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DECLARATION OF THESIS

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ABSTRACT

In facing many operation challenges such as increased expectation in bottom line performances and escalating overhead costs, petrochemical plants nowadays need to continually strive for higher reliability and availability by means of effective improvement tools. Reliability, maintainability and availability (RAM) analysis has been recognised as one of the strategic tools to improve plant's reliability at operation phase. Nevertheless, the application of RAM among industrial practitioners is still limited generally due to the impracticality and complexity of existing approaches. Hence, it is important to enhance the approaches so that they can be practically applied by companies to assist them in achieving their operational goals.

The objectives of this research are to develop frameworks for applying reliability, maintainability and availability analysis of gas processing system at operation phase to improve system operational and maintenance performances. In addition, the study focuses on ways to apply existing statistical approach and incorporate inputs from field experts for prediction of reliability related measures. Furthermore, it explores and highlights major issues involved in implementing RAM analysis in oil and gas industry and offers viable solutions.

In this study, systematic analysis on each RAM components are proposed and their roles as strategic improvement and decision making tools are discussed and demonstrated using case studies of two plant systems. In reliability and maintainability (R&M) analysis, two main steps; exploratory and inferential are proposed. Tools such as Pareto, trend plot and hazard functions; Kaplan Meier (KM) and proportional hazard model (PHM), are used in exploratory phase to identify critical elements to system's R&M performances. In inferential analysis, a systematic methodology is presented to assess R&M related measures. The use of field expert's knowledge is also explored as an alternative approach in the estimation process when

the available data are found inadequate. Here, a methodological framework on elicitation of expert input to assess distribution is proposed and demonstrated. For availability analysis, a simulation approach based on Monte-Carlo is presented to evaluate system's availability and what-if scenarios for various options to help management make strategic decisions and actions.

This research has demonstrated that the proposed frameworks for applying reliability, maintainability and availability analysis are effective and practical in analyzing gas processing system and can be used as a strategic tool for improving system operational and maintenance performances.

ABSTRAK

Dalam menghadapi pelbagai cabaran operasi seperti peningkatan jangkaan keuntungan and kos operasi, kilang petrokimia hari ini perlu berusaha berterusan meningkatkan kebolehpercayaan dan ketersediaan melalui alat penambahbaikan yang berkesan. Analisa kebolehpercayaan, kebolehsenggaraandan ketersediaan (RAM) telah diiktiraf sebagai salah satu alat strategik meningkatkan kebolehpercayaan kilang di fasa operasi. Sungguhpun begitu, aplikasi RAM dikalangan pengamal industri masih terbatas umumnya disebabkan pendekatan sedia ada tidak praktikal and terlalu komplek. Oleh itu, adalah penting untuk meningkatkan pendekatan tersebut supaya ia dapat di praktikkan oleh syarikat dalam membantu mereka mencapai sasaran operasi.

Tujuan penyelidikan ini adalah untuk membangunkan kerangka kerja untuk mengaplikasikