

On the basis of Eq. (7.2) the *B*(*T*) model, which is the probability that defects will be repaired as breakdown repairs in Eq. (7.1) can be represented as follows:

$$B(T) = \int_0^T \frac{T-h_f}{T}\,\frac{\beta}{\emptyset}\left(\frac{h_f}{\emptyset}\right)^{\beta-1} exp\left[-\left(\frac{h_f}{\emptyset}\right)^{\beta}\right] dh_f \tag{7.3}$$

7.3.1.1 Downtime models

The expected downtime per unit possible time of inspection using the delay time approach can be presented as follows (Christer and Waller, 1984a):

$$D(T) = \frac{\partial + k_r T B(T) d_a}{T + \partial} \tag{7.4}$$

Where

T = Inspection time interval

∂ = Downtime as a result of inspection

d_a = Average downtime due to breakdown repair

h_f= Delay time

k_r= Arrival rate of defects per unit time

If Eq. (7.3) is substituted in to Eq. (7.4), $D(T)$ will be represented as:

$$D(T) = \frac{\partial + k_r T \left\{ \int_0^T \frac{T - h_f}{T} \frac{\beta}{\emptyset} \left(\frac{h_f}{\emptyset} \right)^{\beta - 1} exp \left[- \left(\frac{h_f}{\emptyset} \right)^{\beta} \right] dh_f \right\} d_a}{T + \partial} \tag{7.5}$$

7.3.1.2 Expected Cost model

The downtime model in Eq 7.4 may be modified by including three distinct cost components; cost of breakdown, cost of inspection repair and cost of inspection, in order to model the expected cost per unit time function (Christer and Waller, 1984a). The expected cost per unit time of inspection of a marine machinery system, *C(T),* is written as follows:

$$C(T) = \frac{[k_r T\{C_{br} B(T) \ + C_{ii}[1 - B(T)]\} + C_{ic}]}{T + \partial} \tag{7.6}$$

Where

C_{br} = cost of breakdown repair

C_{ii} = cost of inspection repair

C_{ic} = cost of inspection

The three cost variables each need to be evaluated to be applied as an input into $C(T)$ together with the delay time parameters. In order to evaluate breakdown repair cost there is a need to know all of the failure modes of the marine machinery system and the corresponding consequences of the failure. As previously stated, FMEA has been applied in this research. In Chapter 4, the consequences of the failure modes were presented whose values were assigned by experts using an ordinal scale of 1 to 10. These are now expressed in monetary terms. The cost of breakdown repair is evaluated as the sum of the labour cost (L_c), spare parts cost (S_c), equipment downtime time cost (E_{dc}), penalty cost (P_c), and dry-docking cost (D_{dc}) shown as follows:

$$C_{br} = L_c + S_c + E_{dc} + P_c + D_{dc} \tag{7.7}$$

The labour cost can be expressed as the product of the number of maintenance personnel (N_{cm}) that will carry out the repair, the pay rate per hour per person (P_{rm}) and the time duration of repair (T_{dm}). This is shown as follows:

$$L_c = N_{cm}.P_{rm}.T_{dm} \tag{7.8}$$

The cost of inspection repair is presented as follows:

$$C_{ii} = C_{ic} + L_c + S_c + E_{dc} + P_c \tag{7.9}$$

It is obvious from Eq. 7.7 and 7.9 that the cost of break down repair and cost of inspection repair are the same except that (1) inspection cost is included in the cost of inspection repair and dry-docking cost is excluded from it. The dry-docking cost is excluded from inspection repair because defects are addressed before the actual failure occurs and so it will not result in catastrophic failures that can call for unplanned dry-docking of the entire ship system; and (2) the time duration for performing corrective action during breakdown repair is higher than the time duration for carrying inspection repair. The time duration for breakdown repair is generally higher than time taken to perform corrective action for inspection repair because in breakdown repair the defect may not only have resulted in a particular component failure but could also result in both secondary and tertiary effects.

The cost of inspection C_{ic} for the machinery system equipment or component may be expressed as the product of the number of marine maintenance crew (N_{ic}), their pay rate per hour (P_r) and the duration for performing the maintenance added to the product of equipment or component downtime and duration of performing the maintenance, presented as follows:

$$C_{ic} = [(N_{ic} \,.\, P_r\,) + \; E_{dc}]T_d \tag{7.10}$$

Where T_d is the duration of inspection.

7.3.1.3 Expected Reputation model

With the reputation model, the relationship between the impact of failures on the reputation or image of the marine industry can be studied. The failure of marine machinery systems can have a negative impact on the company and as such this model helps in determining the most appropriate time interval to perform maintenance inspection with the intention of reducing or eliminating system downtime whilst boosting the reputation of the company. In similar fashion to developing the cost model and downtime model, the reputation model is presented as follows:

$$R(T) = \frac{k_r T\{R_{br}B(T) \; + R_{ii}[1 - B(T)]\}}{T + \partial} \tag{7.11}$$

Where R_{br} is the company reputation when a failure correction measure is performed as a breakdown repair and R_{ii} is the company reputation when failure corrective action is performed as an inspection repair. In assigning values to the two variables; R_{br} and R_{ii} , an ordinal scale of 1 to 10 is applied by experts. The value assigned is a function of the severity and the occurrence of the failure. In this case, the worst case scenario was assumed for R_{br} since a breakdown repair scheme may sometimes result in catastrophic damage that may affect personnel on board ship, marine machinery system equipment and the environment. For R_{ii} , the best case scenario may be assumed since failures are preventatively mitigated. For the best case scenario 1 is assigned and for the worst case scenario 8 to 10 can be assigned.

A programme was written in Matlab® to evaluate D(T), C(T), and R(T). The Programme is given in Appendix D.

7.3.2 Decision criteria weighting techniques

The AHP technique for determining the weights of decision criteria; D(T), C(T) and R(T) was discussed in Chapter 4.

7.3.3 Ranking of time interval tools

The decision making process involves applying simultaneously three decision criteria which are usually conflicting, in arriving at the most appropriate time interval for inspection of the marine machinery system. Two MCDM techniques; ELECTRE and MAUT were used and compared. The methodological steps for these methods are discussed next:

7.3.3.1 ELECTRE method

ELECTRE is the acronym for Elimination and Et Choice Translating Reality, a multi-criteria technique which utilises the concept of paired comparisons among alternatives with respect to chosen decision criteria. The method was established by Roy and Vinke (Roy and Vincke, 1981) and has since been modified and applied successfully in addressing multi-criteria decision problems in different fields. Shanian et al. (2008) utilised the technique in solving a material selection problem and Sevkli (2010) integrated ELECTRE with a fuzzy logic technique in addressing a supplier selection problem. In this thesis, the technique has been used to solve an inspection interval selection problem in the marine environment. The methodological steps associated with the ELECTRE method as presented in (Anojkumar et al., 2014) are as follows:

Step 1: Formation of the decision matrix: the process starts with formation of a decision matrix, X, with alternatives, j with respect to criteria, i. An example of such a decision matrix with elements x_{ij} is presented in Table 7.1.

Step 2: Normalisation of the decision matrix: the normalisation of the decision matrix is performed in order to convert varying units among different decision criteria into dimensionless form. The normalisation of the decision matrix x_{ij} is carried out as follows:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{m} x_{ij}^2}}, \quad i = 1,2 \dots, n; \; j = 1, \dots, m \tag{7.12}$$

Where r_{ij} is the normalised matrix

Step 3: determination of the weighted normalised matrix:
The weighted normalised matrix (v_{ij}) is obtained as a product of decision criteria weight, w_i , and the normalised matrix as follows:

$$v_{ij} = w_j r_{ij\,,} \quad i = 1, \dots, n\,; \quad j = 1, \dots, m \tag{7.13}$$

Step 4: Determination of the concordance interval matrix: Given a pair of alternatives, A_j and A_k, the concordance index $c_I(j, k)$ can be evaluated as the summation of all weights for those criteria where weighted normalised score of A_j is greater than or equal to $A_{k,}$, as follows:

$$c_I(j,k) = \sum_{v_i(j) \geq v_i(k)} w_i\,, \quad j,k = 1, \dots, m\,; \quad j \neq k \tag{7.14}$$

Where $v_i(j)$ and $v_i(k)$ are the weighted normalised scores of the *jth* and *kth* alternatives respectively. The results obtained from the concordance evaluation are then applied to form the concordance matrix as follows:

$$C_I = \begin{bmatrix} - & c_I(1,2) & \dots & c_I(1,m) \\ c_I(2,1) & - & \dots & c_I(2,m) \\ \vdots & \vdots & \ddots & \vdots \\ c_I(m,1) & c_I(m,2) & \dots & - \end{bmatrix} \tag{7.15}$$

Step 4: Determination of the discordance interval matrix: The first step to producing the discordance matrix, is to determine discordance index. The discordance index $d_I(j, k)$, can be evaluated as:

$$d_I(j,k) = \begin{cases} 0\,, & if \quad v_i(j) \geq v_i(k) \quad i = 1,2, \dots, n \\ \dfrac{\max\limits_{v_i(k) > v_i(j)} [v_i(k) - v_i(j)]}{\max\limits_{i=1,\dots,n} [|v_i(k) - v_i(j)|]}, & otherwise \qquad j,k = 1,2, \dots, m.\ j \neq k \end{cases} \tag{7.16}$$

The discordance matrix is then formed by using the evaluated results from the discordance index, presented as follows:

$$D_I = \begin{bmatrix} - & d_I(1,2) & \dots & d_I(1,m) \\ d_I(2,1) & - & \dots & d_I(2,m) \\ \vdots & \vdots & \ddots & \vdots \\ d_I(m,1) & d_I(m,2) & \dots & - \end{bmatrix} \tag{7.17}$$

Step 5: Determination of the performance index:

The performance of the alternatives is measured using the net superior and inferior values. The net superior values, C_s , upon which the alternatives are ranked, is evaluated as follows:

$$C_s = \sum_{k=1}^{m} C_I(j,k) - \sum_{j=1}^{m} C_I(k,j) \quad j \neq k \tag{7.18}$$

On the other hand the net inferior values, D_s , upon which alternatives are also ranked can be determined as follows:

$$D_s = \sum_{k=1}^{m} D_I(j,k) - \sum_{j=1}^{m} D_I(k,j) \quad j \neq k \tag{7.19}$$

The two indices for measuring performance of alternatives will yield two rankings. The two rankings obtained from the indices can then be averaged to produce the final ranking from which the alternative with the superior rank is selected. The ELECTRE methodology used for the ranking of alternatives, was coded in Matlab® and is presented in appendix D2.

7.3.3.2 Multi-Attribute Utility Theory (MAUT)

Multi-Attribute Utility Theory (MAUT) is one of the MCDM tools for arriving at a specific decision when the decision making process involves different alternatives with conflicting decision criteria. MAUT provides a systematic means for making trade-offs among decision criteria such that an optimum alternative can be selected from numerous options. The beauty of this technique lies in the fact that decision makers' preferences in terms of risk structure can be included in the decision making process, something which is lacking in the other MCDM tools. MAUT has its foundation in the utility theory developed by Neumann and

Morgenstern (Neumann and Morgenstern, 1947) and the elicitation and specific assessment techniques developed by Keeney and Raiffa (Keeney and Raiffa, 1976). With the combination of these techniques, the decision criteria of the decision problem can be represented as individual utility functions which are then aggregated into a single analytical function. The MAUT method has been applied in solving different multi-criteria decision problems in different industries. Hwang (2004) utilised MAUT to establish an optimal scenario that can reduce residents' exposure to radioactive substances during the elementary phase of a nuclear power plant accident. Brito and de Almeida (2009) used MAUT to prioritise the risk of leakage in a natural gas pipeline. The technique was also applied by De Almeida and Bohoris (1996) in a maintenance strategy selection problem. Having been applied in solving other problems, the method is used in this thesis to model the maintenance inspection problem within the marine environment.

The methodological procedure of the MAUT technique is as follows:

Step 1: Formation of the decision problem: The overall aim is to determine the optimal alternative with respect to some decision criteria. The decision problem is generally represented in the form of a matrix, an example is shown in Table 7.1. From Table 7.1, the decision criteria are represented as B_i and the alternatives represented as A_j where i is the number of decision criteria and j is the number of alternatives. In this particular decision problem, i is 3 that is to say the decision problem has three decision criteria which are D(T), C(T) and R(T) and x_{ij} are the elements of the decision matrix which are the values evaluated for alternatives against the decision criteria. The alternatives referred to here are the inspection intervals, the most appropriate of which is to be determined by the decision maker (maintenance practitioner) with respect to the decision criteria; D(T), C(T) and R(T). It is the duty of the decision maker, based on experience and maintenance and failure records of the marine machinery system, to determine alternative inspection intervals (A_j) for the marine machinery system which can be rated in hours, days, weeks, months, etc.

Step 2: Determination of single utility functions: The utility function is used to embed the decision maker's risk preference in the decision making process. For the different decision criteria, utility functions are determined which are then applied to form a multi-attribute utility function. The risk perceptions of the decision maker are of three types which are incorporated into the utility function. The three risk perceptions are; risk prone, risk neutral and risk averse. The three risk perceptions with respect to the utility function are illustrated in Figure 7.3.

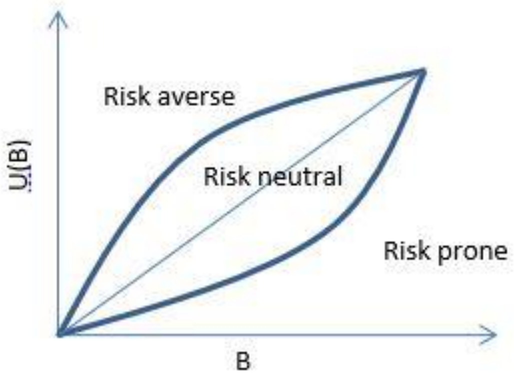

Figure 7.3: Utility function characteristics (Anders and Vaccaro, 2011)

One popular utility function to define decision criteria is the power series function, as follows (Anders and Vaccaro, 2011):

$$u(B_i) = \frac{(B_i - a)^S}{(b - a)^S} \tag{7.20}$$

Where *S* is used to define the risk perception of the decision maker. For a risk-neutral decision maker, *S* is given the value of 1 and for risk prone and risk averse decision makers the value of greater and less than 1 are assigned to S respectively. The maximum and minimum values of the element of decision criterion B_i are *a* and *b* respectively in Eq. 7.20. The outputs of the utility function of decision criteria range from 0 to 1. In this research it was assumed that the decision maker was risk neutral and as such the utility function of the three decision criteria; cost, downtime and reputation are as presented in Eq. 7.21, 7.22 and 7.23 respectively:

$$u(C(T)) = \frac{x_{1j} - a_1}{b_1 - a_1} \tag{7.21}$$

$$u(D(T)) = \frac{x_{2j} - a_2}{b_2 - a_2} \tag{7.22}$$

$$u(R(T)) = \frac{x_{3j} - a_3}{b_3 - a_3} \tag{7.23}$$

The constants a_1, b_1 are the maximum and minimum values of x_{1j} , where x_{1j} are the elements that belong to the decision criterion cost in the decision matrix in Table 7.1. The constants a_2, b_2 are the maximum and minimum values of x_{2j} where x_{2j} are the elements that belong to the decision criterion downtime. Finally, b_3, a_3 represent the maximum and minimum values of x_{3j} where x_{3j} are the elements in the decision matrix that belong to the decision criterion reputation.

Although it was assumed in this research that S was equal to 1, analysis was also conducted for the situation where S was greater than 1 and less than 1 in order to see the effects it would have in the decision making process. This was performed as a sensitivity analysis by applying S in the range of 0 to 2.

Step 3: Determination of multi-attribute utility functions: The individual decision criteria utility functions determined in step 2, together with their respective scaling constants were multiplied and then aggregated using either the additive or the multiplicative technique. In this research the additive technique was utilised and is shown as follows:

$$U(C(T), D(T), R(T)) = w_c u(C(T)) + \ w_d u(D(T)) + \ w_R u(R(T)) \tag{7.24}$$

Where w_c, w_d and w_R are the scaling constants of the utility functions of decision criteria; cost, downtime and reputation respectively as determined using the AHP method detailed in Section 5.3.2.

7.4 Case study 1: Marine diesel engine-sea water cooling pump

The sea water cooling pump is used as a case study in this research to illustrate the applicability of the proposed integrated MCDM techniques and the delay time model. The sea water pump is one of the equipment items of the central cooling system of the marine diesel engine. In Chapters 3 and 4, the FMEA analysis of the entire marine diesel engine was carried out and from the analysis the sea water pump failure modes were identified as being among the most critical failure modes of the marine diesel engine. Knowing the risk contribution, the next step was to define the maintenance strategy to mitigate failures and this was carried out in Chapter 5. The optimum maintenance strategy for the sea water cooling pump, was identified in Chapter 5 to be offline condition based maintenance (inspection). Finally, in this chapter, the optimum interval for performing the inspection activities is determined.

7.4.1 Data collection

The basic data needed as input into D(T), C(T) and R(T) in order to determine the optimum inspection interval for the sea water cooling pump are delay time parameters, cost parameters and reputation parameters.

Central to the delay time analysis is the delay time distribution and this is generally determined using two techniques; the subjective and the objective methods. The objective method usually requires the use of large amounts of equipment failure data in determining delay time distributions but these are not available in most cases. The use of the subjective method on the other hand requires limited data but a lot of time is involved in developing questionnaires and obtaining the required information for estimating delay time (h_f) from experts. For this research, due to difficulty in defining the exact delay time distribution function, a Weibull distribution was assumed. The Weibull distribution was assumed because of its flexibility in representing different failures patterns (Krishnasamy et al., 2005, Wang et al., 2012). Having assumed the Weibull distribution, the delay time probability density function, $f(h_f)$, parameters need to be determined. Due to the unavailability of data to estimate these parameters, one of the combinations of shape and scale parameters which had previously been applied by Cunningham et al. (2011) for a sea water cooling pump was used in this study. The different combinations of shape and scale parameters are presented in Table 7.2. The combination of lower β and higher $\emptyset$ produces a more definite minimum point in a delay time model plot (Cunningham et al., 2011). On this basis a combination of 10 and 5 were chosen from Table7.2 for this research.

Table 7.2: Weibull parameters

Ø	β
10	5
8	6
3	10
2	20

The possible alternative time intervals for inspection of the equipment were determined by considering the failure data of the equipment, maintenance manuals and with the aid of an expert with several years of marine diesel engine maintenance experience.

The arrival rate of defects is another variable that needs to be evaluated in the DTA. The arrival rate of defects and failure rate of equipment items or components are identical if the equipment items or components are maintained based on reactive maintenance (Cunningham et al., 2011). In this study, the failure rates in OREDA (2002) were assumed to have been collected based on reactive maintenance of a system. Based on this assumption, the failure rates in OREDA 2002 for a centrifugal pump were used as the arrival rate of defects. From the OREDA 2002 data handbook, the failure rate for the centrifugal pump is given as 1277 per 10^6 hours for all failure modes.

Having obtained the arrival rate of defects, the next important variables that needed to be determined were downtimes due to breakdown repair and inspection. For both variables, the data already available in the literature was relied upon. Cunningham et al. (2011) had taken downtime due to inspection to be 12.5 minutes. In arriving at 12.5 minutes for downtime due to inspection of a centrifugal pump of the main cooling system of a passenger ferry, the authors considered the time used for visual inspection of suction and discharge pressure, observation of abnormal noise using audio inspection and monitoring of the level of current drawn by the electric motor by means of electrical inspection. The value of 168 hours for the downtime as a result of breakdown repair was obtained from OREDA 2002. This value included the delay in procuring and transporting spare parts.

The three basic cost parameters are cost of inspection (c_{ic}), cost of inspection repair (c_{ii}) and cost of breakdown repair (c_{br}). However cost information was not generally available hence a combination of experts' opinions and logged records were relied on to find reasonable estimates. These estimates were used as input into Eq. 7.7, 7.9 and 7.10 to obtain estimated values of cost of breakdown repair, cost of inspection repair and cost of inspection respectively. The estimated costs generated from the equations are presented as follows:

Cost of breakdown repair (c_{br}) = £52,500
Cost of inspection repair (c_{ii}) = £10,500
Cost of inspection (c_{ic}) = £210

Finally, for the reputation per unit time of the inspection model, two parameters were needed as input into the model. The two, R_{br} and R_{ii} were estimated by experts using an ordinal scale of 1 to 10. The value assigned was a function of the severity and the occurrence of the failure. In this research, the worst case scenario was assumed for R_{br} since breakdown repair may sometimes result in catastrophic damage that may affect personnel on a board ship, marine machinery system equipment and the environment. For R_{ii}, the best case scenario was assumed since failures are preventatively mitigated. On this basis the values of 1 and 10 were assigned for R_{ii} and R_{br} respectively.

7.4.2 Delay time model analysis

The data for the variables of the delay time models were input into Eq. 7.4, 7.5 and 7.6 to evaluate downtime per unit cost, cost per unit time and reputation per unit time for different inspection intervals. The evaluation of Eq. 7.4, 7.5 and 7.6 was achieved using a Matlab programme as presented in Appendix D1. The results obtained for downtime, cost and reputation are presented in Figures 7.4, 7.5 and 7.6 respectively.

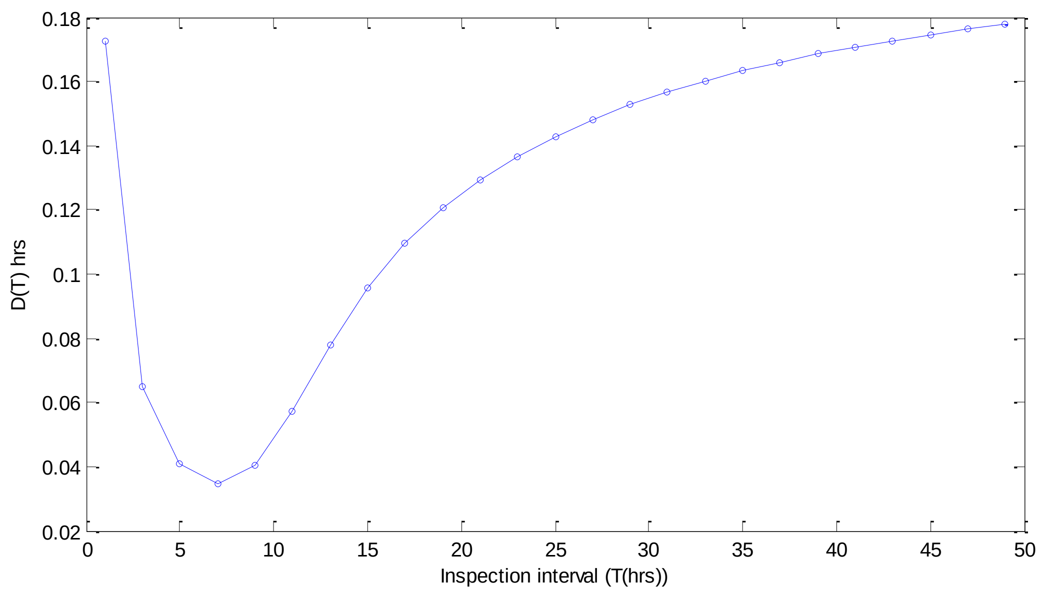

Figure 7.4: Alternative inspection interval vs downtime per unit time

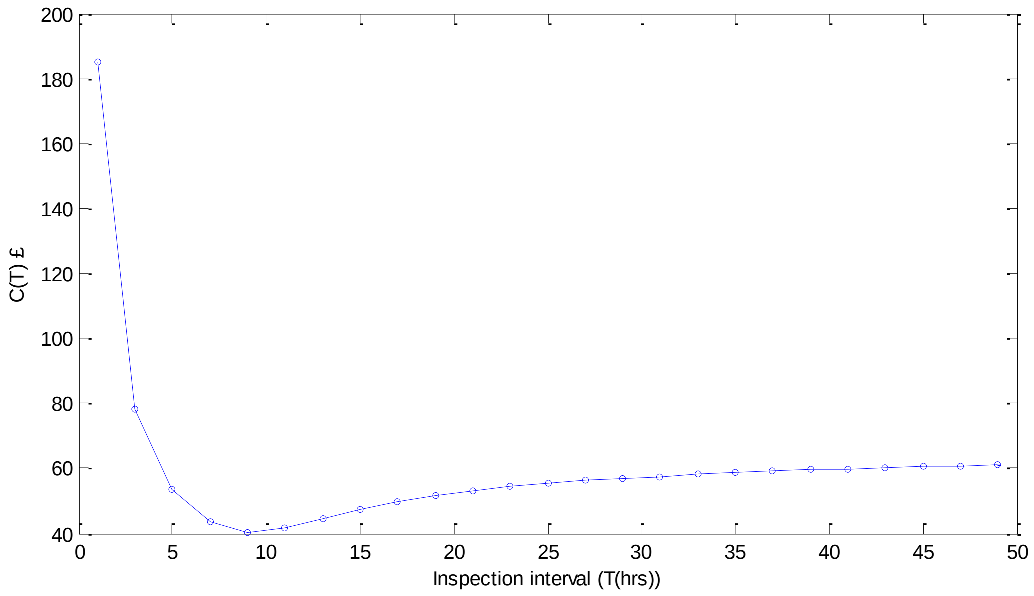

Figure 7.5: Alternative inspection interval vs cost per unit time

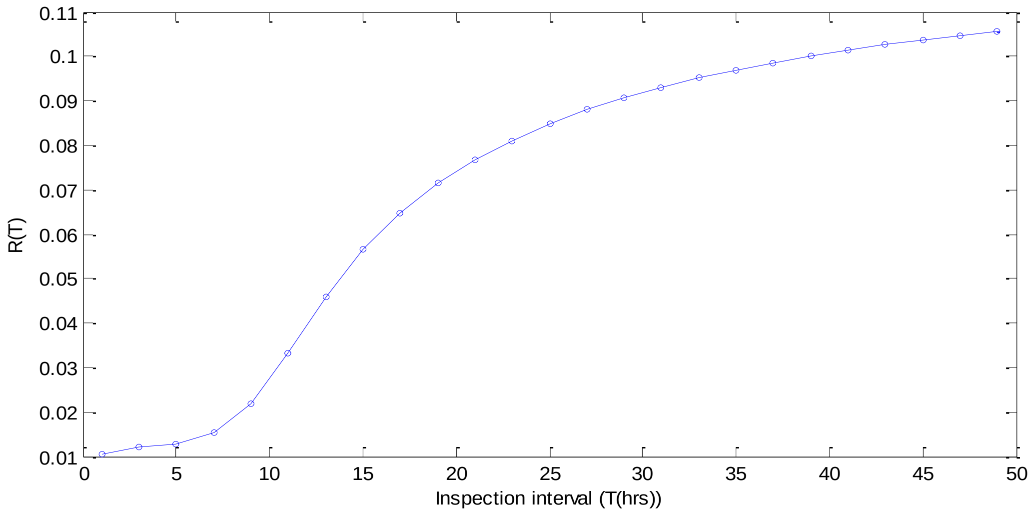

Figure 7.6: Alternative inspection interval vs reputation per unit times

From the figures, it is obvious that the optimum solution for the three decision criteria are in conflict with each other. For the cost per unit time function, C(T), the optimal solution in Figure 7.5 is a 9 hour inspection interval having the lowest possible cost of £40.34. The optimal solution for the downtime per unit time in Figure 7.4 is the inspection interval of 7 hours, corresponding to a downtime per unit time of 0.0345 hours while the optimal solution for the reputation per unit time in Figure 7.6 is an inspection interval of 1 hour with a reputation per unit time of 0.0106. This puts the decision maker or maintenance practitioner in a dilemma with respect to arriving at the most appropriate choice of inspection interval for the cooling water pump. In such a situation, a multi-criteria technique is needed to aid the decision maker in reaching a compromise solution.

7.4.3 Formation of decision matrix using D(T), C(T) and R(T) analysis result

In applying the multi-criteria techniques, the first step is to form a decision matrix. The results of the three decision criteria, D(T), C(T) and R(T) were utilised to produce a decision matrix which is shown in Table 7.3.

Table 7.3: decision matrix

Inspection intervals (T) (hrs)	C(T) £	D(T) (hrs)	R(T)
(1)	184.8950	0.1724	0.0106
(3)	78.0135	0.0650	0.0120
(5)	53.4584	0.0411	0.0128
(7)	43.5487	0.0345	0.0154
(9)	40.3398	0.0403	0.0220
(11)	41.5548	0.0572	0.0332
(13)	44.6597	0.0780	0.0459
(15)	47.5528	0.0958	0.0566
(17)	49.8173	0.1096	0.0648
(19)	51.6109	0.1205	0.0714
(21)	53.0661	0.1294	0.0767
(23)	54.2705	0.1367	0.0811
(25)	55.2839	0.1429	0.0848
(27)	56.1482	0.1482	0.0879
(29)	56.8942	0.1527	0.0907
(31)	57.5445	0.1567	0.0930
(33)	58.1166	0.1601	0.0951
(35)	58.6236	0.1632	0.0970
(37)	59.0761	0.1660	0.0986
(39)	59.4825	0.1685	0.1001
(41)	59.8494	0.1707	0.1014
(43)	60.1823	0.1727	0.1027
(45)	60.4858	0.1746	0.1038
(47)	60.7636	0.1763	0.1048
(49)	61.0188	0.1778	0.1057

7.4.4 Determination of Decision criteria weights using AHP

Applying the AHP techniques discussed in Chapter 4, the weights of the decision criteria, C(T), D(T) and R(T) were obtained as 0.45, 0.3 and 0.25 respectively. AHP is a subjective method for determining the decision criteria weights and the weights determined using the technique may vary from expert to expert. Hence there is a need to determine the impact that varying decision criteria weights may have on the overall ranking of alternative inspection intervals. The above weights are referred to as case ‘1’. Four other scenarios were used to perform the sensitivity analysis of decision criteria weights. The five scenarios are shown in Table 7.4. Note: Cases 2 to 4 were used to demonstrate what happens if experts give extreme values of weights.

Table 7.4: Decision criteria weight cases

Case	C(T)	D(T)	R(T)
1	0.4500	0.3000	0.2500
2	0.2500	0.4500	0.3000
3	0.4500	0.4500	0.1000
4	0.1000	0.8000	0.1000
5	0.3330	0.3330	0.3330

7.4.5 Ranking of alternative inspection intervals

7.4.5.1 ELECTRE method ranking

In utilising the ELECTRE method to determine the optimal inspection interval, the decision matrix in Table 7.3 was normalised using Eq. 7.12 and the result is shown in Table 7.5. The normalised decision matrix was then multiplied by the weights of the decision criteria (case 1) to form the weighted normalised matrix, also presented in Table 7.5. This was followed by the formation of the concordance interval matrix and the discordance interval matrix using Eq. 7.15 and 7.16 respectively. The performance indices, net superior and net inferior values of each of the inspection intervals were evaluated using Eq. 7.18 and 7.19 and the results are shown in Table 7.6. Finally, the inspection intervals were ranked based on their net superior and inferior values and the results are also shown in Table 7.6. The graphical representation of the net superior values of the inspection intervals and corresponding rankings is presented in Figure 7.7 while the net inferior values of inspection intervals and corresponding rankings are shown in Figure 7.8. The performance of the inspection interval can be determined by applying the net superior index; in this case, the inspection interval with the highest superior value is selected as the most appropriate. The performance of the inspection intervals can also be determined using the net inferior index and in this case the inspection interval with the lowest net inferior value is selected as the optimal solution.

From the net superior performance index in Figure 7.7 an inspection interval of 9 hours is the best ranked having the highest net superior value of 21.40 and as such, based on this performance index, it is the most appropriate interval for the inspection of the cooling water pump. The worst solution is the inspection interval of 49 hours which has the lowest net superior value of -22.20.

From Figure 7.8 an inspection interval of 9 hours is the optimal solution to this inspection interval selection problem having the lowest net inferior value of -31.3334. The second ranked inspection interval is 7 hours with a net inferior value of -28.7606 while the lowest ranked inspection interval is 49 hours with a net inferior value 32.7569. The inspection interval of 7 hours might also be recommended because of the closeness of its net inferior value to that of the 9 hour inspection interval.

Table 7.5: Normalised and weighted normalised matrix

Inspection interval (hrs)	Normalised matrix			Weighted normalised matrix		
	C(T)	D(T)	R(T)	C(T)	D(T)	R(T)
1	-0.5615	-0.2516	0.0271	-0.2527	-0.0755	0.0068
3	-0.2369	-0.0949	0.0307	-0.1066	-0.0285	0.0077
5	-0.1624	-0.0600	0.0327	-0.0731	-0.0180	0.0082
7	-0.1323	-0.0503	0.0394	-0.0595	-0.0151	0.0098
9	-0.1225	-0.0588	0.0562	-0.0551	-0.0176	0.0141
11	-0.1262	-0.0835	0.0849	-0.0568	-0.0250	0.0212
13	-0.1356	-0.1138	0.1173	-0.0610	-0.0341	0.0293
15	-0.1444	-0.1398	0.1447	-0.0650	-0.0419	0.0362
17	-0.1513	-0.1599	0.1656	-0.0681	-0.0480	0.0414
19	-0.1567	-0.1758	0.1825	-0.0705	-0.0528	0.0456
21	-0.1612	-0.1888	0.1961	-0.0725	-0.0567	0.0490
23	-0.1648	-0.1995	0.2073	-0.0742	-0.0598	0.0518
25	-0.1679	-0.2085	0.2168	-0.0756	-0.0626	0.0542
27	-0.1705	-0.2163	0.2247	-0.0767	-0.0649	0.0562
29	-0.1728	-0.2228	0.2318	-0.0778	-0.0669	0.0580
31	-0.1748	-0.2287	0.2377	-0.0786	-0.0686	0.0594
33	-0.1765	-0.2336	0.2431	-0.0794	-0.0701	0.0608
35	-0.1780	-0.2382	0.2479	-0.0801	-0.0714	0.0620
37	-0.1794	-0.2422	0.2520	-0.0807	-0.0727	0.0630
39	-0.1806	-0.2459	0.2559	-0.0813	-0.0738	0.0640
41	-0.1818	-0.2491	0.2592	-0.0818	-0.0747	0.0648
43	-0.1828	-0.2520	0.2625	-0.0822	-0.0756	0.0656
45	-0.1837	-0.2548	0.2653	-0.0827	-0.0764	0.0663
47	-0.1845	-0.2573	0.2679	-0.0830	-0.0772	0.0670
49	-0.1853	-0.2595	0.2702	-0.0834	-0.0778	0.0675

Table 7.6: ELECTRE II ranking of inspection interval

Inspection interval-T(hrs)	Net Superior (Cs)	Rank	Net Inferior (Ds)	Rank
1	-9.6000	18	18.5128	20
3	0.4000	12	-3.6121	12
5	14.6000	5	-19.8601	6
7	20.7000	2	-28.7606	2
9	21.4000	1	-31.3334	1
11	18.8000	3	-28.3360	3
13	15.3000	4	-24.2709	4
15	13.3000	6	-20.5569	5
17	11.3000	7	-17.0863	7
19	9.3000	8	-13.7215	8
21	7.3000	9	-10.4810	9
23	4.4000	10	-7.2684	10
25	2.4000	11	-4.1309	11
27	0.4000	13	-1.0329	13
29	-1.6000	14	2.1071	14
31	-3.6000	15	5.1549	15
33	-5.6000	16	8.3169	16
35	-7.6000	17	11.3789	17
37	-9.6000	18	14.3998	18
39	-11.6000	20	17.4303	19
41	-13.6000	21	20.5311	21
43	-16.2000	22	23.6260	22
45	-18.2000	23	26.6009	23
47	-20.2000	24	29.6356	24
49	-22.2000	25	32.7569	25

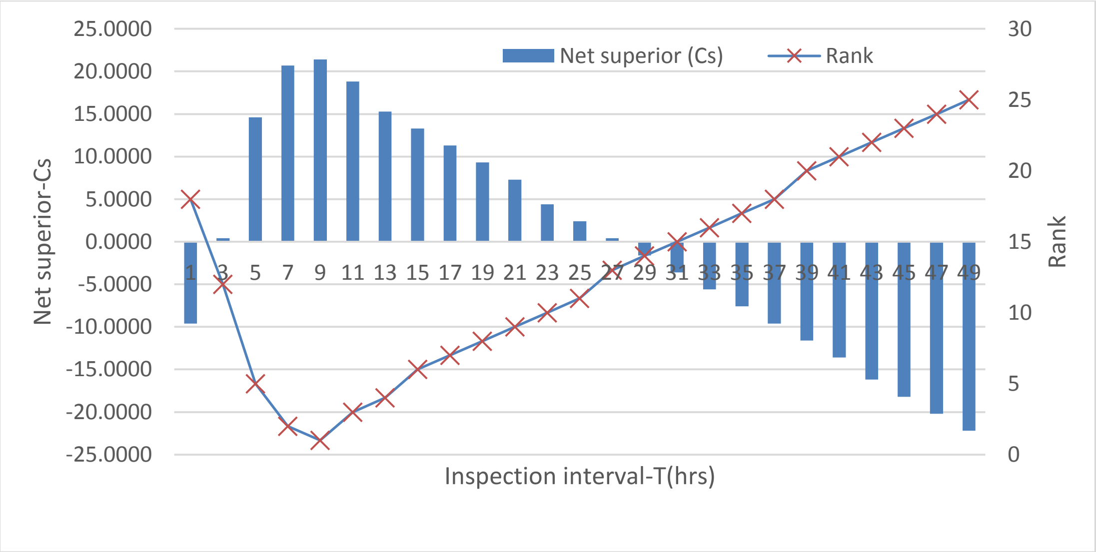

Figure 7.7: Net superior values and corresponding ranks of inspection interval

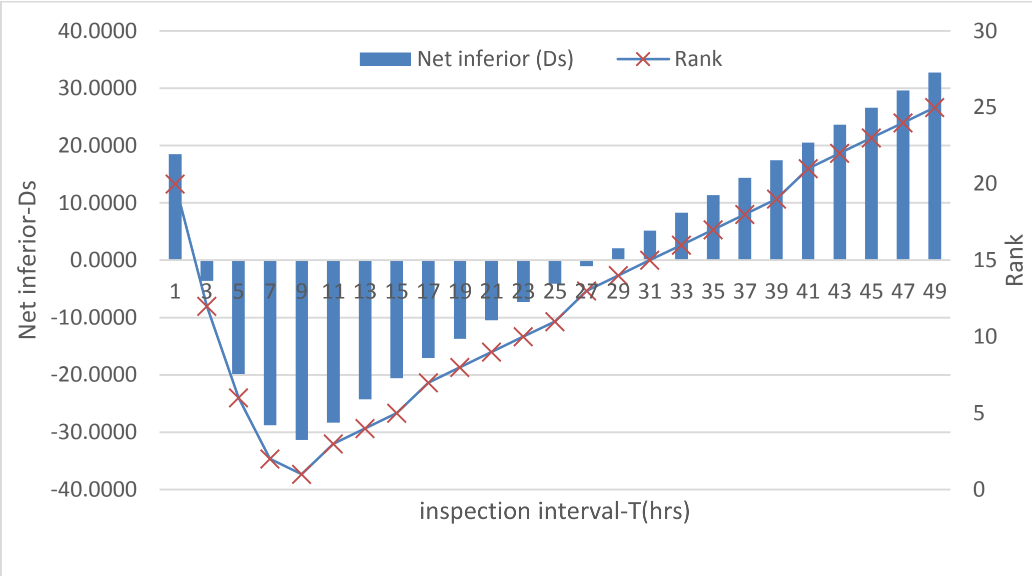

Figure 7.8: Net inferior (Ds) values and corresponding ranks of inspection intervals

Sensitivity analysis

One of the variables that affects the ranking of alternative inspection intervals produced by the ELECTRE method is the decision criteria weight. In this study, AHP was used to determine decision criteria weights. The technique is highly subjective and as such different experts or decision makers might assign different weights to each decision criterion. In order to study the effects of varying weights that may be assigned by the decision makers on the rankings of inspection intervals obtained from the ELECTRE method, a sensitivity analysis was performed using various combinations of decision criteria weight. The various combinations of decision criteria weights applied for the sensitivity analysis study are presented in Table 7.4. From the sensitivity analysis study, the performance indices net superior and net inferior values obtained for alternative inspection intervals in the five different combinations of decision criteria weights (cases 1-5) are presented in Figures 7.9 and 7.10 and in tabular format in Tables D4 and D5 in Appendix D4. The corresponding rankings of inspection interval based on the net superior and net inferior values are presented in Figures 7.11 and 7.12 respectively and in tabular form in Tables D6 and D7 respectively in Appendix D4.

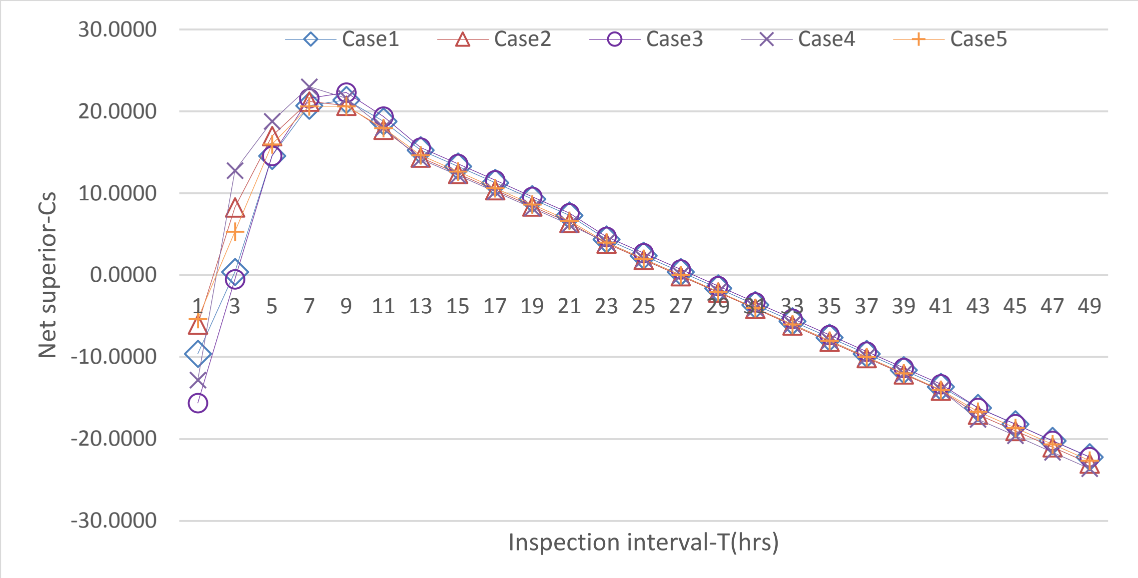

Figure 7.9: Net superior-Cs values from decision criteria weight sensitivity analysis

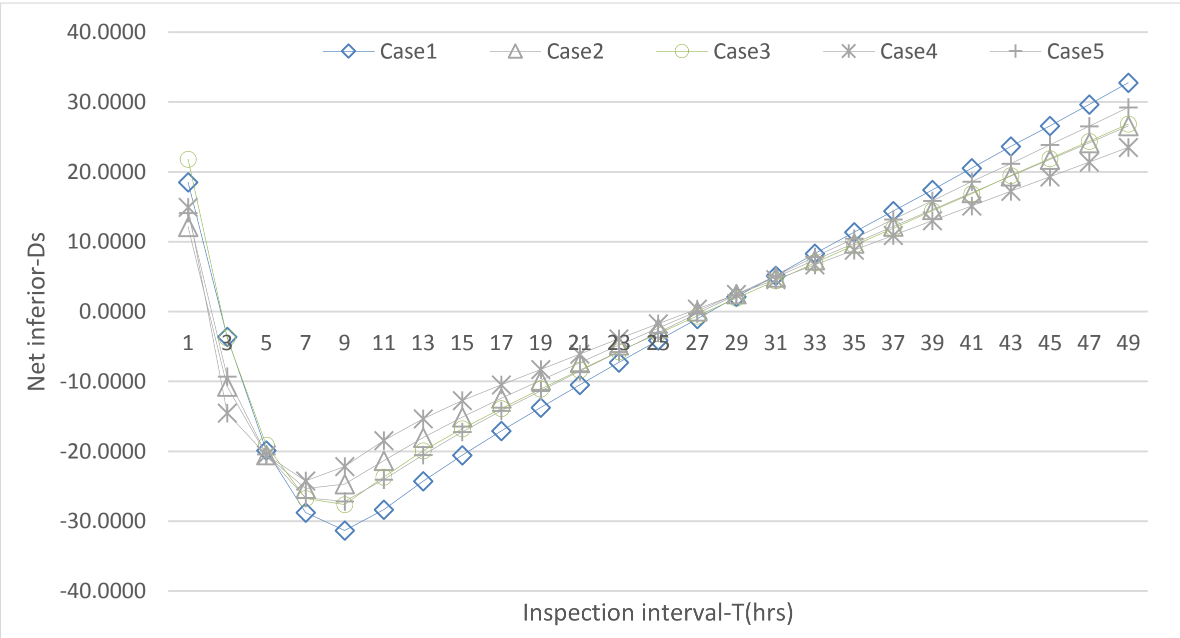

Figure 7.10: Net inferior-Ds values from decision criteria weight sensitivity analysis

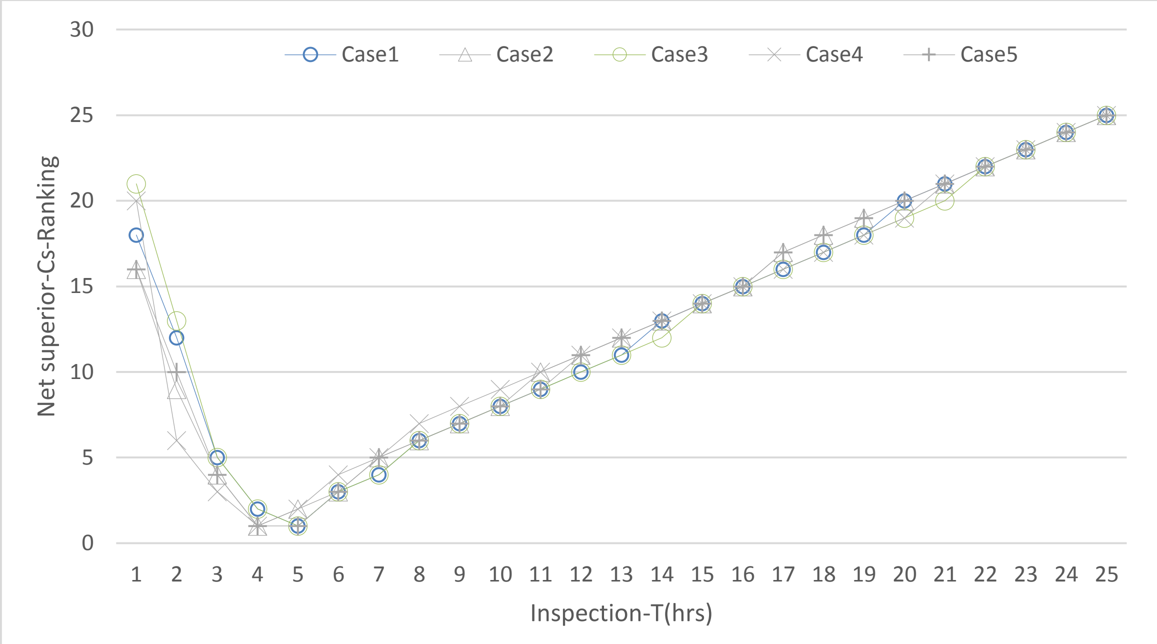

Figure 7.11: Net superior-Cs rankings from decision criteria weight sensitivity analysis

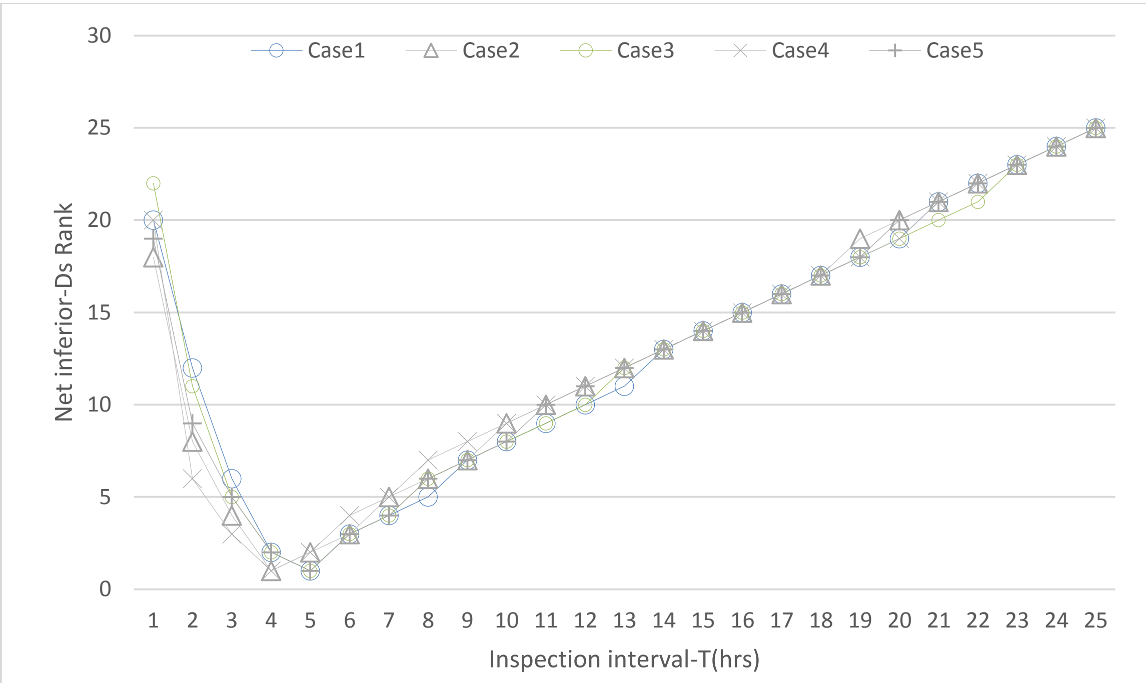

Figure 7.12: Net inferior-Ds rankings from decision criteria weight sensitivity analysis

From the result of the net superior performances of the alternative inspection intervals in Figure 7.9 and the corresponding rankings in Figure 7.11, the optimal inspection interval for the five cases varies from 7 hours to 9 hours. The optimal inspection interval for the five cases based on the net superior index is presented in Table 7.7. The optimal inspection interval for the five cases based on net inferior index in Figure 7.10 and the corresponding ranking of inspection intervals in Figure 12 also vary from 7 hours to 9 hours. The optimal inspection interval for the five cases based on the net inferior index are tabulated in Table 7.8.

Table 7.7: Optimal inspection interval for five cases

Case	Net superior-Cs	Optimal inspection interval	Rank
case1	21.4000	9	1
case2	21.2000	7	1
case3	22.3000	9	1
case4	23.0000	7	1
case5	20.6460	7 or 9	1

Table 7.8: Optimal inspection interval for five cases

Case	Net inferior-Ds	Optimal inspection interval	Rank
case1	-31.3334	9	1
case2	-25.3237	7	1
case3	-27.6102	9	1
case4	-24.2337	7	1
case5	-27.1454	9	1

7.4.5.2 MAUT method rankings

The MAUT technique used in the ranking of inspection intervals commenced with the formation of the decision matrix shown in Table 7.3. The first step to solving the decision matrix in Table 7.3 using the MAUT method was to define the range of each decision criterion, the results of which are shown in Table 7.9. The values in Table 7.9 were then used as inputs into Eq. 7.21 to 7.23 to calculate the utility values of each alternative inspection interval against the decision criteria. Finally, the multi-attribute function values of each inspection interval were evaluated by aggregating utility values of the alternative inspection intervals multiplied by decision criteria weights as expressed in Eq. 7.24. The multi-attribute function values of each of the inspection intervals obtained using Eq. 7.24 are shown in Table 7.10 and Figure 7.13.

Table 7.9: Range of decision criteria

Decision criteria	Worst value	Best value
C(T)	184.895	40.3398
D(T)	0.1778	0.0345
R(T)	0.1057	0.0106

Table 7.10: MAUT ranking

Inspection interval-T(hrs)	U(C(T),D(T),R(T)	Rank
1	0.1301	21
3	0.8022	5
5	0.9518	3
7	0.9927	1
9	0.9556	2
11	0.8487	4
13	0.7170	6
15	0.6044	7
17	0.5172	8
19	0.4482	9
21	0.3919	10
23	0.3457	11
25	0.3065	12
27	0.2730	13
29	0.2444	14
31	0.2192	15
33	0.1977	16
35	0.1780	17
37	0.1604	18
39	0.1446	19
41	0.1307	20
43	0.1179	22
45	0.1059	23
47	0.0952	24
49	0.0857	25

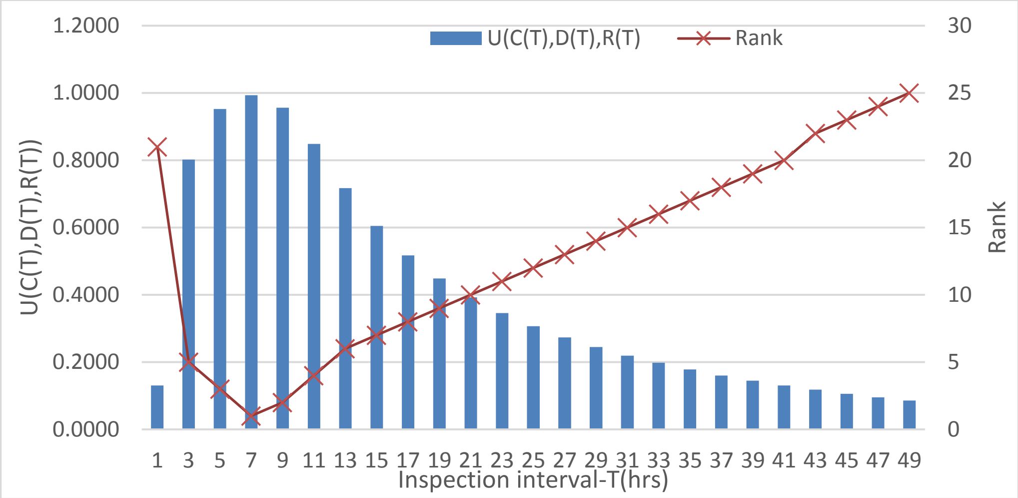

Figure 7.13: Multi-attribute utility function U(C(T), D(T), R(T)) based on inspection intervals

From Table 7.10 and Figure 7.13, an inspection interval of 7 hours is in the first position having the highest multi-attribute utility function value of 0.9927 and as such it is the optimum solution for the inspection interval selection problem. The inspection interval in second position is 9 hours, having multi-attribute utility function value of 0.9556. The inspection interval in last position is 49 hours, having the lowest multi-attribute function value i.e. 0.0857.

Sensitivity analysis

The results obtained above using the MAUT technique are when the decision maker is risk neutral, in which case R is equal to 1. However there are situations where the decision maker may be risk prone or risk averse and in such situations R is greater than 1 (risk prone) or less than 1 (risk averse). The effect of the risk perception of the decision maker was investigated to see how it would affect the rankings of the inspection interval. Based on this a range of R from 0 to 2 was used and the results obtained are shown in Figure 7.14 and Table D1 in Appendix D4.

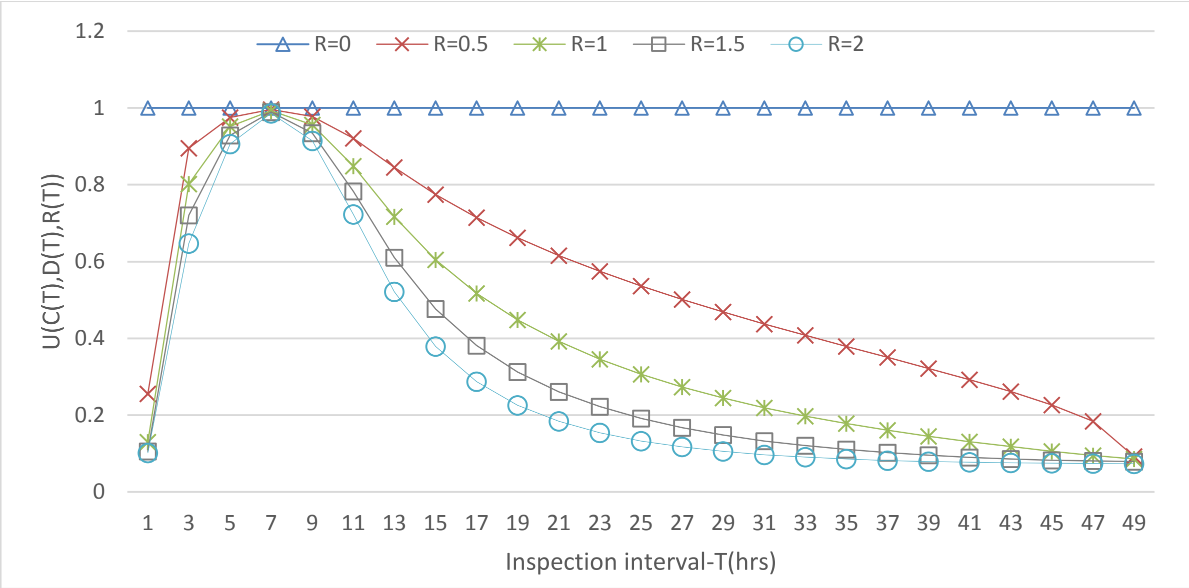

Figure 7.14: Sensitivity analysis of R

From Figure 7.14, the inspection interval of 7 hours has the maximum multi-attribute utility function value when R=0.5, 1, 1.5 and 2. From this it obvious that the result produced when the decision maker is risk averse, neutral and risk prone is the same. From the graph it is obvious that when R is assigned with the value of zero, no reasonable result can be produced i.e. the alternative inspection intervals cannot be prioritised. In a case in the literature (see the work of Anders and Vaccaro, 2011) it was shown that there was difference in the result produced when the decision maker is risk-averse but with no distinction between results produces by risk-neutral and risk prone persons however in the present work the result was same for all categories of decision maker.

Another factor that has strong influence on the outcome of the MAUT analysis is the weight of the decision criteria. The data in Table 7.4 was used as input data into the MAUT method in performing the sensitivity analysis of decision criteria weights. This was done to determine the effects of varying weights of decision criteria on the output of the MAUT method. The multi-attribute utility function values obtained from the five cases and the corresponding rankings of the inspection intervals are presented in Figures 7.15 and 7.16 and in Tables D2 and D3 in Appendix D4. From Figure 7.15, the inspection interval of 7 hours has the highest value of multi-attribute utility function value for the five cases and as such was ranked 1 in Figure 7.16. For the optimal inspection interval to have remained the same for the five cases shows that the MAUT technique is very robust and less sensitive to decision criteria weight changes.

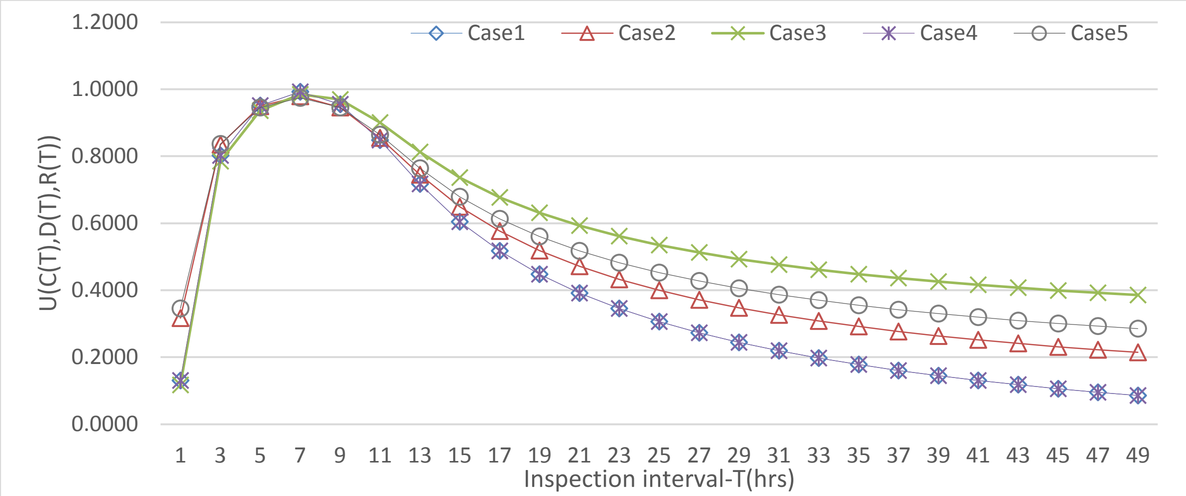

Figure 7.15: Multi-attribute utility function values for varying weights of decision criteria

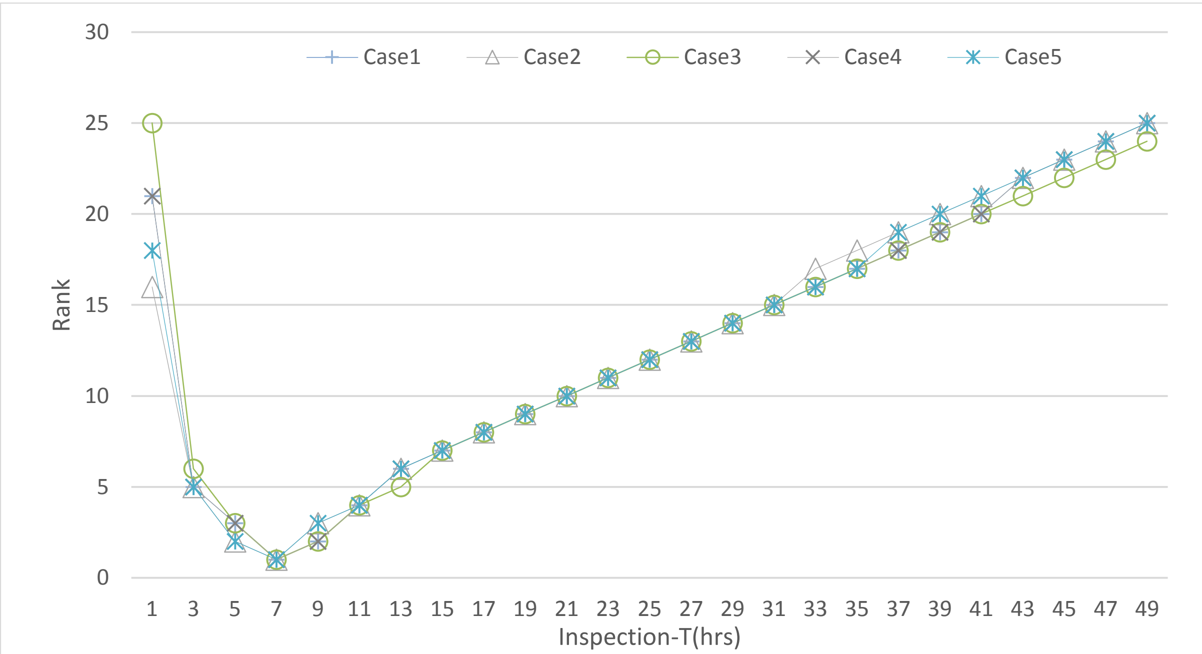

Figure 7.16: Inspection intervals rank for varying weights of decision criteria

7.4.6 Comparison of MAUT and ELECTRE ranking methods

The rankings of the inspection interval alternatives produced by the two methods are shown in Table 7.11 and Figure 7.17. From Figure 7.17 it is obvious that the two techniques, ELECTRE and MAUT yield very similar results. The rankings produced from the two

ELECTRE ranking indices, the net superior (represented in the graph as ELECTRE (Cs)) and the net inferior (represented in the graph as ELECTRE (Ds)) are the same for most of the inspection intervals with only a few having a rank difference of one between them. When the results of the two ranking indices of ELECTRE are also compared with the result generated from the MAUT method, the results are also very similar. To further show the relationship between the three ranking systems, a Spearman rank correlation test was performed. The Spearman correlation coefficients obtained between ELECTRE (Cs) and ELECTRE (Ds), between MAUT and ELECTRE (Cs) and between MAUT and ELECTRE (Ds) are 0.928, 0.998 and 0.906 respectively. The near perfect correlation obtained among the three ranking methods revealed that they can be applied individually to rank alternative inspection intervals for marine machinery systems so that the optimal solution can be obtained. The optimal solution obtained for the water cooling pump from ELECTRE (Cs) and ELECTRE (Ds) was an inspection interval of 9 hours and for the MAUT technique is 7 hours. The two techniques can also be compared in terms of robustness. From the results of the five cases in the sensitivity analysis of decision criteria weights, the MAUT method gave the same optimal solution in all cases while the ELECTRE method had an optimal solution that varied from 7 hours to 9 hours. This shows that the MAUT technique is more robust and less sensitive to decision criteria weight changes than the ELECTRE method. The MAUT method is therefore recommended for the marine industry for determining optimal inspection intervals.

Table 7.11: Comparison of methods

Inspection interval	ELECTRE		MAUT
	Net superior (Cs)	Net inferior (Ds)	
1	18	20	21
3	12	12	5
5	5	6	3
7	2	2	1
9	1	1	2
11	3	3	4
13	4	4	6
15	6	5	7
17	7	7	8
19	8	8	9
21	9	9	10
23	10	10	11
25	11	11	12
27	13	13	13
29	14	14	14
31	15	15	15
33	16	16	16
35	17	17	17
37	18	18	18
39	20	19	19
41	21	21	20
43	22	22	22
45	23	23	23
47	24	24	24
49	25	25	25

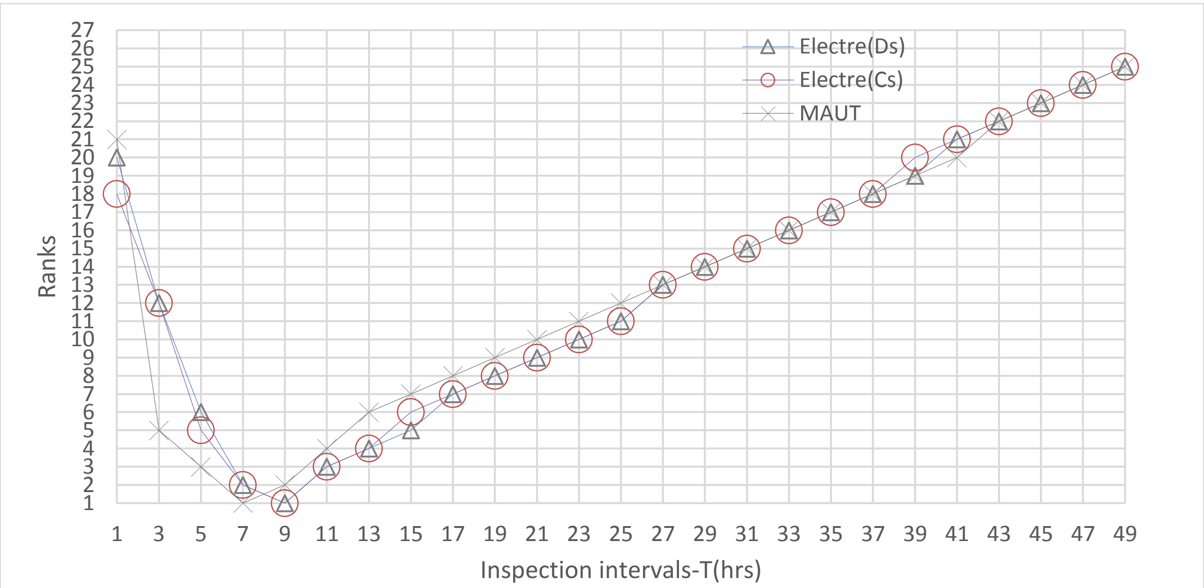

Figure 7.17: Comparative ranking of alternative inspection intervals

7.5 Summary

In monitoring the condition of an asset, the two options are continuous condition monitoring and periodic condition monitoring. The periodic monitoring approach is commonly used because it is more cost effective than the continuous condition monitoring approach. However the major challenge of the periodic condition monitoring technique is the determination of the most appropriate interval for performing inspection. Traditionally, maintenance practitioners rely on their experience in determining the most appropriate time for carrying out inspection activities. The delay time approach has been reported in the literature, however in determining the optimal inspection interval most of the authors applied a single decision criterion (cost or downtime). The purpose of this research was to apply multiple decision criteria in obtaining the optimal inspection interval. Three decision criteria; cost, downtime and reputation were chosen for measuring performance of an inspection interval.

The delay time concept was used to model the relationship between inspection intervals and the corresponding cost, downtime and reputation due to system failure. Since the optimal solutions obtained from the three decision criteria are in conflict with each other, the three decision criteria results were aggregated with two MCDM techniques; MAUT and ELECTRE. To illustrate the applicability of the proposed methodology for determining an optimal inspection interval, a case study of a sea water cooling pump was investigated. From the analysis, the rankings of alternative inspection intervals produced from both the MAUT and ELECTRE methods were very similar. To further prove the similarity between the two MCDM techniques, the Spearman rank correlation coefficient between the techniques was evaluated and showed a near perfect relationship. This confirms that the two techniques can be applied individually or in combination to rank and select the best inspection policy for marine machinery systems.

The robustness of the two methods; MAUT and ELECTRE was tested via sensitivity analysis of the decision criteria weight. The five different combinations of decision criteria weights chosen for the sensitivity analysis revealed that the MAUT method is more robust and less sensitive to decision criteria weight variations. The preference of the decision maker for decision criteria weightings was accommodated through use of AHP which can both quantitatively and qualitatively determine the weight of decision criteria. Despite the suitability of both techniques for optimal inspection interval determination, the MAUT method was recommended for the marine machinery system for the following reasons:

(1) The risk preference of maintenance practitioners is accommodated in the MAUT method which is not something that is available in the ELECTRE method and

(2) The MAUT method is more robust, as evidenced by the sensitivity analysis of the decision criteria weight.

In this study, the MAUT and ELECTRE methods have been validated for inspection selection problems within the framework of marine machinery systems however they could also be applied in solving inspection selection problems for other related engineering systems.

Chapter 8 Conclusions, Contributions and Recommendation for future work

8.1 Conclusions

Ship systems will not remain safe and reliable no matter how well designed and manufactured they are if they are not properly maintained. However over-maintenance may result in system degradation and excessive costs that may lead to increases in the operational cost of the system. On the other hand, under-maintenance may result in system failures that may be catastrophic. Hence there is a need for a sound and effective system to be in place for the maintenance of ship systems such that their availability and cost of maintenance are optimised. Basically, there are three key elements of a maintenance system which are; risk assessment, maintenance strategy selection and maintenance task interval determination.

RCM is one of the more commonly used methods for the optimisation of these three key elements of a maintenance management system. From the extensive literature survey performed it was obvious that the tools used in the RCM methodology have flaws which limit the effectiveness of the approach in optimising ship system availability. Hence the main purpose of this research was to develop alternative tools to enhance the RCM methodology such that ship systems are more effectively maintained and managed for improved availability and reduced downtime and at a reasonable cost which will invariably result in a significant reduction in operational cost. To achieve this aim different methodologies were developed for risk assessment, maintenance strategy selection and maintenance interval determination.

In the area of risk prioritisation four methods were proposed in this study; an averaging technique integrated with RPN, averaging technique integrated with VIKOR, averaging technique integrated with TOPSIS and averaging technique integrated with CP. For the four proposed techniques, the novel averaging technique was used in aggregating multiple experts' opinions that may be imprecise, while the RPN, TOPSIS, VIKOR and CP methods were used in the ranking of the risk of the individual failure modes. The suitability and validity of the proposed methods were demonstrated with case studies of partial and full marine machinery systems and case studies from the literature. The results showed that the four proposed methods are strongly correlated and can individually be applied for risk prioritisation more efficiently than the classical FMEA and other approaches in literature.

In the area of maintenance strategy selection three hybrid MCDM maintenance strategy selection methods were proposed: (1) Delphi-AHP (2) Delphi-AHP-PROMETHEE and (3) Delphi-AHP-TOPSIS. From the analysis of the results, the three proposed methodologies yielded the same optimum solution for the cooling water pump of the marine diesel engine for both; the single expert decision making process and the group decision making process. Based on the information that was obtained from the experts, the decision criterion 'safety', was found to be the driving force for the selection of the maintenance strategy. The scheduled on-condition task or OFCBM, which was the optimum solution for maintaining the cooling water pump of the diesel engine in both scenarios, was in-line with the current best practice in the marine industry. The proposed methods avoid the limitations of RCM logic tree analysis which has an inability to rank alternative maintenance strategies and they are also less computationally intensive than approaches in the literature.

In the area of maintenance task interval determination two of the five maintenance task options utilised in maintenance management were modelled. The maintenance tasks considered were; (1) scheduled replacement and (2) scheduled on-condition task.

- For the scheduled replacement interval determination age replacement models were integrated with TOPSIS. While the ARM were used in modelling decision criteria, TOPSIS was applied in aggregating decision criteria and in the ranking of alternative replacement intervals. From the results of the analysis it can be concluded that the proposed methodology is both simple and robust. The approach has the advantage of including criteria weighting with both objective and subjective components whereas most previous research only included subjective components.
- For the inspection interval determination two MCDM tools; MAUT and ELECTRE were combined with the delay time model. The suitability of the integrated delay time and the MCDM model was demonstrated with a case study of a cooling water pump of a marine diesel engine. From the results both the MAUT and the ELECTRE methods produced the same optimal inspection interval for the cooling water pump. The proposed approaches have the advantage of simultaneously using multiple decision criteria in determining optimum inspection interval as opposed to current approaches in literature that use a single criterion.

In these proposed methodologies seven different MCDM tools: VIKOR, CP, TOPSIS, AHP, PROMETHEE, MAUT and ELECTRE were used for the ranking of alternatives in the areas of risk assessment, maintenance strategy selection and maintenance interval determination. However each of these tools has the capability to rank alternatives in all three elements of the maintenance system. Their individual use will depend on the practitioners' and/or analysts' choice which may be guided by ease of implementation (computational effort) and suitability (Løken, 2007). To guide the practitioner with respect to making a choice on the basis of ease of implementation Table 8.1 is presented below. From the table there are two categories of MCDM tools based on the different criteria such as Hand calculation in measuring ease of implementation; those that are easy to implement such as CP and MAUT with or without software and those that are difficult to implement without software such as ELECTRE and PROMETHEE.

Table 8.1: Degree of ease of implementation of MCDM tools

Computational effort	MCDM tools						
	TOPSIS	VIKOR	CP	AHP	ELECTRE	MAUT	PROMETHEE
Hand calculation	×	×	✓	×	×	✓	×
Spreadsheet	✓	✓	✓	✓	×	✓	×
Software tool	✓	×	×	✓	✓	×	✓
Software code	✓	✓	✓	✓	×	✓	×

Hand calculation/spreadsheet: Tick- easy to calculate using hand calculation/spreadsheet & Cross-difficult to calculate using hand calculation/spreadsheet
Software tool: Tick- software available & Cross-software not available
Software code: Tick- easy to code & Cross- difficult to code

The work demonstrated is an enhanced RCM system and in reality RCM methodologies are already routine for whole ship maintenance and as such the proposed enhance RCM does not need scaling up to make it applicable to entire ship maintenance. Concerning the practicality of a shipping company implementing the proposed enhanced RCM methodology, this will generally require a team which should consist of both external and internal experts, technical managers, superintended engineers and chief engineers and a statistician who will be able to identify appropriate functions such as the Weillbull distribution. Once the expert team has implemented the enhanced RCM methodology it would be straightforward for practitioners on board to utilise.

8.2 Research Contribution

This research presents the development of various tools in order to support the RCM methodology and to improve its effectiveness in marine maintenance system applications. This will result in an improvement in marine system reliability at minimum cost. The contribution of this research has been disseminated through journal and conference publications listed in the publication section. In particular the research contributions with regard to addressing the limitations of RCM in the optimisation of the three major elements of maintenance management are as follows:

(1) Development of a methodology for the assessment of the risk of marine machinery systems. The innovation of this risk assessment methodology is in the combination of different MCDM tools such as VIKOR, CP, and TOPSIS in addressing the limitations of classical FMEA that is frequently used within the framework of RCM in the risk assessment of marine systems. Although VIKOR, CP and TOPSIS have been applied individually by practitioners in solving other multi-criteria decision problems they have not been used in solving the fundamental risk prioritization problem. The incorporation of the averaging technique into the approaches further makes the methodology unique as it allows for the use of both precise and imprecise ratings provided by experts to be applied as input into VIKOR, CP and TOPSIS which each normally use only precise data, thereby providing a more efficient technique for risk prioritization that is highly beneficial to the marine industry. An additional important feature of this proposed methodology is in the breakaway from the use of a subjective weighting technique, such as AHP, in assigning decision criteria weights, by also integrating the variance and entropy methods into VIKOR, CP and TOPSIS.

(2) Development of a methodology for maintenance strategy selection based on the integration of the RCM concept with multi-criteria decision making methods. The novelty in the proposed methodology lies in the combination of different MCDM tools such as AHP, PROMETHEE and TOPSIS for solving the problem of maintenance strategy selection within the framework of marine system maintenance. Another important feature of the proposed methodology is the incorporation of the Delphi method into AHP, PROMETHEE and TOPSIS. The Delphi method was introduced in order to collect, identify and screen decision criteria such that the most important decision criteria are applied in selecting the optimal maintenance strategy for the marine system.

(3) Development of a methodology for the determination of the optimal interval for scheduled replacement. The innovation of the methodology is based on the integration of the Age Replacement Model (ARM) with the TOPSIS technique which has never been used before for preventive replacement interval determination in the maritime environment. Another important feature of the proposed methodology is the combination of an efficient decision criteria weighting framework into the ARM and TOPSIS models. The efficient decision criteria weighting framework integrates both subjective and objective techniques in evaluating the weights of decision criteria, as opposed to the use of only a subjective technique for land based system applications found in literature. The weighting framework is so flexible that it allows maintenance practitioners to either use a subjective criteria weighting technique or an objective weighting technique or a combination of both techniques.

(4) Development of a methodology for the determination of the optimal interval for scheduled inspection. The novelty again lies in the combination of MCDM tools (MAUT and ELECTRE methods) with a delay time model in determining the optimum intervals for performing inspections for systems for the first time within the maritime maintenance framework. Another important feature of the methodology is the use of the delay time concept in the development of a company reputation model. The company reputation is used as a decision criterion in addition to already established cost and downtime decision criteria delay time models in determining inspection intervals for maintaining plant system equipment.

8.3 Limitations encountered

One of the greatest challenges that was encountered in the execution of this study was the problem of real life data availability. The lack of reliable real life data in terms of both quantity and quality in most scenarios was the reason behind the use of experts' opinions and data from literature as alternatives in this research.

8.4 Recommendation for future work

8.4.1 Risk assessment

The technique that was applied in this study for risk assessment, FMEA, is a well-established qualitative technique which is useful in making maintenance decisions. However a quantitative approach is more reliable in making such decisions. On this basis, a quantitative approach such as FTA may be exploited in determining risk of failure modes of marine machinery systems. Furthermore, in this study the FMEA that was performed on the marine diesel engine, could be extended to the whole ship system. In addition, three MCDM tools; VIKOR, CP and TOPSIS have been used however other MCDM techniques such as EXPROM 2 may also be applied in determination of the risk of failure modes of marine machinery systems.

8.4.2 Maintenance strategy selection

Although the proposed methodologies have been validated for marine machinery system they can also be applied to other related engineering systems and, depending on the preferences of the maintenance practitioners, the decision criteria can further be reduced in order to make the evaluation process easier. Furthermore, other techniques such as the MAUT, VIKOR and EXPROM 2 may be applied for the ranking of alternative maintenance strategies. There may also be the need to capture the expert information imprecisely rather than obtaining precise data from experts. In such a scenario, information from experts would be in the form of an estimated interval and, in addressing this, the fuzzy logic technique may be integrated within the proposed methodologies.

8.4.3 Maintenance interval determination

The five maintenance strategies considered in this study are; scheduled overhaul, scheduled replacement, offline condition based maintenance (inspection) and online condition based maintenance. From these five maintenance strategies, methodologies have been developed for determining the optimum interval for carrying out offline condition based maintenance and scheduled replacement (SRP) tasks. For future work a methodology could be developed for determining the interval for performing scheduled overhaul and scheduled replacement.

8.4.3.1 Scheduled replacement interval determination

The methodology for determining the scheduled replacement interval in this study is based on a multi-criteria decision framework, the three decision criteria being; cost, downtime and reliability. The cost and downtime models were adapted from the Barlow and Hunter (1960) age replacement model. The TOPSIS methodology was applied in simultaneously obtaining the ranking of alternative replacement intervals for marine machinery systems from the three decision criteria. For future work other MCDM tools such as MAUT and ANP may be exploited for the ranking of the alternative replacement intervals such that an optimum solution can be obtained. For example, the MAUT method will allow the maintenance risk perception to be included in the decision making process which is not possible in the proposed method in this research and the ANP allowed for the interrelationship between the decision criteria to be utilised in the analysis process which again is not possible in the method utilised in this study. For the three decision criteria models the failure distribution of the systems that were studied were assumed to follow a Weibull distribution, however other well know distributions such as exponential and normal distributions should be investigated. Alternatively system failure data could be obtained to determine the exact distribution rather than assuming it.

8.4.3.2 Inspection interval determination

In determining the intervals for performing the inspection for the system under investigation, the delay time model was integrated with the multi-criteria decision tools ELECTRE and MAUT. The delay time was used to model the three decision criteria; cost, downtime and reputation, while the ranking of alternative inspection intervals was performed using MAUT and ELECTRE. For the delay time models the Weibull distribution was assumed as the distribution probability of the delay time. For future work other known distributions such as exponential and normal distributions could also be studied. A database system should be developed such that the shipping industry can easily gather delay time information. For the ranking of alternative inspection intervals the use of other MCDM techniques such as EXPROM 2 and PROMETHEE can be explored.

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APPENDICES

Appendix A: Risk assessment

Appendix B: Maintenance strategy selection

Appendix C: Scheduled replacement interval determination

Appendix D: Inspection interval determination

Appendix A: **Risk Assessment**

A.1 FMEA analysis sheet for the marine diesel engine

The information used in the formation of the FMEA analysis sheet were obtained in bits from the following sources: (Cicek and Celik, 2013, Cicek et al., 2010b, American Bureau of Shipping, 2004, Bejger, 2011, Dunford, 2011, Mokashi et al., 2002, Lazakis, 2011), experts opinion and logged records.

Equipment items	Failure modes	Failure cause	Local effects	Global effects	Detection system
BASIC ENGINE					
Piston	1. Hole in the piston crown	Dripping of fuel valve	Escape of combustion gas into the crankcase	Reduced engine performance, engine stop possible, explosion possible	
Piston	2. Piston ring scuffing	Lack of lubrication, liner roundness fault	Oil smoke from exhaust, Blow-by and scuffing mark on liner surface	Reduced engine performance	
Piston	3. Cracked ring	Excessive gap pressure, worn-out ring groove	Oil smoke from exhaust, loss of power	Reduced engine performance	
Piston	4. Ring /groove side face wear	Liquid fuel degrading lubricant in ring grooves, solid residue	Loss of power	Reduced engine performance	
Piston	5. Piston ring stuck in grooves	Insufficient clearance during installation, deposits	Excessive clearance, fire blow	Reduce engine output, Stop engine	
Piston	6. Piston stuck	Loose con rod nut, lack of lube oil at piston head	Loss of power in the affected cylinder, con rod damage, cracked piston pin	Stop engine, explosion probable	
Piston	7. Piston flame face excessive wear	Flame impingement from poor atomisation	Overheating and excessive pressure into crank case	Reduce engine output, Stop engine	Standby pump start functioning
Main bearing	8. Failing to lubricate	Oil pressure too low	Friction and excessive heat	Reduced engine performance, engine stoppage, engine damage	
Piston rod stuffing box	9. Wearing out of packing rings	Lose of sealing	Spark and blow by	Reduce engine performance, engine stop possible, explosion possible	
Piston rod stuffing box	10. Malfunctionin g	Incorrect spring mounted in piston rod stuffing box, faulty oil scraper rings	Escape of combustion gas into the crankcase	Stop engine, explosion probable	

Equipment items	Failure modes	Failure cause	Local effects	Global effects	Detection system
Crankshaft	11. Cracking	Loss of effective lubrication, bearing misalignment, poor maintenance, design fault, flooding of cylinders with cooling	Damage to connecting rod, engine block	Reduced engine output, stop engine, damage to engine	
Crankshaft	12. Bending	Overloading, faulty crankshaft damper, grounding and/or fouling of propeller, bearing misalignment, engine power imbalance	Crankshaft deformation, damage to con rod	Reduced engine output, stop engine, damage to engine	
Crankshaft	13. Journal surface damage	Loss of effective lubrication, bearing misalignment, fouling of the propeller	Damage to con rod,	Reduced engine output, stop engine, damage to engine	
Cylinder head	14. Warping	Overheating , improper installation, fatigue	loss of compression, head gasket leak, high temperature alarm	Stop engine	High temperature/ pressure alarm
	15. Cracking	Prolong overheating, improper installation	Loss of compression, engine misfires and runs erratically, cylinder damage	Stop engine	
Connecting rod	16. Breaks	Piston pin snap, improper tightening of con rod bolts, fatigue	Loss of power, bent crankshaft	Engine damage, stop engine, explosion possible	Alarm
Camshaft, cams and chain drive	17. Cam break	Loose con rod striking camshaft, lube wear	Inlet valve and exhaust valve failure	Stop engine, engine damage	

Equipment items	Failure modes	Failure cause	Local effects	Global effects	Detection system
Cylinder Liner	18. Leak in the cylinder liner	Overheating causing liner sealant to break down	Loss of compression in affected cylinder A, exhaust gases escape into jacket cooling water system, cooling water escape into cylinder	Reduced engine performance, engine damage	Cooling water pressure fluctuation
Cylinder liner	19. Worn	Fatigue, degraded lube oil	Loss of compression, Increased lube oil consumption	Reduced engine performance	Exhaust temperature increment for affected cylinder
Cylinder liner	20. Damaged/deformed	Continuous normal use (fatigue), Degraded lube oil, improper cylinder oil feed rate, Under-cooling of scavenge air.	Loss of compression in affected cylinder A, Increased cylinder lube oil consumption during combustion	Reduced engine performance, engine failure	Exhaust temperature increment for affected cylinder
Cooling water jacket	21. External leak	Corrosion due to improper treatment of fresh water, Jacket overheating, Leaking seal ring at bottom of cylinder liner	Insufficient delivering of cooling water to engine cylinder	Partial loss of containment of fresh water, reduced engine performance,	Water release alert operators
Cooling water jacket	22. Restricted passage	Poorly treated fresh water, dirt's in cooling water	Cylinder overheating, cylinder liner cracking	Reduced engine performance	Cylinder cooling water temperature increment
Crankcase relief valve	23. Inoperable	Not seated properly	Allow air escape into crankcase	Reduce engine performance, explosion probable	
SCAVENGE AIR SYSTEM					
Air cooler and pipes	24. Blinded	Sea water contamination	Excessive air temperature, excessive exhaust temperature	Low engine output, high fuel consumptions	High temperature alarm

Equipment items	Failure modes	Failure cause	Local effects	Global effects	Detection system
Air filter	25.Plug	Contamination	Reduced airflow through compressor, inefficient compressor operation	Reduced engine power and increased fuel consumption	
Scavenge air port	26. Fouled	Contamination from exhaust gases	Insufficient air supply to engine, improper combustion, excessive smoke	Reduced engine output	High exhaust temperature alarm
Turbocharger	27. Worn compressor wheel blades	Ingestion of abrasive material, wheel rubbing compressor housing	Restricted air flow to the engine, excessive exhaust smoke.	Reduced engine power and increased fuel consumption	"
Turbocharger	28. Faulty shaft bearing and seals	Lack of lubrication or oil delay, carbon deposits, oil deterioration, excessive bearing clearance	Binding between the compressor and turbine wheels and their housing, reduced turbo's speed and effective boost delivery	Reduce output from engine, high fuel consumption	High exhaust temperature alarm
EXHAUST GAS SYSTEM					
Turbocharger	29. Turbocharger bearing failure	Lack of lubrication	Seal damage, wheel rub	Lower engine output, high fuel consumption	High exhaust temperature
Turbocharger	30. Worn turbine wheel blades	Ingestion of foreign objects, wheel rubbing turbine housing	Air leak into exhaust, excessive exhaust smoke.	Reduced engine power and increased fuel consumption	High exhaust temperature
Exhaust valve	31. valve burned	Weak valve spring	leak compression	Misfire in the affected cylinder, reduced engine power	Differential temperature of exhaust gas
AIR STARTING SYSTEM					
Starting air compressor	32. Operates at degraded head/flow performance	Fatigue,	Reduction in air pressure	Loss of service air, reduce engine performance	

Equipment items	Failure modes	Failure cause	Local effects	Global effects	Detection system
Starting air compressor	33. No start signal	Sensor failure or mis-calibrated, wiring fault, loss of power for control unit	Low pressure and air flow	Interruption of engine output	Low pressure indicated on air pressure gauge
Starting air compressor	34. Fails to start on demand	Control system faulty, valves faulty,	Loss of engine start capability	No significant effect	Standby compressor start functioning
Starting air distributors	35. Leakage	Fatigue,	Loss of start air	Partial loss of engine start capability	
Starting valves	36. Stuck	Control system faulty, valves faulty, faulty air distributor due to ingress of hard foreign object	Engine oscillated but did not gain speed when started		Alarm
Air intake filter	37. Plug	Contaminants, Lack of maintenance	Reduced air flow through compressor	Inefficient compressor operation and possible damage, Low or no air flow to engine	Alarm
FUEL OIL SYSTEM					
Fuel system-pipes, filter	38. pipe leakage/ rupture, sludges in fuel line	deposits, low quality fuel oil	Hot spot , fuel oil spill	Stop engine, fire probable	Visual, high temperature deviation,
Fuel system-pipes, filter	39. Clogged fuel filter	Contaminants, Lack of maintenance	Restriction in fuel flow (low fuel pressure), erratic cylinder firing	Engine speed drop, stop engine	Differential pressure alarm
High pressure fuel pump	40. Low supply pressure	Suction valve opens too early or late	Engine operates erratically	Reduced engine performance, stop engine	Low pressure alarm
Transfer/supply/Booster pump	41. Running without oil	Wear-out gear	Low supply pressure	Reduce output from engine	,,
	42. Abnormal sound	Bearing defective/ shaft displacement	Overloading of electric motor	Reduce output from engine	,,
Fuel valve	43. Fuel valve leaked	Erosion, deposits	Excessive temperature after individual unit dropped	Reduce output from engine, hot spot	High exhaust temperature alarm

Equipment items	Failure modes	Failure cause	Local effects	Global effects	Detection system
Fuel valve	44. Seizure of injection valve spindle in open position	Control system failure	Excessive fuel injected into the affected cylinder, high exhaust temperature, black smoke	Reduced engine performance, environmental damage	High exhaust temperature alarm
Fuel valve	45. Fuel valve nozzle obstructed	Inadequate maintenance, incorrect fuel temperature, contaminants, poor fuel quality	Poor combustion, discoloured exhaust	Reduced engine performance, followed by engine failure	High exhaust temperature alarm
Fuel valve	46.Early opening of fuel valve	Low service pressure	Rough running, loss of compression and poor starting	Reduced engine performance	Low pressure alarm
Fuel valve	47. Dripping	Oversized injection mechanisms	Sticking of piston rings in their groove	Reduced engine performance, engine damage	High exhaust temperature alarm
CYLINDER LUBRICATING OIL SYSTEM					
Cylinder lubricating oil pump	48. External leak/ rupture	Pump housing erosion, mechanical seal failure	Release of cylinder lubricating oil in machinery space, large leak triggers stand by pump to start	No significant effect	Standby pump start functioning
Cylinder lubricating oil pump	49. Fails in operation	Pump motor seizing, failure of pump coupling	Interrupted lubrication supply to cylinders, stand by pump starts	No significant effect	Standby pump start functioning
Cylinder lubricating oil pump	50. Fails to stop on demand	Relay switch defective or failed	Cylinder lubricating oil pump continues to operate	No significant effect	
Cylinder lubricating oil pump	51. Operates at reduced head	Worn pump gears, Pump housing leak	Insufficient pressure or flow of lubricant to cylinders	No significant effect	Low pressure alarm, standby pump start functioning

Equipment items	Failure modes	Failure cause	Local effects	Global effects	Detection system
Cylinder lub. oil system- valves and piping	52. Piping leakage, burst flange	Poor quality fuel, contaminants, loose flange, overheating due to failure of gaskets	leakage of oil, low oil pressure, wear of cylinders	Stopped engine due low oil pressure, fire probable especially at high temp.	Visual inspection
Cylinder lub. oil filter	53. clogged	Accumulation of carbon or foreign matter	Improper cleaning, low lube oil pressure	Reduced engine performance, stop engine	Differentia l pressure
MAIN LUBE OIL SYSTEM					
Main lube oil pump	54. External leak/ rupture	Erosion, failed pump housing gasket	Large leak triggers stand by pump to start	No significant effect	Standby pump start functioning
Main lube oil pump	55. Fails in operation	Failure of motor pump, motor pump seizing, failure of motor coupling	lubrication oil supply interruption to main engine and turbocharger, stand by pump starts	No significant effect	Standby pump start functioning
Main lube oil pump	56. Fails to stop on demand	Relay switch defective or failed	Lube oil pump operates continuously	No significant effect	Standby pump start functioning
Main lube oil pump	57. Operates at reduced head	Worn pump gears, Pump housing leak	Lube oil pressure too low, low pressure alarm trigger stand by pump to function	No significant effect	Standby pump start functioning
Lube oil system- valves and piping	58. Piping leakage, burst flange	Poor quality fuel, contaminants, loose flange, overheating due to failure of gaskets	leakage of oil, low oil pressure, wear of engine components	Stopped engine due low oil pressure, fire probable especially at high temp.	Physical inspection
Lube oil filter	59. clogged	Accumulation of carbon or foreign matter	Improper cleaning, low lube oil pressure	Reduced engine performance, stop engine	
CENTRAL WATER COOLING SYSTEM					
Sea water Pipes	60. leakage	Fatigue, corrosion	Reduced flow, flooding of engine room, loss of cooling	Isolation of affected part result to minor effect	Bilge alarm

Equipment items	Failure modes	Failure cause	Local effects	Global effects	Detection system
Sea water cooling pump	61. Fail to run	Electrical or mechanical fault	Start-up of standby pump	No significant effect	Bilge alarm
Central cooler	62. Leakage	Corrosion	Inadequate cooling	high engine temperature	High temperature alarm
Lube oil cooler	63. Abnormal temperature	Fouling	Operational capability of lube oil cooler reduced	Excessive engine temperature, engine stop possible	High temperature alarm
Sea chest strainer	64. Obstruction	Marine growth, debris	None; the other is sufficient to provide seawater	None	High temperature of central cooler
Engine preheating unit	65. Unable to start,	Dirty jacket, pump motor failure	wear, structural cracks	Engine start failure	Alarm
MONITORING SYSTEM, CONTROL AND INSTRUMENTATION					
Governor	66. Failure to respond to input load change	Failure of speed sensor	Constant engine speed	Reduced engine performance	Engine alar m
Governor	67. Loosened output linkage	Linkage parts wears, engine vibration	Output linkage seizure	Reduced engine performance	,,
Governor	68. Irregular bridge input signal	Bridge control failure, loose wire connection	Engine speed fluctuates	Reduced engine performance	,,
Governor	69. No bridge input signal	Electronic control failure, bridge control failure	Zero engine speed	Stop engine, complete loss of propulsion	,,
Governor	70. Low rpm input signal	Failure of speed sensor, broken wire connection	Tripping of over speed protective device	Stop engine, complete loss of propulsion	,,
Splash-oil monitoring system	71. Tripped	Excessive Lube oil temperature, piston or bearing runs hot or start seizing	Fails to generate alarm signal for alarm system	Stop engine, explosion	
Oil mist detector	72. Blocked	Clogged filter, no vacuum, damaged valve	Cannot detect oil mist in the crankcase	Stop engine, explosion	
Oil mist detector	73. Inoperable	Improper calibration of oil mist detector, lack of maintenance	Cannot detect oil mist in the crankcase	Stop engine, explosion	

Equipment items	Failure modes	Failure cause	Local effects	Global effects	Detection system
oil mist detector	74. Tripped	Sensitivity wrongly set, excessive piston ring clearance, too much water in lubricating oil, seizing of piston	Cannot detect oil mist in the crankcase	Stop engine, explosion	Fire alarm

A.2 Expert assigned failure mode rating for the marine diesel engine

Failure modes	O	S	D
1	7:30%	3	4:70%
	8:60%		
2	7	6:50%	8
3	5	6	5: 90%
4	7	3	3: 80%
5	7: 80%	6	5: 50%
6	6:85%	6	5:65%
7	8	2: 60%	2
8	8:90%	7	7:70%
9	7	6:70%	8:90%
10	10	4:60%	6
11	9: 70%	2	2
12	8	3	3
13	9	2: 70%	2
14	7	5: 90%	3: 50%
15	8	3: 70%	4: 80%
16	9	3	2
17	8:70%	3: 65%	2:70%
18	9: 50%	6	2:90%
19	5	5	4
20	8	6	2:70%
21	7:70%	3	4:70%
22	7	3:60%	5
23	7:80%	2	9:90%
	6:20%		8:10%
24	5	4:60%	5:50%
25	6:90%	5:70%	3:50%
26	6	5	6:60%
27	5	5:50%	3
28	6	4	3:50%
29	5:50%	4	3
30	5	5:50%	3
31	5:50%	8:50%	3:80%
32	6	5	4:60%
33	5	4:50%	3:70%
34	6:90%	2	2:90%
35	6	4	3:70%
36	5	6:90%	1

Failure modes	O	S	D
37	6:70%	5:70%	3:50%
38	6	7:80%	2
39	6	7:60%	2:70%
40	5	8	5
41	5	8	5
42	6	7	4
43	5	7:60%	2:90%
44	4:60%	9:50%	2
45	5	8:70%	2
46	6	7	6
47	4	8	2
48	4	3:70%	2:90%
49	5	2	2:70%
50	4:70%	2:65%	2:90%
51	6:70%	2	3
52	6:50%	9	3
53	7:70%	7	4:50%
54	4	2	2:90%
55	5	2	2:70%
56	4:70%	2	2:90%
57	6:70%	3:55%	3
58	6:50%	8:50%	3
59	7:70%	7	4:50%
60	5:85%	5	2:90%
61	5:70%	2	2
62	5:50%	2:70%	3
63	8	5	4
64	4	4:80%	5:50%
65	4	6	4
66	1	9	3: 90%
67	2	9	3:70%
68	2	9	3
69	2	10	2
70	1	10	1
71	3:40%	9:90%	9:60%
72	3	8:85%	9:70%
73	2	9	10
74	2	8:70%	9:70%

A.3 Decision matrix for failure modes of the marine diesel engine

Failure modes	O	S	D
1	7.5	3	4.5
2	7	5.8	8
3	5	6	5.1
4	7	3	3.5
5	6.7	6	5.3
6	5.9	6	5.2
7	8	3.4	2
8	7.8	7	6.6
9	7	5.9	7.8
10	10	4.6	6
11	8	2	2
12	8	3	3
13	9	3.1	2
14	7	5.1	4.3
15	8	3.8	4.3
16	9	3	2
17	7.3	3.9	3.1
18	7.3	6	2.4
19	5	5	4
20	8	6	3.1
21	6.6	3	4.5
22	7	4	5
23	6.8	2	8.9
24	5	4.6	5.3
25	6	5.2	4.3
26	6	5	5.8
27	5	5.3	3
28	6	4	4.3
29	5.3	4	3
30	5	5.3	3
31	5.3	6.8	3.5
32	6	5	4.6
33	5	4.8	3.8
34	6	2	2.4
35	6	4	3.8
36	5	6	1
37	5.9	5.2	4.3
38	6	6.7	2

Failure modes	O	S	D
39	6	6.4	3.1
40	5	8	5
41	5	8	5
42	6	7	4
43	5	6.4	2.4
44	4.6	7.3	2
45	5	7.3	2
46	6	7	6
47	4	8	2
48	4	3.8	2.4
49	5	2	3.1
50	4.5	3.2	2.4
51	5.9	2	3
52	5.8	9	3
53	6.6	7	4.8
54	4	2	2.4
55	5	2	3.1
56	4.5	2	2.4
57	5.9	4.1	3
58	5.8	6.8	3
59	6.6	7	4.8
60	5.1	5	2.4
61	5.2	2	2
62	5.3	3.1	3
63	8	5	4
64	4	4.3	5.3
65	4	6	4
66	1	9	3.3
67	2	9	3.8
68	2	9	3
69	2	10	2
70	1	10	1
71	4.5	8.7	7.6
72	3	7.6	8
73	2	9	10
74	2	7.3	8

A.4 Failure modes performance index and rankings for the marine diesel engine

Failure modes	VIKOR	Rank	CP	Rank	TOPSIS	Rank	AVRPN	Rank	AVTOPSIS	Rank
1	0.7146	56	0.4372	56	0.3575	50	101.25	35	0.4531	28
2	0.2271	11	0.2575	9	0.5957	6	324.8	2	0.6413	2
3	0.3288	19	0.3104	17	0.4757	27	153	20	0.4639	26
4	0.7549	64	0.4549	58	0.3168	62	73.5	47	0.4046	47
5	0.2828	15	0.2884	15	0.5202	18	213.06	9	0.5426	10
6	0.3046	17	0.2981	16	0.4992	22	184.08	12	0.5057	18
7	0.7170	57	0.4591	61	0.3299	60	54.4	57	0.4171	42
8	0.0770	2	0.2117	2	0.6488	3	360.36	1	0.6707	1
9	0.2186	10	0.2543	8	0.5969	5	322.14	3	0.6393	3
10	0.3843	27	0.3295	24	0.5235	17	276	5	0.6193	4
11	0.9167	67	0.5236	70	0.2916	64	32	65	0.3919	51
12	0.7455	61	0.4590	60	0.3347	58	72	50	0.4314	36
13	0.7361	59	0.4701	64	0.3479	54	55.8	56	0.4461	33
14	0.4326	32	0.3440	30	0.4412	35	153.51	19	0.4881	22
15	0.5943	50	0.3990	48	0.3978	43	130.72	26	0.4868	23
16	0.7504	63	0.4747	65	0.3448	55	54	58	0.4441	35
17	0.6309	53	0.4184	53	0.3528	53	88.257	42	0.4279	38
18	0.4078	28	0.3475	33	0.4476	34	105.12	33	0.4675	25
19	0.5028	43	0.3713	41	0.3776	45	100	36	0.3886	54
20	0.3309	20	0.3266	22	0.4807	25	148.8	21	0.5135	16
21	0.7359	58	0.4419	57	0.3332	59	89.1	41	0.4174	41
22	0.5695	47	0.3835	45	0.4024	42	140	22	0.4772	24
23	0.7482	62	0.4560	59	0.4330	36	121.04	29	0.5276	14
24	0.5227	44	0.3674	40	0.3963	44	121.9	28	0.4232	40
25	0.4420	35	0.3475	34	0.4232	37	134.16	24	0.4497	31
26	0.4277	30	0.3317	25	0.4594	30	174	15	0.4973	20
27	0.4885	40	0.3789	42	0.3678	47	79.5	44	0.3664	60
28	0.6132	51	0.4012	50	0.3550	52	103.2	34	0.4118	44
29	0.6668	55	0.4295	55	0.2971	63	63.6	54	0.3379	64
30	0.4885	40	0.3789	42	0.3678	47	79.5	44	0.3664	60
31	0.3226	18	0.3112	19	0.4818	24	126.14	27	0.4484	32
32	0.4620	39	0.3508	38	0.4206	40	138	23	0.4536	27
33	0.5370	45	0.3833	44	0.3591	49	91.2	38	0.3748	57
34	0.9527	69	0.5258	71	0.2333	67	28.8	70	0.3148	66
35	0.6274	52	0.4095	52	0.3398	56	91.2	38	0.3952	50
36	0.5830	48	0.4011	49	0.3696	46	30	68	0.3452	62
37	0.4444	37	0.3484	35	0.4208	39	131.924	25	0.4454	34
38	0.4400	34	0.3446	32	0.4501	33	80.4	43	0.4288	37
39	0.3594	23	0.3265	21	0.4613	29	119.04	30	0.4502	30
40	0.1438	5	0.2455	5	0.5895	8	200	10	0.5284	12

Failure modes	VIKOR	Rank	CP	Rank	TOPSIS	Rank	AVRPN	Rank	AVTOPSIS	Rank
41	0.1438	5	0.2455	5	0.5895	8	200	10	0.5284	12
42	0.2535	13	0.2849	14	0.5236	16	168	16	0.5003	19
43	0.4434	36	0.3538	39	0.4219	38	76.8	46	0.3895	53
44	0.4449	38	0.3433	29	0.4570	31	67.16	52	0.3971	49
45	0.4354	33	0.3386	27	0.4642	28	73	48	0.4115	45
46	0.1367	4	0.2420	4	0.5900	7	252	6	0.5748	6
47	0.4260	29	0.3362	26	0.4831	23	64	53	0.4021	48
48	0.7433	60	0.4613	62	0.2323	68	36.48	62	0.2508	72
49	0.9564	70	0.5215	68	0.2160	69	31	66	0.2838	68
50	0.8170	66	0.4822	66	0.2157	71	34.56	64	0.2599	71
51	0.9379	68	0.5169	67	0.2432	66	35.4	63	0.3242	65
52	0.2499	12	0.2690	12	0.5851	10	156.6	18	0.5197	15
53	0.1703	7	0.2600	10	0.5626	12	221.76	7	0.5538	8
54	1.0000	74	0.5405	74	0.1612	74	19.2	73	0.2129	74
55	0.9564	70	0.5215	68	0.2160	69	31	66	0.2838	68
56	0.9882	73	0.5363	72	0.1796	73	21.6	71	0.2396	73
57	0.6384	54	0.4203	54	0.3200	61	72.57	49	0.3691	59
58	0.3538	22	0.3179	20	0.4778	26	118.32	31	0.4525	29
59	0.1703	7	0.2600	10	0.5626	12	221.76	7	0.5538	8
60	0.5461	46	0.4022	51	0.3365	57	61.2	55	0.3437	63
61	0.9830	72	0.5376	73	0.1971	72	20.8	72	0.2673	70
62	0.7952	65	0.4695	63	0.2539	65	49.29	60	0.3148	67
63	0.4317	31	0.3485	36	0.4502	32	160	17	0.5127	17
64	0.5892	49	0.3923	46	0.3570	51	91.16	40	0.3725	58
65	0.3838	26	0.3443	31	0.4195	41	96	37	0.3831	56
66	0.3824	25	0.3423	28	0.5099	20	29.7	69	0.3917	52
67	0.2965	16	0.3108	18	0.5377	14	68.4	51	0.4242	39
68	0.3400	21	0.3295	23	0.5188	19	54	58	0.4054	46
69	0.3789	24	0.3500	37	0.5324	15	40	61	0.4171	43
70	0.4888	42	0.3937	47	0.5015	21	10	74	0.3851	55
71	0.0234	1	0.1881	1	0.6894	1	297.54	4	0.6129	5
72	0.1712	9	0.2463	7	0.6068	4	182.4	13	0.5346	11
73	0.1196	3	0.2304	3	0.6682	2	180	14	0.5742	7
74	0.2570	14	0.2777	13	0.5680	11	116.8	32	0.4932	21

Appendix B: Maintenance Strategy Selection

B.1 Delphi Survey Questionnaire

The Delphi survey questionnaires sent to 10 experts in the first and second rounds are presented in B.1.1 and B1.2 respectively.

B.1.1 Delphi Survey Round 1 Questionnaire

Dear Sir/Madam,
I am a PhD Research Student at Newcastle University conducting research entitled, **DEVELOPMENT OF A METHODOLOGY FOR SELECTING OPTIMAL MAINTENANCE STRATEGIES FOR MARINE SYSTEMS**

The Research Aim is to develop a holistic methodology to enable plant managers to select an optimal maintenance strategy for each piece of equipment in the marine machinery system from a set of possible alternatives. In our approach we are embedding Multi-Criteria Decision Making tool (Analytic Hierarchy process) within the Reliability Centered Maintenance framework, for selecting maintenance strategy for failure mechanisms of a marine machinery system.

As part of the effort to achieve the research objectives I would like you to kindly take a few minutes to respond to this questionnaire. All information provided will be used for academic statistical analysis only and the data source will be kept anonymous. Therefore please feel at ease in filling out the answers. Please note that this is the first round of questionnaire; the second round of questionnaire (summary of result of first round questionnaire) will be forwarded to you in four weeks' time.

Table B1 on page 2 is a list of proposed criteria for selecting the maintenance strategy in addressing potential failure mechanisms of a marine diesel engine and diesel generator. Please rate each of the criteria with respect to its value in determining the appropriate maintenance strategy for each component of the system, where **1** indicates **not necessary**, **2** indicates **useful but not essential** and **3** indicates **essential**.

Table B1 Round 1 Delphi survey questionnaire

S/N	Maintenance strategy selection criteria and description	Ratings (1= not necessary, 2= necessary but not essential 3= essential)		
		1	2	3
1	**Minimisation of operation loss:** This criterion refers to potential operation loss that may be experienced as a result of the chosen maintenance strategy.			
2	**Maintenance efficiency**: The criterion refers to maintenance efficiency of each maintenance strategy in addressing system failure mechanism.			
3	**Spare parts inventories:** Spare parts inventories demand for each of the maintenance strategy.			
4	**Equipment risk level**: This criterion considers how critical the component failure in question is to the system; this will tell to a greater extent the maintenance approach to use.			
5	**Planning flexibility:** This criterion considers comparing different maintenance strategies in terms of ability to track potential failure and/or defer failure maintenance.			
6	**Improved Safety**: This criterion considers the maintenance strategy that will better improve safety of personnel and system.			
7	**System reliability:** This criterion considers the level of system reliability that will be attained for each maintenance strategy.			
8	**Compatibility:** Applicability of each of the maintenance strategy.			
9	**Technical expertise requirement:** The degree of expertise required for each of the maintenance strategy.			
10	**Acceptance by labour:** This criterion refers to how acceptable each maintenance strategy is to the crew.			
11	**Fault identification:** This criterion refers to potential component failure detection ability of each of the maintenance strategies.			
12	**Availability:** This criterion considers which strategy has greater ability to improve system availability.			
13	**Manufacturer recommendation:** This refers to maintenance strategies recommended by manufacturers for mitigating a particular system failure.			
14	**Environmental requirement:** The criterion considers ability of each maintenance strategy in meeting the required level of environmental safety			
15	**Available monetary resources:** Available finance for maintaining system.			
16	**Image damage:** The criterion compares maintenance strategies in terms of contribution to damage of the company image.			
17	**Plant damage:** This criterion considers the level of damage to plant systems that may result from implementing a particular maintenance strategy.			
18	**Assurance cost:** This refer to the cost of insuring the system for each type of maintenance strategy.			
19	**Enhanced competitiveness:** The criterion looks at the maintenance strategy that will improve the company's competitiveness.			
20	**System failure characteristics:** The component failure characteristics; wear-in failure, random and wear-out failure.			
21	**Maintenance cost:** The resultant cost in terms of hardware, software and labour over a period of time for each type of maintenance strategy.			
22	**Crew training cost:** The cost value of training required by the crew members in order to acquire the expertise needed for implementation of each strategy.			

2. If you have any suggestion of any criteria for selecting maintenance strategy not listed in the above 22 criteria, please list below:

…………………………………………………………………………………………….

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B1.2 Delphi Survey Round 2 Questionnaire

Dear Sir/Madam,

I wish to thank you for your participation and prompt response in the first round of the Delphi survey. As stated in the first survey, the Delphi method is an iterated technique for processing opinions of experts till a reasonable consensus is reach on the subject under investigation.

Please re-evaluate the second round questionnaire in Table 1 (Note: it is the same questionnaire in the first round I sent to you four weeks ago) with the knowledge of the summary of results of the ten-man experts' responses you inclusive from the first round presented in Table 2.

The summary of results presented in Table 2 shows the average or mean and the standard deviation of scores returned by ten experts for each of the proposed maintenance selection strategy criteria for marine diesel engine using a three point scale in which **1** indicates **not necessary**, **2** indicates **useful but not essential** and **3** indicates **essential**. From the result using the Delphi elimination rule, criteria with mean value below 2.7 is dropped. Based on this rule the following maintenance selection criteria will be eliminated:

1. Planning flexibility
2. Compatibility
3. Acceptance by labour
4. Availability
5. Manufacturer's recommendation
6. Image damage
7. Assurance.

Table B2 Round 2 Delphi survey questionnaire

S/N	Maintenance strategy selection criteria and description	Ratings (1= not necessary, 2= necessary but not essential 3= essential)		
		1	2	3
1	**Minimisation of operation loss:** This criterion refers to potential operation loss that may be experienced as a result of the chosen maintenance strategy.			
2	**Maintenance efficiency**: The criterion refers to maintenance efficiency of each maintenance strategy in addressing system failure mechanism.			
3	**Spare parts inventories:** Spare parts inventories demand for each of the maintenance strategy.			
4	**Equipment risk level**: This criterion considers how critical the component failure in question is to the system; this will tell to a greater extent the maintenance approach to use.			
5	**Planning flexibility:** This criterion considers comparing different maintenance strategies in terms of ability to track potential failure and/or defer failure maintenance.			
6	**Improved Safety**: This criterion considers the maintenance strategy that will better improve safety of personnel and system.			
7	**System reliability:** This criterion considers the level of system reliability that will be attained for each maintenance strategy.			
8	**Compatibility:** Applicability of each of the maintenance strategy.			
9	**Technical expertise requirement:** The degree of expertise required for each of the maintenance strategy.			
10	**Acceptance by labour:** This criterion refers to how acceptable each maintenance strategy is to the crew.			
11	**Fault identification:** This criterion refers to potential component failure detection ability of each of the maintenance strategies.			
12	**Availability:** This criterion considers which strategy has greater ability to improve system availability.			
13	**Manufacturer recommendation:** This refers to maintenance strategies recommended by manufacturers for mitigating a particular system failure.			
14	**Environmental requirement:** The criterion considers ability of each maintenance strategy in meeting the required level of environmental safety			
15	**Available monetary resources:** Available finance for maintaining system.			
16	**Image damage:** The criterion compares maintenance strategies in terms of contribution to damage of the company image.			
17	**Plant damage:** This criterion considers the level of damage to plant systems that may result from implementing a particular maintenance strategy.			
18	**Assurance cost:** This refer to the cost of insuring the system for each type of maintenance strategy.			
19	**Enhanced competitiveness:** The criterion looks at the maintenance strategy that will improve the company's competitiveness.			
20	**System failure characteristics:** The component failure characteristics; wear-in failure, random and wear-out failure.			
21	**Maintenance cost:** The resultant cost in terms of hardware, software and labour over a period of time for each type of maintenance strategy.			
22	**Crew training cost:** The cost value of training required by the crew members in order to acquire the expertise needed for implementation of each strategy.			

2. If you have any comments, please state below:

……………………………………………………………………………………………….

……………………………………………………………………………………………….

……………………………………………………………………………………………….

……………………………………………………………………………………………….

B.2: Survey Questionnaire for the development of the AHP model for maintenance strategy selection for marine machinery systems

Dear Sir/Madam,

The purpose of this questionnaire is to perform a pair comparison judgement of three different maintenance strategies; corrective maintenance, preventive maintenance and condition based maintenance with respect to evaluation criteria in order to choose the most appropriate strategy for maintaining sea water pump of a central cooling system of a marine diesel engine. In order words, your opinions is being sort in deciding on the most appropriate maintenance strategy for maintaining sea water pump of a central cooling system of a marine diesel engine.

Kindly take some of your precious time to respond to question 1, 2 and 3 and freely express your opinion by marking X in the appropriate column as your response will be treated anonymously and only be used for statistical analysis.

We will appreciate if you respond as soon as possible.

Thanks for your anticipated cooperation.

Question 1. Perform pairwise comparison of main criteria with respect to the main goal; maintenance strategy selection.

For Table B3 carry out a pair wise comparison of main criteria for selecting maintenance strategy for sea water pump of a central cooling system of a marine diesel engine. If the main criterion on the left column of the table is more important to the one on the right, mark X to the left of ‘Equal’ otherwise mark to the right and if they are of equal importance mark X on ‘Equal’.

Question 2. Perform pairwise comparison of sub-criteria with respect to 4 main criteria and bearing in mind the main objective.

Do a pairwise comparison of sub-criteria in Tables 2 to 5 with respect to main criteria. If the sub-criterion on the left column of the table is more important to the one on the right, mark X to the left of 'Equal' otherwise mark to the right and if they are of equal importance mark X on 'Equal'.

Question 3. Perform a Pairwise comparison of maintenance strategy with respect to 16 criteria and having in mind the main goal.

For each criterion in Tables 6 to 20 compare the maintenance strategy on the left column to the one on the right column. If a maintenance strategy on the left column is more important to the one on the right, mark X to the left of 'Equal' otherwise mark to the right and if they are of equal importance in maintaining sea water pump of a central cooling system of marine diesel engine with respect to a criterion mark X on 'Equal'.

Table B3: Importance of one main criterion over another with respect to selection of maintenance strategy

Question	Main criteria	Extreme	Very strong	Strong	Moderate	Equal	Moderate	Strong	Very strong	Extreme	Main criteria
1	Cost (C)										Safety (S)
2	Cost (C)										Added value (AV)
3	Cost (C)										Applicability (A)
4	Safety (S)										Added value (AV)
5	Safety (S)										Applicability (A)
6	Added value (AV)										Applicability (A)

Table B4: Importance of one sub-criterion over another with respect to main criterion 1 (Cost)

Question	Criteria	Extreme	Very strong	Strong	Moderate	Equal	Moderate	Strong	Very strong	Extreme	Criteria
1	Spare parts inventories cost(C1)										Maintenance cost (C2)
2	Spare parts inventories cost (C1)										Crew training cost (C3)
3	Spare parts inventories cost (C1)										Equipment damage cost (C4)
4	Maintenance cost C2)										Crew training cost (C3)
5	Maintenance cost (C2)										Equipment damage cost (C4)
6	Crew training cost (C3)										Equipment damage cost (C4)

Table B5: Importance of one sub-criterion over another with respect to main criterion 2 (Safety)

Question	Criteria	Extreme	Very strong	Strong	Moderate	Equal	Moderate	Strong	Very strong	Extreme	Criteria
1	Personnel (S1)										Equipment (S2)
2	Personnel (S1)										Environment (S3)
4	Equipment (S2)										Environment (S3)

Table B6: Importance of one sub-criterion over another with respect to main criterion 3 (Added value)

Question	Criteria	Extreme	Very strong	Strong	Moderate	Equal	Moderate	Strong	Very strong	Extreme	Criteria
1	Minimisation of operation loss (AV1)										Equipment reliability (AV2)

Table B7: Importance of one sub-criterion over another with respect to main criterion 4 (Applicability)

Question	Criteria	Extreme	Very strong	Strong	Moderate	Equal	Moderate	Strong	Very strong	Extreme	Criteria
1	System failure characteristics (A1)										Availability Monetary resource (A2)
2	System failure characteristics (A1)										Equipment risk level (A3)
3	Available monetary resource (A2)										Equipment risk level (A3)

Table B8: Importance of one maintenance strategy over another with respect to criterion Spare parts inventories costs

Question	Maintenance strategy	Extreme	Very strong	Strong	Moderate	Equal	Moderate	Strong	Very strong	Extreme	Maintenance strategy
1	Corrective maintenance										Scheduled overhaul
2	Corrective maintenance										Scheduled replacement
3	Corrective maintenance										Offline condition based maintenance
4	Corrective maintenance										Online condition based maintenance
5	Scheduled overhaul										Scheduled replacement
6	Scheduled overhaul										Offline condition based maintenance
7	Scheduled overhaul										Online condition based maintenance
8	Scheduled replacement										Offline condition based maintenance
9	Scheduled replacement										Online condition based maintenance
10	Offline condition based maintenance										Online condition based maintenance

Table B9: Importance of one maintenance strategy over another with respect to criterion Maintenance cost

Question	Maintenance strategy	Extreme	Very strong	Strong	Moderate	Equal	Moderate	Strong	Very strong	Extreme	Maintenance strategy
1	Corrective maintenance										Scheduled overhaul
2	Corrective maintenance										Scheduled replacement
3	Corrective maintenance										Offline condition based maintenance
4	Corrective maintenance										Online condition based maintenance
5	Scheduled overhaul										Scheduled replacement
6	Scheduled overhaul										Offline condition based maintenance
7	Scheduled overhaul										Online condition based maintenance
8	Scheduled replacement										Offline condition based maintenance
9	Scheduled replacement										Online condition based maintenance
10	Offline condition based maintenance										Online condition based maintenance

Table B10: Importance of one maintenance strategy over another with respect to criterion Crew training cost

Question	Maintenance strategy	Extreme	Very strong	Strong	Moderate	Equal	Moderate	Strong	Very strong	Extreme	Maintenance strategy
1	Corrective maintenance										Scheduled overhaul
2	Corrective maintenance										Scheduled replacement
3	Corrective maintenance										Offline condition based maintenance
4	Corrective maintenance										Online condition based maintenance
5	Scheduled overhaul										Scheduled replacement
6	Scheduled overhaul										Offline condition based maintenance
7	Scheduled overhaul										Online condition based maintenance
8	Scheduled replacement										Offline condition based maintenance
9	Scheduled replacement										Online condition based maintenance
10	Offline condition based maintenance										Online condition based maintenance

Table B11: Importance of one maintenance strategy over another with respect to criterion Equipment damage cost

Question	Maintenance strategy	Extreme	Very strong	Strong	Moderate	Equal	Moderate	Strong	Very strong	Extreme	Maintenance strategy
1	Corrective maintenance										Scheduled overhaul
2	Corrective maintenance										Scheduled replacement
3	Corrective maintenance										Offline condition based maintenance
4	Corrective maintenance										Online condition based maintenance
5	Scheduled overhaul										Scheduled replacement
6	Scheduled overhaul										Offline condition based maintenance
7	Scheduled overhaul										Online condition based maintenance
8	Scheduled replacement										Offline condition based maintenance
9	Scheduled replacement										Online condition based maintenance
10	Offline condition based maintenance										Online condition based maintenance

Table B12: Importance of one maintenance strategy over another with respect to criterion Personnel safety

Question	Maintenance strategy	Extreme	Very strong	Strong	Moderate	Equal	Moderate	Strong	Very strong	Extreme	Maintenance strategy
1	Corrective maintenance										Scheduled overhaul
2	Corrective maintenance										Scheduled replacement
3	Corrective maintenance										Offline condition based maintenance
4	Corrective maintenance										Online condition based maintenance
5	Scheduled overhaul										Scheduled replacement
6	Scheduled overhaul										Offline condition based maintenance
7	Scheduled overhaul										Online condition based maintenance
8	Scheduled replacement										Offline condition based maintenance
9	Scheduled replacement										Online condition based maintenance
10	Offline condition based maintenance										Online condition based maintenance

Table B13: Importance of one maintenance strategy over another with respect to criterion Equipment safety

Question	Maintenance strategy	Extreme	Very strong	Strong	Moderate	Equal	Moderate	Strong	Very strong	Extreme	Maintenance strategy
1	Corrective maintenance										Scheduled overhaul
2	Corrective maintenance										Scheduled replacement
3	Corrective maintenance										Offline condition based maintenance
4	Corrective maintenance										Online condition based maintenance
5	Scheduled overhaul										Scheduled replacement
6	Scheduled overhaul										Offline condition based maintenance
7	Scheduled overhaul										Online condition based maintenance
8	Scheduled replacement										Offline condition based maintenance
9	Scheduled replacement										Online condition based maintenance
10	Offline condition based maintenance										Online condition based maintenance

Table B14: Importance of one maintenance strategy over another with respect to criterion Environment safety

Question	Maintenance strategy	Extreme	Very strong	Strong	Moderate	Equal	Moderate	Strong	Very strong	Extreme	Maintenance strategy
1	Corrective maintenance										Scheduled overhaul
2	Corrective maintenance										Scheduled replacement
3	Corrective maintenance										Offline condition based maintenance
4	Corrective maintenance										Online condition based maintenance
5	Scheduled overhaul										Scheduled replacement
6	Scheduled overhaul										Offline condition based maintenance
7	Scheduled overhaul										Online condition based maintenance
8	Scheduled replacement										Offline condition based maintenance
9	Scheduled replacement										Online condition based maintenance
10	Offline condition based maintenance										Online condition based maintenance

Table B15: Importance of one maintenance strategy over another with respect to criterion Minimisation of operation loss

Question	Maintenance strategy	Extreme	Very strong	Strong	Moderate	Equal	Moderate	Strong	Very strong	Extreme	Maintenance strategy
1	Corrective maintenance										Scheduled overhaul
2	Corrective maintenance										Scheduled replacement
3	Corrective maintenance										Offline condition based maintenance
4	Corrective maintenance										Online condition based maintenance
5	Scheduled overhaul										Scheduled replacement
6	Scheduled overhaul										Offline condition based maintenance
7	Scheduled overhaul										Online condition based maintenance
8	Scheduled replacement										Offline condition based maintenance
9	Scheduled replacement										Online condition based maintenance
10	Offline condition based maintenance										Online condition based maintenance

Table B16: Importance of one maintenance strategy over another with respect to criterion Equipment reliability

Question	Maintenance strategy	Extreme	Very strong	Strong	Moderate	Equal	Moderate	Strong	Very strong	Extreme	Maintenance strategy
1	Corrective maintenance										Scheduled overhaul
2	Corrective maintenance										Scheduled replacement
3	Corrective maintenance										Offline condition based maintenance
4	Corrective maintenance										Online condition based maintenance
5	Scheduled overhaul										Scheduled replacement
6	Scheduled overhaul										Offline condition based maintenance
7	Scheduled overhaul										Online condition based maintenance
8	Scheduled replacement										Offline condition based maintenance
9	Scheduled replacement										Online condition based maintenance
10	Offline condition based maintenance										Online condition based maintenance

Table B17: Importance of one maintenance strategy over another with respect to criterion System failure characteristics

Question	Maintenance strategy	Extreme	Very strong	Strong	Moderate	Equal	Moderate	Strong	Very strong	Extreme	Maintenance strategy
1	Corrective maintenance										Scheduled overhaul
2	Corrective maintenance										Scheduled replacement
3	Corrective maintenance										Offline condition based maintenance
4	Corrective maintenance										Online condition based maintenance
5	Scheduled overhaul										Scheduled replacement
6	Scheduled overhaul										Offline condition based maintenance
7	Scheduled overhaul										Online condition based maintenance
8	Scheduled replacement										Offline condition based maintenance
9	Scheduled replacement										Online condition based maintenance
10	Offline condition based maintenance										Online condition based maintenance

Table B18: Importance of one maintenance strategy over another with respect to criterion Available monetary resource

Question	Maintenance strategy	Extreme	Very strong	Strong	Moderate	Equal	Moderate	Strong	Very strong	Extreme	Maintenance strategy
1	Corrective maintenance										Scheduled overhaul
2	Corrective maintenance										Scheduled replacement
3	Corrective maintenance										Offline condition based maintenance
4	Corrective maintenance										Online condition based maintenance
5	Scheduled overhaul										Scheduled replacement
6	Scheduled overhaul										Offline condition based maintenance
7	Scheduled overhaul										Online condition based maintenance
8	Scheduled replacement										Offline condition based maintenance
9	Scheduled replacement										Online condition based maintenance
10	Offline condition based maintenance										Online condition based maintenance

Table B19: Importance of one maintenance strategy over another with respect to criterion Equipment risk level

Question	Maintenance strategy	Extreme	Very strong	Strong	Moderate	Equal	Moderate	Strong	Very strong	Extreme	Maintenance strategy
1	Corrective maintenance										Scheduled overhaul
2	Corrective maintenance										Scheduled replacement
3	Corrective maintenance										Offline condition based maintenance
4	Corrective maintenance										Online condition based maintenance
5	Scheduled overhaul										Scheduled replacement
6	Scheduled overhaul										Offline condition based maintenance
7	Scheduled overhaul										Online condition based maintenance
8	Scheduled replacement										Offline condition based maintenance
9	Scheduled replacement										Online condition based maintenance
10	Offline condition based maintenance										Online condition based maintenance

B.3 Comparison judgement from three experts

B3.1 Comparison judgement for AHP models obtained from expert 1

Table B20: Sub-criteria comparison matrix with respect to safety

	Personnel	Equipment	Environment
Personnel	1	3	3
Equipment	1/3	1	1
Environment	1/3	1	1

Table B21: Sub-criteria comparison matrix with respect to added value

	Minimisation of operation loss	Equipment reliability
Minimisation of operation loss	1	1
Equipment reliability	1	1

Table B22: Sub-criteria comparison matrix with respect to applicability

	System failure characteristics	Available monetary resources	Equipment risk level
System failure characteristics	1	1	1
Available monetary resources	1	1	1
Equipment risk level	1	1	1

Table B23: maintenance alternatives comparison matrix with respect to sub-criterion maintenance cost

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1/3	1/3	1/7	1/7
SOH	3	1	1	1/3	1/3
SRP	3	1	1	1/3	1/3
OFCBM	7	3	3	1	3
ONCBM	7	3	3	1/3	1

Table B24: maintenance alternatives comparison matrix with respect to sub-criterion Crew training cost

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1	1	3	5
SOH	1	1	1	3	5
SRP	1	1	1	3	5
OFCBM	1/3	1/3	1/3	1	3
ONCBM	1/2	1/2	1/2	1/3	1

Table B25: maintenance alternatives comparison matrix with respect to sub-criterion equipment damage cost

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1	1	1/3	1/2
SOH	1	1	1	1/3	1/3
SRP	1	1	1	1/3	1/3
OFCBM	3	3	3	1	1
ONCBM	5	3	3	1	1

Table B26: maintenance alternatives comparison matrix with respect to sub-criterion personnel safety

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1	1	1/3	1/2
SOH	1	1	1	1/3	1/3
SRP	1	1	1	1/3	1/3
OFCBM	3	3	3	1	1
ONCBM	5	3	3	1	1

Table B27: maintenance alternatives comparison matrix with respect to sub-criterion equipment safety

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1/3	1/3	1/3	1/2
SOH	3	1	1	1/3	1/3
SRP	3	1	1	1/3	1/3
OFCBM	3	3	3	1	1
ONCBM	5	3	3	1	1

Table B28: maintenance alternatives comparison matrix with respect to sub-criterion environment safety

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1/3	1/3	1/3	1/2
SOH	3	1	1	1/3	1/3
SRP	3	1	1	1/2	1/3
OFCBM	3	3	5	1	1
ONCBM	5	3	3	1	1

Table B29: maintenance alternatives comparison matrix with respect to sub-criterion minimisation of operation loss

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1/3	1/3	1/2	1/2
SOH	3	1	1	1/3	1/3
SRP	3	1	1	1/2	1/3
OFCBM	5	3	5	1	1
ONCBM	5	3	3	1	1

Table B30: maintenance alternatives comparison matrix with respect to sub-criterion equipment reliability

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1/3	1/3	1/2	1/2
SOH	3	1	1	1/3	1/3
SRP	3	1	1	1/3	1/3
OFCBM	5	3	3	1	1
ONCBM	5	3	3	1	1

Table B31: maintenance alternatives comparison matrix with respect to sub-criterion equipment failure characteristics

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1	1	1	1
SOH	1	1	1	1	1
SRP	1	1	1	1	1
OFCBM	1	1	1	1	1
ONCBM	1	1	1	1	1

Table B32: maintenance alternatives comparison matrix with respect to sub-criterion available monetary resources

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1	1	1	3
SOH	1	1	1	1	3
SRP	1	1	1	1	3
OFCBM	1	1	1	1	3
ONCBM	1/3	1/3	1/3	1/3	1

Table B33: maintenance alternatives comparison matrix with respect to sub-criterion equipment risk level

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1/3	1/3	1/2	1/2
SOH	3	1	1	1/3	1/3
SRP	3	1	1	1/3	1/3
OFCBM	5	3	3	1	1
ONCBM	5	3	3	1	1

B3.2: Comparison judgement for AHP models obtained from expert 2

Table B34: Criteria matrix with respect to overall goal

	Cost	Safety	Added value	Applicability
Cost	1	1/3	1/3	1
Safety	3	1	3	3
Added value	3	1/3	1	3
Applicability	1	1/3	1/3	1

Table B35: Sub-criteria comparison matrix with respect to main criterion cost

	Spare parts inventories	Maintenance cost	Crew training cost	Equipment damage cost
Spare parts inventories	1	1/6	1/6	1/3
Maintenance cost	6	1	1	3
Crew training cost	6	1	1	3
Equipment damage cost	3	1/3	1/3	1

Table B36: Sub-criteria comparison matrix with respect to safety

	Personnel	Equipment	Environment
Personnel	1	3	3
Equipment	1/3	1	1
Environment	1/3	1	1

Table B37: Sub-criteria comparison matrix with respect to added value

Minimisation of operation loss	1	1
Equipment reliability	1	1

Table B38: Sub-criteria comparison matrix with respect to applicability

	Equipment failure characteristics	Available monetary resources	Equipment risk level
Equipment failure characteristics	1	1/3	1
Available monetary resources	3	1	3
Equipment risk level	1	1/3	1

Table B39: maintenance alternatives comparison matrix with respect to sub-criterion spare parts inventories cost

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1/3	1/3	1/2	1/2
SOH	3	1	1	1/3	1
SRP	3	1	1	1/3	1
OFCBM	5	3	3	1	1
ONCBM	5	1	1	1	1

Table B40: maintenance alternatives comparison matrix with respect to sub-criterion maintenance cost

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1/3	1/3	1/2	1/2
SOH	3	1	1	1/3	1
SRP	3	1	1	1/2	1
OFCBM	5	3	5	1	1
ONCBM	5	1	1	1	1

Table B41: maintenance alternatives comparison matrix with respect to sub-criterion Crew training cost

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1	1	3	5
SOH	1	1	1	3	5
SRP	1	1	1	3	5
OFCBM	1/3	1/3	1/3	1	3
ONCBM	1/2	1/2	1/2	1/3	1

Table B42: maintenance alternatives comparison matrix with respect to sub-criterion equipment damage cost

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1/3	1/3	1/2	1/2
SOH	3	1	1	1/3	1
SRP	3	1	1	1/3	1/2
OFCBM	5	3	3	1	1
ONCBM	5	1	5	1	1

Table B43: maintenance alternatives comparison matrix with respect to sub-criterion personnel safety

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1/3	1/3	1/2	1/2
SOH	3	1	1	1	1/3
SRP	3	1	1	1/3	1/2
OFCBM	5	1	3	1	1
ONCBM	5	3	5	1	1

Table B44: maintenance alternatives comparison matrix with respect to sub-criterion equipment safety

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1/3	1/3	1/3	1/2
SOH	3	1	1	1/3	1/3
SRP	3	1	1	1/3	1/3
OFCBM	3	3	3	1	1
ONCBM	5	3	3	1	1

Table B45: maintenance alternatives comparison matrix with respect to sub-criterion environment safety

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1/3	1/3	1/2	1/2
SOH	3	1	1	1/3	1
SRP	3	1	1	1/2	1
OFCBM	5	3	5	1	3
ONCBM	5	1	1	1/3	1

Table B46: maintenance alternatives comparison matrix with respect to sub-criterion minimisation of operation loss

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1/3	1/3	1/2	1/2
SOH	3	1	1	1/3	1/3
SRP	3	1	1	1/3	1/2
OFCBM	5	3	3	1	1
ONCBM	5	3	5	1	1

Table B47: maintenance alternatives comparison matrix with respect to sub-criterion equipment reliability

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1	1	1/2	1/2
SOH	1	1	3	1/3	1/3
SRP	1	1/3	1	1/3	1/2
OFCBM	5	3	3	1	1
ONCBM	5	3	5	1	1

Table B48: maintenance alternatives comparison matrix with respect to sub-criterion equipment failure characteristics

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1	1	1/3	3
SOH	1	1	1	1/3	3
SRP	1	1	1	1	3
OFCBM	1	1	1	1	3
ONCBM	1/3	1/3	1/3	1/3	1

Table B49: maintenance alternatives comparison matrix with respect to sub-criterion available monetary resources

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1	1	1/3	3
SOH	1	1	1	1/3	3
SRP	1	1	1	1	3
OFCBM	3	3	1	1	3
ONCBM	1/3	1/3	1/3	1/3	1

Table B50: maintenance alternatives comparison matrix with respect to sub-criterion equipment risk level

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1/3	1/3	1/2	1/2
SOH	3	1	1	1/3	1/3
SRP	3	1	1	1/3	1/3
OFCBM	5	3	3	1	1
ONCBM	5	3	3	1	1

B3.3: Comparison judgement for AHP models obtained from expert 3

Table B51: Criteria matrix with respect to overall goal

	Cost	Safety	Added value	Applicability
Cost	1	1/9	1/3	1/7
Safety	9	1	9	3
Added value	3	1/9	1	1/7
Applicability	7	1/3	7	1

Table B52: Sub-criteria comparison matrix with respect to main criterion cost

	Spare parts inventories	Maintenance cost	Crew training cost	Equipment damage cost
Spare parts inventories	1	5	3	5
Maintenance cost	1/5	1	1	5
Crew training cost	1/3	1	1	5
Equipment damage cost	1/5	1/5	1/5	1

Table B53: Sub-criteria comparison matrix with respect to safety

	Personnel	Equipment	Environment
Personnel	1	7	9
Equipment	1/7	1	3
Environment	1/9	1/3	1

Table B54: Sub-criteria comparison matrix with respect to added value

	Minimisation of operation loss	Equipment reliability
Minimisation of operation loss	1	1
Equipment reliability	1	1

Table B55: Sub-criteria comparison matrix with respect to applicability

	System failure characteristics	Available monetary resources	Equipment risk level
System failure characteristics	1	1/3	1/7
Available monetary resources	3	1	1/3
Equipment risk level	7	3	1

Table B56: maintenance alternatives comparison matrix with respect to sub-criterion spare parts inventories cost

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1/3	1/3	1/2	1/2
SOH	3	1	1	1/2	1/3
SRP	3	1	1	1/3	1/3
OFCBM	5	5	3	1	1
ONCBM	5	3	3	1	1

Table B57: maintenance alternatives comparison matrix with respect to sub-criterion maintenance cost

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1/3	1/3	1/2	1/2
SOH	3	1	1	1/2	1/3
SRP	3	1	1	1/3	1/3
OFCBM	5	5	3	1	3
ONCBM	5	3	3	1/3	1

Table B58: maintenance alternatives comparison matrix with respect to sub-criterion Crew training cost

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	3	3	1	3
SOH	1/3	1	1	1/3	1
SRP	1/3	1	1	1	3
OFCBM	1	3	1	1	3
ONCBM	1/3	1	1/3	1/3	1

Table B59: maintenance alternatives comparison matrix with respect to sub-criterion equipment damage cost

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1/3	1/2	1/2	3
SOH	3	1	1/3	1/3	3
SRP	5	3	1	1	7
OFCBM	5	3	1	1	5
ONCBM	1/3	1/3	1/7	1/2	1

Table B60: maintenance alternatives comparison matrix with respect to sub-criterion personnel safety

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1/3	1/3	1/2	1/7
SOH	3	1	1	1/3	1/3
SRP	3	1	1	1/3	1/3
OFCBM	5	3	3	1	1
ONCBM	7	3	3	1	1

Table B61: maintenance alternatives comparison matrix with respect to sub-criterion equipment safety

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1/3	1/3	1/3	1/2
SOH	3	1	1	1/3	1/3
SRP	3	1	1	1/3	1/3
OFCBM	3	3	3	1	1
ONCBM	5	3	3	1	1

Table B62: maintenance alternatives comparison matrix with respect to sub-criterion environment safety

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1/3	1/2	1/2	3
SOH	3	1	1/3	1/3	3
SRP	5	3	1	1	7
OFCBM	5	3	1	1	5
ONCBM	1/3	1/3	1/7	1/2	1

Table B63: maintenance alternatives comparison matrix with respect to sub-criterion minimisation of operation loss

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1/3	1/3	1/2	1/2
SOH	3	1	1	1/3	1/3
SRP	3	1	1	1/3	1/2
OFCBM	5	3	3	1	1
ONCBM	5	3	5	1	1

Table B64: maintenance alternatives comparison matrix with respect to sub-criterion equipment reliability

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1/3	1/3	1/2	1/2
SOH	3	1	1	1/2	1/2
SRP	3	1	1	1/3	1/3
OFCBM	5	5	3	1	1
ONCBM	5	5	3	1	1

Table B65: maintenance alternatives comparison matrix with respect to sub-criterion equipment failure characteristics

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1	1	1	1
SOH	1	1	1	1	1
SRP	1	1	1	1	1
OFCBM	1	1	1	1	1
ONCBM	1	1	1	1	1

Table B66: maintenance alternatives comparison matrix with respect to sub-criterion available monetary resources

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	3	3	1	3
SOH	1/3	1	1	1/3	1/3
SRP	1/3	1	1	1/3	1
OFCBM	3	3	3	1	1
ONCBM	1/3	3	1	1	1

Table B67: maintenance alternatives comparison matrix with respect to sub-criterion equipment risk level

	CM	SOH	SRP	OFCBM	ONCBM
CM	1	1/3	1/3	1/9	1/2
SOH	3	1	1/3	1/3	1/3
SRP	3	3	1	1/3	1
OFCBM	9	3	3	1	3
ONCBM	5	3	1	1/3	1

B.4: Questionnaire produce to obtained information for PROMETHEE and TOPSIS

Dear Sir,

The purpose of this questionnaire is to determine the most appropriate maintenance strategy from among five maintenance alternatives for sea water pump of a central cooling system of a marine diesel engine. The five maintenance strategies are: Corrective maintenance (CM), Scheduled overhaul (SOH), Scheduled replacement (SRP), Offline-Condition based maintenance (OFCBM) and Online-Condition based maintenance (ONCBM).

Please rank the five maintenance strategies with respect to the 4 decision criteria using a 5 point Likert scale i.e.1 to 5. Ranking score 1 represent very bad and 5 represent very good. Note lower cost is preferred to higher cost and higher benefit is preferred to lower benefit.

For example considering criteria cost; if I rate Corrective maintenance (CM), Scheduled overhaul (SOH), Scheduled replacement (SRP), Offline-Condition based maintenance (OFCBM) and Online-Condition based maintenance (ONCBM) to be 5, 4, 3, 2 and 1 respectively; it means applying corrective maintenance will result to lowest spare parts inventories cost while applying Online-Condition based maintenance will result to highest spare parts inventories cost. Also considering criteria AV2; Corrective maintenance (CM), Scheduled overhaul (SOH), Scheduled replacement (SRP), Offline-Condition based maintenance (OFCBM) and Online-Condition based maintenance (ONCBM) to be 1, 2, 3, 4 and 5 respectively; it means condition based maintenance will result to best equipment reliability and corrective maintenance least equipment reliability while others are in between.

Table B68: PROMOTHEE and TOPSIS questionnaire

	Corrective maintenance (CM)	Scheduled overhaul (SOH)	Scheduled replacement (SRP)	Offline-Condition based maintenance (OFCBM)	Online-Condition based maintenance (ONCBM)
Spare parts inventories cost: (C1)					
Maintenance cost (C2)					
Crew training cost (C3)					
Equipment damage cost (C4)					
Personnel safety (S1)					
Equipment Safety (S2)					
Environment safety (S3)					
Minimisation of operation loss (AV1)					
Equipment reliability (AV2)					
System failure characteristics (A1)					
Available monetary resources (A2)					
Equipment risk level (A3)					

Maintenance alternatives rating with respect to criteria: 1= very bad…, 5 very good

Appendix C: Scheduled Replacement Interval Determination

C.1: Matlab Program for calculating Reliability function, Cost function and Downtime function

```
b=3.432;a=31699;ca=8000;cb=2000;Ta=3;Tb=15; % input data
f=@(x)(x.*((b./a).*((x./a).^(b-1)).*exp((-(x./a).^b)))); % probability density function calculation
 j=5000:1000:34000; % replacement alternative intervals
tp=zeros(1,length(j));q=zeros(1,length(j));Rtp=zeros(1,length(j));Ctp=zeros(1,length(j));Dtp=
zeros(1,length(j));
t=zeros(1,length(j));
for i=1:length(j);
    tp=j(i);
    t(i)=tp;
    q(i)=quadgk(f,0,t(i));
    Rtp(i)=exp(-(t(i)/a).^b); % Reliability per unit time calculation
    Ctp(i)=(ca.*(1-Rtp(i))+cb.*Rtp(i))/(q(i)+Tb.*(1-Rtp(i))+(Ta+t(i)).*Rtp(i)); % cost per unit time calculation
    Dtp(i)=(Tb.*(1-Rtp(i))+Ta.*Rtp(i))/(q(i)+(Tb.*(1-Rtp(i)))+(Ta+t(i)).*Rtp(i)); % Downtime per unit time calculation
end
figure;plot(t,Ctp,'bo','linewidth',1.0)
title('cost vs time');xlabel('time(tp(s))');ylabel('Ctp')
figure;plot(t,Dtp,'bo','linewidth',1.0)
title('downtime vs time')
figure;plot(t,Rtp,'bo','linewidth',1.0)
title('reliabilty vs time')
```

C.2 Sensitivity analysis of parameters of decision criteria

Table C1: TOPSIS performance index of sensitivity analysis β

Replacement interval alternatives	Performance index (dp)								
	-20%	-15%	-10%	-5%	0%	+5%	+10%	+15%	+20%
A1	0.7662	0.7578	0.7497	0.7422	0.7352	0.7288	0.7229	0.7176	0.7127
A2	0.8216	0.8142	0.8068	0.8000	0.7932	0.7873	0.7814	0.7762	0.7715
A3	0.8649	0.8585	0.8524	0.8462	0.8401	0.8348	0.8294	0.8244	0.8198
A4	0.8974	0.8930	0.8880	0.8829	0.8777	0.8729	0.8680	0.8634	0.8594
A5	0.9194	0.9177	0.9148	0.9115	0.9073	0.9034	0.8993	0.8952	0.8914
A6	0.9295	0.9318	0.9323	0.9315	0.9293	0.9267	0.9237	0.9205	0.9173
A7	0.9264	0.9338	0.9387	0.9417	0.9427	0.9427	0.9414	0.9398	0.9377
A8	0.9133	0.9245	0.9336	0.9407	0.9458	0.9494	0.9511	0.9517	0.9517
A9	0.8940	0.9080	0.9200	0.9303	0.9387	0.9457	0.9509	0.9549	0.9576
A10	0.8707	0.8869	0.9011	0.9137	0.9245	0.9339	0.9419	0.9486	0.9541
A11	0.8444	0.8624	0.8786	0.8930	0.9058	0.9171	0.9270	0.9357	0.9433
A12	0.8154	0.8351	0.8529	0.8690	0.8835	0.8965	0.9081	0.9184	0.9276
A13	0.7840	0.8051	0.8244	0.8420	0.8580	0.8725	0.8856	0.8974	0.9081
A14	0.7503	0.7725	0.7930	0.8119	0.8293	0.8452	0.8597	0.8729	0.8850
A15	0.7144	0.7374	0.7588	0.7788	0.7973	0.8145	0.8303	0.8448	0.8582
A16	0.6765	0.6999	0.7220	0.7428	0.7622	0.7803	0.7972	0.8128	0.8274
A17	0.6370	0.6605	0.6828	0.7040	0.7240	0.7428	0.7604	0.7769	0.7925
A18	0.5960	0.6191	0.6414	0.6626	0.6828	0.7020	0.7201	0.7372	0.7535
A19	0.5538	0.5763	0.5981	0.6190	0.6391	0.6582	0.6764	0.6938	0.7104
A20	0.5110	0.5324	0.5533	0.5735	0.5930	0.6118	0.6297	0.6470	0.6635
A21	0.4678	0.4879	0.5075	0.5267	0.5452	0.5631	0.5805	0.5971	0.6132
A22	0.4249	0.4433	0.4614	0.4790	0.4962	0.5130	0.5292	0.5450	0.5602
A23	0.3827	0.3992	0.4154	0.4314	0.4469	0.4621	0.4768	0.4913	0.5054
A24	0.3419	0.3561	0.3703	0.3843	0.3979	0.4113	0.4243	0.4371	0.4495
A25	0.3033	0.3152	0.3272	0.3390	0.3504	0.3618	0.3728	0.3836	0.3941
A26	0.2678	0.2773	0.2868	0.2965	0.3056	0.3149	0.3237	0.3323	0.3408
A27	0.2361	0.2435	0.2507	0.2582	0.2652	0.2721	0.2789	0.2853	0.2917
A28	0.2097	0.2150	0.2202	0.2256	0.2306	0.2356	0.2401	0.2447	0.2490
A29	0.1895	0.1930	0.1967	0.2002	0.2036	0.2069	0.2098	0.2127	0.2153
A30	0.1759	0.1783	0.1808	0.1831	0.1854	0.1876	0.1894	0.1912	0.1926

Table C2 Ranking of sensitivity analysis of β

Replacement interval alternatives	Ranking								
	-20%	-15%	-10%	-5%	0%	+5%	+10%	+15%	+20%
A1	13	14	15	16	16	17	17	18	18
A2	10	11	12	13	14	14	15	16	16
A3	8	9	10	10	11	12	13	13	14
A4	5	6	7	8	9	9	10	11	11
A5	3	4	5	6	6	7	8	9	9
A6	1	2	3	3	4	5	6	6	7
A7	2	1	1	1	2	3	4	4	5
A8	4	3	2	2	1	1	1	2	3
A9	6	5	4	4	3	2	2	1	1
A10	7	7	6	5	5	4	3	3	2
A11	9	8	8	7	7	6	5	5	4
A12	11	10	9	9	8	8	7	7	6
A13	12	12	11	11	10	10	9	8	8
A14	14	13	13	12	12	11	11	10	10
A15	15	15	14	14	13	13	12	12	12
A16	16	16	16	15	15	15	14	14	13
A17	17	17	17	17	17	16	16	15	15
A18	18	18	18	18	18	18	18	17	17
A19	19	19	19	19	19	19	19	19	19
A20	20	20	20	20	20	20	20	20	20
A21	21	21	21	21	21	21	21	21	21
A22	22	22	22	22	22	22	22	22	22
A23	23	23	23	23	23	23	23	23	23
A24	24	24	24	24	24	24	24	24	24
A25	25	25	25	25	25	25	25	25	25
A26	26	26	26	26	26	26	26	26	26
A27	27	27	27	27	27	27	27	27	27
A28	28	28	28	28	28	28	28	28	28
A29	29	29	29	29	29	29	29	29	29
A30	30	30	30	30	30	30	30	30	30

Table C3: TOPSIS Performance index of sensitivity analysis of ϕ

Replacement interval alternatives	Ranking								
	-20%	-15%	-10%	-5%	+0%	+5%	+10%	+15%	+20%
A1	0.8638	0.8364	0.8056	0.7717	0.7352	0.6967	0.6566	0.6164	0.6164
A2	0.9028	0.8801	0.8542	0.8253	0.7932	0.7589	0.7227	0.6855	0.6855
A3	0.9315	0.9131	0.8918	0.8676	0.8401	0.8106	0.7787	0.7459	0.7459
A4	0.9512	0.9375	0.9205	0.9005	0.8777	0.8526	0.8253	0.7967	0.7967
A5	0.9607	0.9530	0.9412	0.9259	0.9073	0.8865	0.8632	0.8389	0.8389
A6	0.9576	0.9577	0.9527	0.9428	0.9293	0.9129	0.8938	0.8733	0.8733
A7	0.9446	0.9509	0.9529	0.9501	0.9427	0.9316	0.9168	0.9008	0.9008
A8	0.9257	0.9362	0.9431	0.9465	0.9458	0.9409	0.9321	0.9205	0.9205
A9	0.9024	0.9165	0.9269	0.9343	0.9387	0.9400	0.9376	0.9316	0.9316
A10	0.8749	0.8928	0.9064	0.9167	0.9245	0.9300	0.9329	0.9329	0.9329
A11	0.8431	0.8653	0.8822	0.8953	0.9058	0.9142	0.9207	0.9252	0.9252
A12	0.8072	0.8339	0.8544	0.8705	0.8835	0.8943	0.9035	0.9112	0.9112
A13	0.7671	0.7986	0.8230	0.8423	0.8580	0.8713	0.8828	0.8930	0.8930
A14	0.7230	0.7594	0.7879	0.8106	0.8293	0.8452	0.8591	0.8717	0.8717
A15	0.6754	0.7166	0.7493	0.7756	0.7973	0.8160	0.8326	0.8476	0.8476
A16	0.6248	0.6706	0.7073	0.7372	0.7622	0.7839	0.8033	0.8209	0.8209
A17	0.5717	0.6216	0.6622	0.6956	0.7240	0.7488	0.7711	0.7917	0.7917
A18	0.5170	0.5703	0.6143	0.6512	0.6828	0.7108	0.7363	0.7599	0.7599
A19	0.4615	0.5173	0.5643	0.6042	0.6391	0.6703	0.6991	0.7258	0.7258
A20	0.4060	0.4634	0.5126	0.5552	0.5930	0.6274	0.6595	0.6896	0.6896
A21	0.3516	0.4093	0.4599	0.5047	0.5452	0.5827	0.6181	0.6516	0.6516
A22	0.2991	0.3558	0.4071	0.4534	0.4962	0.5366	0.5753	0.6121	0.6121
A23	0.2493	0.3039	0.3548	0.4021	0.4469	0.4898	0.5316	0.5717	0.5717
A24	0.2030	0.2544	0.3040	0.3516	0.3979	0.4432	0.4879	0.5311	0.5311
A25	0.1609	0.2082	0.2558	0.3031	0.3504	0.3978	0.4450	0.4912	0.4912
A26	0.1237	0.1662	0.2112	0.2577	0.3056	0.3546	0.4040	0.4526	0.4526
A27	0.0921	0.1295	0.1715	0.2169	0.2652	0.3151	0.3662	0.4163	0.4163
A28	0.0669	0.0997	0.1388	0.1828	0.2306	0.2809	0.3325	0.3838	0.3838
A29	0.0498	0.0787	0.1149	0.1570	0.2036	0.2531	0.3043	0.3554	0.3554
A30	0.0422	0.0681	0.1016	0.1411	0.1854	0.2330	0.2826	0.3322	0.3322

Table C4: Ranking of sensitivity analysis of ϕ

Replacement interval alternatives	Ranking								
	-20 %	-15%	-10%	-5%	+0%	+5%	+10%	+15%	+20%
A1	10	11	13	15	16	18	20	21	21
A2	7	9	11	12	14	15	17	19	19
A3	5	7	8	10	11	13	14	16	16
A4	3	4	6	7	9	10	12	13	13
A5	1	2	4	5	6	8	9	11	11
A6	2	1	2	3	4	6	7	8	8
A7	4	3	1	1	2	3	5	6	6
A8	6	5	3	2	1	1	3	4	4
A9	8	6	5	4	3	2	1	2	2
A10	9	8	7	6	5	4	2	1	1
A11	11	10	9	8	7	5	4	3	3
A12	12	12	10	9	8	7	6	5	5
A13	13	13	12	11	10	9	8	7	7
A14	14	14	14	13	12	11	10	9	9
A15	15	15	15	14	13	12	11	10	10
A16	16	16	16	16	15	14	13	12	12
A17	17	17	17	17	17	16	15	14	14
A18	18	18	18	18	18	17	16	15	15
A19	19	19	19	19	19	19	18	17	17
A20	20	20	20	20	20	20	19	18	18
A21	21	21	21	21	21	21	21	20	20
A22	22	22	22	22	22	22	22	22	22
A23	23	23	23	23	23	23	23	23	23
A24	24	24	24	24	24	24	24	24	24
A25	25	25	25	25	25	25	25	25	25
A26	26	26	26	26	26	26	26	26	26
A27	27	27	27	27	27	27	27	27	27
A28	28	28	28	28	28	28	28	28	28
A29	29	29	29	29	29	29	29	29	29
A30	30	30	30	30	30	30	30	30	30

Table C5: TOPSIS performance index of sensitivity analysis of cost ratio

Replacement interval alternatives	TOPSIS performance index						
	Ca:Cb=2	Ca:Cb=3	Ca:Cb=4	Ca:Cb=5	Ca:Cb=6	Ca:Cb=7	Ca:Cb=8
A1	0.6830	0.7124	0.7352	0.7534	0.7679	0.7795	0.7888
A2	0.7411	0.7710	0.7932	0.8104	0.8236	0.8338	0.8420
A3	0.7890	0.8189	0.8401	0.8559	0.8676	0.8765	0.8833
A4	0.8282	0.8577	0.8777	0.8921	0.9023	0.9097	0.9153
A5	0.8599	0.8886	0.9073	0.9201	0.9287	0.9346	0.9388
A6	0.8850	0.9124	0.9293	0.9401	0.9469	0.9511	0.9539
A7	0.9039	0.9288	0.9427	0.9507	0.9549	0.9572	0.9585
A8	0.9158	0.9363	0.9458	0.9501	0.9519	0.9525	0.9530
A9	0.9196	0.9339	0.9387	0.9402	0.9404	0.9403	0.9405
A10	0.9148	0.9229	0.9245	0.9245	0.9241	0.9237	0.9240
A11	0.9024	0.9060	0.9058	0.9050	0.9043	0.9038	0.9040
A12	0.8842	0.8848	0.8835	0.8823	0.8813	0.8806	0.8809
A13	0.8614	0.8600	0.8580	0.8564	0.8551	0.8541	0.8543
A14	0.8349	0.8320	0.8293	0.8271	0.8254	0.8241	0.8242
A15	0.8050	0.8009	0.7973	0.7946	0.7923	0.7905	0.7905
A16	0.7723	0.7667	0.7622	0.7586	0.7557	0.7534	0.7532
A17	0.7368	0.7297	0.7240	0.7194	0.7157	0.7128	0.7124
A18	0.6990	0.6901	0.6828	0.6770	0.6725	0.6689	0.6684
A19	0.6593	0.6482	0.6391	0.6319	0.6263	0.6219	0.6213
A20	0.6181	0.6043	0.5930	0.5841	0.5773	0.5722	0.5714
A21	0.5761	0.5591	0.5452	0.5343	0.5262	0.5203	0.5193
A22	0.5340	0.5133	0.4962	0.4830	0.4733	0.4665	0.4654
A23	0.4926	0.4676	0.4469	0.4309	0.4194	0.4116	0.4104
A24	0.4527	0.4229	0.3979	0.3786	0.3649	0.3560	0.3547
A25	0.4153	0.3803	0.3504	0.3271	0.3109	0.3008	0.2994
A26	0.3814	0.3410	0.3056	0.2777	0.2583	0.2469	0.2454
A27	0.3519	0.3063	0.2652	0.2320	0.2088	0.1958	0.1943
A28	0.3272	0.2770	0.2306	0.1917	0.1640	0.1495	0.1480
A29	0.3077	0.2543	0.2036	0.1600	0.1281	0.1125	0.1112
A30	0.2931	0.2380	0.1854	0.1395	0.1059	0.0915	0.0908

Table C6: Ranking of sensitivity analysis of cost ratio

Replacement interval alternatives	Ranking						
	Ca:Cb=2	Ca:Cb=3	Ca:Cb=4	Ca:Cb=5	Ca:Cb=6	Ca:Cb=7	Ca:Cb=8
A1	18	17	16	16	15	15	15
A2	15	14	14	13	13	12	12
A3	13	12	11	11	10	10	9
A4	11	10	9	8	8	7	7
A5	9	7	6	6	5	5	5
A6	6	5	4	4	3	3	2
A7	4	3	2	1	1	1	1
A8	2	1	1	2	2	2	3
A9	1	2	3	3	4	4	4
A10	3	4	5	5	6	6	6
A11	5	6	7	7	7	8	8
A12	7	8	8	9	9	9	10
A13	8	9	10	10	11	11	11
A14	10	11	12	12	12	13	13
A15	12	13	13	14	14	14	14
A16	14	15	15	15	16	16	16
A17	16	16	17	17	17	17	17
A18	17	18	18	18	18	18	18
A19	19	19	19	19	19	19	19
A20	20	20	20	20	20	20	20
A21	21	21	21	21	21	21	21
A22	22	22	22	22	22	22	22
A23	23	23	23	23	23	23	23
A24	24	24	24	24	24	24	24
A25	25	25	25	25	25	25	25
A26	26	26	26	26	26	26	26
A27	27	27	27	27	27	27	27
A28	28	28	28	28	28	28	28
A29	29	29	29	29	29	29	29
A30	30	30	30	30	30	30	30

Table C7: TOPSIS performance index of sensitivity analysis of ratio of Tb to Ta

Replacement interval alternatives	Ranking							
	Tb:Ta=2	Tb:Ta=3	Tb:Ta=4	Tb:Ta=5	Tb:Ta=6	Tb:Ta=7	Tb:Ta=8	Tb:Ta=9
A1	0.6916	0.7108	0.7248	0.7352	0.7430	0.7489	0.7535	0.7573
A2	0.7503	0.7701	0.7836	0.7932	0.8004	0.8055	0.8095	0.8129
A3	0.7988	0.8183	0.8315	0.8401	0.8464	0.8508	0.8541	0.8568
A4	0.8379	0.8577	0.8698	0.8777	0.8831	0.8866	0.8892	0.8913
A5	0.8694	0.8889	0.9005	0.9073	0.9117	0.9143	0.9163	0.9178
A6	0.8944	0.9129	0.9236	0.9293	0.9326	0.9346	0.9358	0.9368
A7	0.9129	0.9296	0.9384	0.9427	0.9449	0.9460	0.9467	0.9472
A8	0.9232	0.9372	0.9435	0.9458	0.9468	0.9471	0.9474	0.9476
A9	0.9251	0.9346	0.9379	0.9387	0.9388	0.9388	0.9389	0.9391
A10	0.9182	0.9234	0.9246	0.9245	0.9243	0.9241	0.9242	0.9244
A11	0.9042	0.9064	0.9063	0.9058	0.9054	0.9050	0.9052	0.9054
A12	0.8847	0.8851	0.8843	0.8835	0.8829	0.8825	0.8826	0.8829
A13	0.8612	0.8603	0.8590	0.8580	0.8572	0.8566	0.8567	0.8570
A14	0.8342	0.8323	0.8306	0.8293	0.8282	0.8274	0.8275	0.8276
A15	0.8040	0.8013	0.7991	0.7973	0.7960	0.7949	0.7949	0.7950
A16	0.7708	0.7673	0.7645	0.7622	0.7604	0.7590	0.7589	0.7590
A17	0.7350	0.7304	0.7268	0.7240	0.7218	0.7200	0.7198	0.7198
A18	0.6967	0.6909	0.6864	0.6828	0.6801	0.6779	0.6776	0.6776
A19	0.6563	0.6491	0.6434	0.6391	0.6357	0.6331	0.6327	0.6326
A20	0.6144	0.6054	0.5984	0.5930	0.5890	0.5860	0.5855	0.5853
A21	0.5714	0.5603	0.5517	0.5452	0.5404	0.5370	0.5364	0.5362
A22	0.5282	0.5146	0.5041	0.4962	0.4906	0.4867	0.4861	0.4859
A23	0.4854	0.4689	0.4563	0.4469	0.4403	0.4359	0.4352	0.4350
A24	0.4440	0.4243	0.4091	0.3979	0.3904	0.3855	0.3847	0.3845
A25	0.4051	0.3817	0.3636	0.3504	0.3418	0.3365	0.3357	0.3354
A26	0.3694	0.3424	0.3211	0.3056	0.2958	0.2902	0.2894	0.2890
A27	0.3381	0.3073	0.2827	0.2652	0.2541	0.2483	0.2474	0.2471
A28	0.3118	0.2779	0.2502	0.2306	0.2184	0.2127	0.2119	0.2115
A29	0.2911	0.2546	0.2250	0.2036	0.1910	0.1856	0.1849	0.1846
A30	0.2759	0.2381	0.2073	0.1854	0.1730	0.1685	0.1681	0.1677

Table C8: Ranking of sensitivity analysis of ratio of Tb to Ta

Replacement interval alternatives	Ranking							
	Tb:Ta=2	Tb:Ta=3	Tb:Ta=4	Tb:Ta=5	Tb:Ta=6	Tb:Ta=7	Tb:Ta=8	Tb:Ta=9
A1	18	17	17	16	16	16	16	16
A2	15	14	14	14	13	13	13	13
A3	13	12	11	11	11	11	11	11
A4	10	10	9	9	8	8	8	8
A5	8	7	7	6	6	6	6	6
A6	6	5	5	4	4	4	4	4
A7	4	3	2	2	2	2	2	2
A8	2	1	1	1	1	1	1	1
A9	1	2	3	3	3	3	3	3
A10	3	4	4	5	5	5	5	5
A11	5	6	6	7	7	7	7	7
A12	7	8	8	8	9	9	9	9
A13	9	9	10	10	10	10	10	10
A14	11	11	12	12	12	12	12	12
A15	12	13	13	13	14	14	14	14
A16	14	15	15	15	15	15	15	15
A17	16	16	16	17	17	17	17	17
A18	17	18	18	18	18	18	18	18
A19	19	19	19	19	19	19	19	19
A20	20	20	20	20	20	20	20	20
A21	21	21	21	21	21	21	21	21
A22	22	22	22	22	22	22	22	22
A23	23	23	23	23	23	23	23	23
A24	24	24	24	24	24	24	24	24
A25	25	25	25	25	25	25	25	25
A26	26	26	26	26	26	26	26	26
A27	27	27	27	27	27	27	27	27
A28	28	28	28	28	28	28	28	28
A29	29	29	29	29	29	29	29	29
A30	30	30	30	30	30	30	30	30

Appendix D: Inspection Interval Determination

D.1 Matlab Program for determining D(T), C(T) and R(T) under various delay time failure distribution

```
% % % % % WEILBUL DISTRIBUTION ROUTINE
d=0.2083;k=0.001277;db=168;a=5;b=10;CB=52000;CIR=10500;CI=210;ld=0.1;RBR=10;RII
=1;
q=zeros(1,length(j));DT=zeros(1,length(j));CT=zeros(1,length(j));q1=zeros(1,length(j));q2=z
eros(1,length(j))
j=1:2:50;
ms=3; %markere size
 for i=1:length(j);
 T=j(i);
   t(i)=T(:,1);
   f=@(h)((T-h).*((a./b).*((h./b).^(a-1)).*exp((-(h./b).^a))));
   q(i)=1./T*integral(f,0,T);
   CTw(i)=(k*T*(CB.*q(i)+CIR.*(1-q(i)))+CI)./(T+d);
   RTw(i)=(k*T*(RBR.*q(i)+RII.*(1-q(i)))))./(T+d);
   DTw(i)=((d+k.*T.*q(i)).*db)./(T+d);
end
figure;plot(t,CTw,'-bo','linewidth',1.0,'MarkerSize',ms)
title('cost vs time');xlabel('time(T(s))');ylabel('CTw');
 figure;plot(t,RTw,'bo','linewidth',1.0,'MarkerSize',ms)
title('Reputation vs time');xlabel('time(T(s))');ylabel('RTw')
 figure;plot(t,DTw,'-bo','linewidth',1.0,'MarkerSize',ms)
title('downtime vs time');xlabel('time(T(s))');ylabel('DTw')

 % % % % % EXPONENTIAL DISTRIBUTION ROUTINE
for i=1:length(j);
 T=j(i);
   t(i)=T(:,1);
   f1=@(h)((T-h).*(ld*exp(-ld*h)));
   q1(i)=1./T*integral(f1,0,T);
```

```
    CTe(i)=(k*T*(CB.*q1(i)+CIR.*(1-q1(i)))+CI)./(T+d);
    RTe(i)=(k*T*(RBR.*q1(i)+RII.*(1-q1(i)))))./(T+d);
    DTe(i)=((d+k*T.*q1(i)).*db)./(T+d);
end
figure;plot(t,CTe,'-bo','linewidth',1.0,'MarkerSize',ms)
title('cost vs time');xlabel('time(T(s))');ylabel('CTe')
 figure;plot(t,RTe,'-bo','linewidth',1.0,'MarkerSize',ms)
title('Reputation vs time');xlabel('time(T(s))');ylabel('RTe')
 figure;plot(t,DTe,'-bo','linewidth',1.0,'MarkerSize',ms)
title('downtime vs time');xlabel('time(T(s))');ylabel('DTe')

% % % % % NORMAL DISTRIBUTION ROUTINE
for i=1:length(j);
 T=j(i);
    t(i)=T(:,1);
    f2=@(h)((T-h)./T).*((2/((2*pi)^(0.5)).*exp(-(h.^2)/2)));
    q2(i)=integral(f2,0,T);
    CTn(i)=(k*T.*(CB.*q2(i)+CIR.*(1-q2(i)))+CI)./(T+d);
    RTn(i)=(k*T*(RBR.*q2(i)+RII.*(1-q2(i)))))./(T+d);
    DTn(i)=((d+k*T.*q2(i))*db)/(T+d);
end
figure;plot(t,CTn,'-bo','linewidth',1.0,'MarkerSize',ms)
title('cost vs time');xlabel('time(T(s))');ylabel('CTn')
 figure;plot(t,RTn,'-bo','linewidth',1.0,'MarkerSize',ms)
title('Reputation vs time');xlabel('time(T(s))');ylabel('RTn')
 figure;plot(t,DTn,'-bo','linewidth',1.0,'MarkerSize',ms)
title('downtime vs time');xlabel('time(T(s))');ylabel('DTn')
 figure;plot(t,DTw,'-or',t,DTe,'-*b',t,DTn,'-dk','linewidth',1.0,'MarkerSize',ms)
title('downtime                                                            vs
time');xlabel('time(T(s))');ylabel('DTw,DTe,DTn,(hr)');legend('Weilbul','Exponential','Normal'
)
 figure;plot(t,CTw,'-or',t,CTe,'-*b',t,CTn,'-dk','linewidth',1.0,'MarkerSize',ms)
title('costvs
time');xlabel('time(T(s))');ylabel('CTw,CTe,CTn,(hr)');legend('Weilbul','Exponential','Normal'
)
```

```
figure;plot(t,RTw,'-or',t,RTe,'-*b',t,RTn,'-dk','linewidth',1.0,'MarkerSize',ms)
title('Reputation                                                              vs
time');xlabel('time(T(s))');ylabel('RTw,RTe,RTn,(hr)');legend('Weilbul','Exponential','Normal'
)
```

D.2 Computer programme for the ELECTRE method

```
tic
% enter criteria vector
C1=[1350; 1680; 1560; 1470]; %; 256];
C2=[1850; 1650; 1950; 1850]; %; 610];
C3=[7.5; 8.5; 6.5; 9.5];%; 60];
C4=[2.58; 3.75; 4.86; 3.16];%; 86];
C5=[93.5; 95.3; 88.6; 98.4];% 89];
C6=[0.045; 0.068; 0.095; 0.072];%; 0.01];
% C7=[2.75; 2.63; 2.5; 4; 2.59];

% Enter Criteria weights
w=[0.2336 0.1652 0.3355 0.1021 0.0424 0.1212];
Wcheck=sum(w(:));   % Wcheck=1

%length of a CRITERIA matrix is the same as the number of alternatives
% build the decision matrix D

% CONCATENATE CRITERIA TO FORM DECISION MATRIX D
D=[C1 C2 C3 C4 C5 C6];% C7] % Size of D is no. of alternative by no. of criteria
L=size(D);
LA=size(D,1); %NUMBER OF ALTERNATIVE
LC=size(D,2); %NUMBER OF CRITERIA

% normalize the Decision Matrix D

j=1:LC;
SumD=(sum((D(:,j).^2))).^0.5;
% SumD=sum(D(:,j));  % Alternative Normalizing technique
```

```
 r=zeros(); V=zeros();  %pre-allocation
for i=1:LA
    for j=1:LC;
        r(i,j)=D(i,j)/SumD(j); % Normalized MATRIX
        V(i,j)=r(i,j).*w(j); % Weight Normalized MATRIX
    end
end

%Concordance calculation
wc=w;
for i=1:LA
     for i1=LA:-1:1
          E1=V(i,:);
        E2=V(i1,:);
        E12=[];
        for j=1:LC;
            a=E1(1,j);
             b=E2(1,j);
         if a>=b;
            E12_1=j;
            else
            E12_1=0;
        end
            E12=[E12 E12_1];
            for k=1:length(E12)
        if E12(k)==0;
            wc(k)=0;
        else
            wc(k)=w(k);
        end


        end
        EC=sum(wc(:));
       % RETURN ZERO FOR ALL DIAGONAL MATRIX ELEMENT,i.e COMPARING
SAME
```

```
     % ALTERNATIVES
      if i==i1
        ECM(i,i1)=0;
      else
      ECM(i,i1)=EC;
      end

      end

   end
end

%DISCONCORDANCE calculation
% wc=w;
for i=1:LA
    for i1=LA:-1:1
        E1=V(i,:);
          E2=V(i1,:);
          E12=[];
      for j=1:LC;
          a=E1(1,j);
           b=E2(1,j);
           cc=b-a;
           c(1,j)=cc;
           cmax=max(c(:));
           abscmax=max(abs(c(:)));
           dd=cmax./abscmax;
      end
      d(i,i1)=dd;
     % RETURN ZERO FOR ALL DIAGONAL MATRIX ELEMENT, i.e. COMPARING SAME
     % ALTERNATIVES
      if i==i1
        d(i,i1)=0;
      else
```

```
        end
      end
end

% COMPUTATION OF NET SUPERIOR AND INFERIOR VALUES
ca=zeros(); da=zeros();
for i=1:length(ECM)
    ca(i)=sum(ECM(i,:))-sum(ECM(:,i)); %
    da(i)=sum(d(i,:))-sum(d(:,i));  %
end

toc
```

D.3 MATLAB computer program for MAUT analysis

```
tic
% enter criteria vector
C1=[210; 212; 212; 206.5; 206.5; 187.5; 210; 593; 212.5]; %; 256];
C2=[330; 632.5; 655; 1575; 360; 1825; 1930; 4405; 1655]; %; 610];
C3=[54.5; 46; 87.5; 38; 111.5; 80; 21; 14.05; 120];%; 60];
C4=[0.00111; 0.00117; 0.000515; 0.00026; 0.00089; 0.00071; 0.00002055; 0.00135;
0.00113];%; 86];
C5=[150; 355; 305; 483; 190; 532.5; 771; 1250; 448.5];% 89];
C6=[0.673; 0.7045; 0.864; 1.175; 0.8665; 6.97; 7.99; 79.6; 1.73];%; 0.01];
% C7=[2.75; 2.63; 2.5; 4; 2.59];

% Enter Criteria weights
w=[0.291 0.079 0.206 0.188 0.098 0.139];
Wcheck=sum(w(:));   % Wcheck=1

%length of a CRITERIA matrix is the same as the number of alternatives
% build the decision matrix D

% CONCATENATE CRITERIA TO FORM DECISION MATRIX D
D=[C1 C2 C3 C4 C5 C6];% C7] % Size of D is no. of alternative by no. of criteria
```

```
 L=size(D);
LA=size(D,1); %NUMBER OF ALTERNATIVE
LC=size(D,2); %NUMBER OF CRITERIA

%Input alternative inspection
Tmin=50;
Tmax= 300;
% Tinterval=0.55;
% T=Tmin:Tintval:Tmax;
T=linspace(Tmin,Tmax,length(C1));

R=1; % Factor that determines the decision maker RISK Perception
 % Standardize the D matrix
for j=1:LC%
   for i=1:LA
U(i,j)=((D(i,j)-min(D(:,j)))/range(D(:,j)))^R;
u(i,j)=U(i,j)*w(j); %weight factor multiplied standardized matrix U.
A(i)=sum(u(i,:));  %Alternatives evaluation
   end
end
 figure; plot(T,A,'-*b') ;title('plot of  ... vs ...'),xlabel('T ,,,,'),ylabel('A''''')'
legend('A')
```

D.4: Sensitivity Analysis of decision criteria weight on MAUT and ELECTRE methods

Table D1: sensitivity analysis of R on MAUT method

Inspection interval	R=0	R=0.5	R=1	R=1.5	R=2
1	1	0.2553	0.1301	0.1059	0.1011
3	1	0.8950	0.8022	0.7201	0.6474
5	1	0.9756	0.9518	0.9286	0.9061
7	1	0.9963	0.9927	0.9892	0.9858
9	1	0.9775	0.9556	0.9345	0.9140
11	1	0.9208	0.8487	0.7830	0.7231
13	1	0.8454	0.7170	0.6104	0.5217
15	1	0.7745	0.6044	0.4760	0.3789
17	1	0.7141	0.5172	0.3812	0.2870
19	1	0.6620	0.4482	0.3125	0.2259
21	1	0.6157	0.3919	0.2610	0.1837
23	1	0.5744	0.3457	0.2219	0.1542
25	1	0.5364	0.3065	0.1914	0.1327
27	1	0.5012	0.2730	0.1673	0.1170
29	1	0.4686	0.2444	0.1482	0.1054
31	1	0.4374	0.2192	0.1328	0.0967
33	1	0.4082	0.1977	0.1206	0.0904
35	1	0.3791	0.1780	0.1104	0.0854
37	1	0.3502	0.1604	0.1021	0.0817
39	1	0.3212	0.1446	0.0955	0.0790
41	1	0.2923	0.1307	0.0902	0.0770
43	1	0.2616	0.1179	0.0861	0.0755
45	1	0.2265	0.1059	0.0828	0.0745
47	1	0.1842	0.0952	0.0805	0.0738
49	1	0.0926	0.0857	0.0793	0.0734

Table: D2 Sensitivity analysis of decision weights on MAUT method

	U(C(T),D(T),R(T))				
	Cases				
Inspection interval	Case1	Case2	Case3	Case4	Case5
1	0.1301	0.3170	0.1170	0.1301	0.3455
3	0.8022	0.8347	0.7855	0.8022	0.8364
5	0.9518	0.9496	0.9361	0.9518	0.9457
7	0.9927	0.9793	0.9850	0.9927	0.9748
9	0.9556	0.9458	0.9698	0.9556	0.9456
11	0.8487	0.8553	0.9012	0.8487	0.8643
13	0.7170	0.7446	0.8128	0.7170	0.7644
15	0.6044	0.6499	0.7367	0.6044	0.6789
17	0.5172	0.5768	0.6777	0.5172	0.6129
19	0.4482	0.5186	0.6309	0.4482	0.5603
21	0.3919	0.4715	0.5929	0.3919	0.5177
23	0.3457	0.4326	0.5616	0.3457	0.4826
25	0.3065	0.3997	0.5351	0.3065	0.4529
27	0.2730	0.3718	0.5125	0.2730	0.4277
29	0.2444	0.3475	0.4931	0.2444	0.4057
31	0.2192	0.3266	0.4761	0.2192	0.3869
33	0.1977	0.3083	0.4614	0.1977	0.3703
35	0.1780	0.2917	0.4481	0.1780	0.3553
37	0.1604	0.2770	0.4362	0.1604	0.3421
39	0.1446	0.2638	0.4255	0.1446	0.3301
41	0.1307	0.2521	0.4161	0.1307	0.3196
43	0.1179	0.2412	0.4074	0.1179	0.3096
45	0.1059	0.2312	0.3993	0.1059	0.3007
47	0.0952	0.2222	0.3921	0.0952	0.2926
49	0.0857	0.2142	0.3856	0.0857	0.2854

Table D3: Sensitivity analysis of decision weights on MAUT method

Inspection interval	Rank				
	Cases				
	Case1	Case2	Case3	Case4	Case5
1	21	16	25	21	18
3	5	5	6	5	5
5	3	2	3	3	2
7	1	1	1	1	1
9	2	3	2	2	3
11	4	4	4	4	4
13	6	6	5	6	6
15	7	7	7	7	7
17	8	8	8	8	8
19	9	9	9	9	9
21	10	10	10	10	10
23	11	11	11	11	11
25	12	12	12	12	12
27	13	13	13	13	13
29	14	14	14	14	14
31	15	15	15	15	15
33	16	17	16	16	16
35	17	18	17	17	17
37	18	19	18	18	19
39	19	20	19	19	20
41	20	21	20	20	21
43	22	22	21	22	22
45	23	23	22	23	23
47	24	24	23	24	24
49	25	25	24	25	25

Table D4: Sensitivity analysis of criteria weights on ELECTRE method

Inspection interval	Net superior-Cs				
	Cases				
	Case1	Case2	Case3	Case4	Case5
1	-9.6000	-6.0000	-15.6000	-12.8000	-5.3280
3	0.4000	8.3000	-0.5000	12.8000	5.3280
5	14.6000	17.0000	14.6000	18.8000	15.9840
7	20.7000	21.2000	21.6000	23.0000	20.6460
9	21.4000	20.7000	22.3000	21.6000	20.6460
11	18.8000	17.8000	19.4000	18.0000	17.9820
13	15.3000	14.4000	15.6000	14.2000	14.6520
15	13.3000	12.4000	13.6000	12.2000	12.6540
17	11.3000	10.4000	11.6000	10.2000	10.6560
19	9.3000	8.4000	9.6000	8.2000	8.6580
21	7.3000	6.4000	7.6000	6.2000	6.6600
23	4.4000	3.9000	4.7000	4.0000	3.9960
25	2.4000	1.9000	2.7000	2.0000	1.9980
27	0.4000	-0.1000	0.7000	0.0000	0.0000
29	-1.6000	-2.1000	-1.3000	-2.0000	-1.9980
31	-3.6000	-4.1000	-3.3000	-4.0000	-3.9960
33	-5.6000	-6.1000	-5.3000	-6.0000	-5.9940
35	-7.6000	-8.1000	-7.3000	-8.0000	-7.9920
37	-9.6000	-10.1000	-9.3000	-10.0000	-9.9900
39	-11.6000	-12.1000	-11.3000	-12.0000	-11.9880
41	-13.6000	-14.1000	-13.3000	-14.0000	-13.9860
43	-16.2000	-17.0000	-16.2000	-17.6000	-16.6500
45	-18.2000	-19.0000	-18.2000	-19.6000	-18.6480
47	-20.2000	-21.0000	-20.2000	-21.6000	-20.6460
49	-22.2000	-23.0000	-22.2000	-23.6000	-22.6440

Table D5: Sensitivity analysis of criteria weights on ELECTRE method

Inspection interval	Net inferior-Ds				
	Cases				
	Case1	Case2	Case3	Case4	Case5
1	18.5128	12.1476	21.8051	14.9637	14.1230
3	-3.6121	-10.7083	-3.7312	-14.5321	-9.2914
5	-19.8601	-20.5044	-19.0842	-20.5061	-20.4293
7	-28.7606	-25.3237	-26.7308	-24.2337	-26.6678
9	-31.3334	-24.6787	-27.6102	-22.1782	-27.1454
11	-28.3360	-21.3563	-23.7004	-18.4531	-24.0575
13	-24.2709	-18.0548	-19.9284	-15.3387	-20.5413
15	-20.5569	-15.0960	-16.7871	-12.7464	-17.2422
17	-17.0863	-12.4071	-13.9012	-10.4893	-14.2029
19	-13.7215	-9.8273	-11.0728	-8.2830	-11.3424
21	-10.4810	-7.3167	-8.3731	-6.0885	-8.5275
23	-7.2684	-4.8265	-5.7347	-3.8858	-5.7622
25	-4.1309	-2.3714	-3.1573	-1.7382	-3.0243
27	-1.0329	0.0635	-0.6467	0.3790	-0.2590
29	2.1071	2.5108	1.9506	2.4966	2.3847
31	5.1549	4.9196	4.4018	4.6027	5.1546
33	8.3169	7.3689	6.9562	6.7164	7.8380
35	11.3789	9.7791	9.4957	8.8202	10.4686
37	14.3998	12.1717	11.9263	10.9183	13.2175
39	17.4303	14.5680	14.4231	13.0163	15.8704
41	20.5311	16.9888	16.8821	15.1186	18.6135
43	23.6260	19.4067	19.4760	17.2202	21.1668
45	26.6009	21.7787	21.9105	19.3105	23.8572
47	29.6356	24.1718	24.3735	21.4049	26.5442
49	32.7569	26.5959	26.8572	23.5058	29.2547

Table D6: Sensitivity analysis of criteria weights on ELECTRE method

Inspection interval	Net superior-Cs Rank				
	Cases				
	Case1	Case2	Case3	Case4	Case5
1	18	16	21	20	16
3	12	9	13	6	10
5	5	4	5	3	4
7	2	1	2	1	1
9	1	2	1	2	1
11	3	3	3	4	3
13	4	5	4	5	5
15	6	6	6	7	6
17	7	7	7	8	7
19	8	8	8	9	8
21	9	10	9	10	9
23	10	11	10	11	11
25	11	12	11	12	12
27	13	13	12	13	13
29	14	14	14	14	14
31	15	15	15	15	15
33	16	17	16	16	17
35	17	18	17	17	18
37	18	19	18	18	19
39	20	20	19	19	20
41	21	21	20	21	21
43	22	22	22	22	22
45	23	23	23	23	23
47	24	24	24	24	24
49	25	25	25	25	25

Table D7: Sensitivity analysis of criteria weights on ELECTRE method

Inspection interval	Net inferior-Ds Rank				
	Cases				
	Case1	Case2	Case3	Case4	Case5
1	20	18	22	20	19
3	12	8	11	6	9
5	6	4	5	3	5
7	2	1	2	1	2
9	1	2	1	2	1
11	3	3	3	4	3
13	4	5	4	5	4
15	5	6	6	7	6
17	7	7	7	8	7
19	8	9	8	9	8
21	9	10	9	10	10
23	10	11	10	11	11
25	11	12	12	12	12
27	13	13	13	13	13
29	14	14	14	14	14
31	15	15	15	15	15
33	16	16	16	16	16
35	17	17	17	17	17
37	18	19	18	18	18
39	19	20	19	19	20
41	21	21	20	21	21
43	22	22	21	22	22
45	23	23	23	23	23
47	24	24	24	24	24
49	25	25	25	25	25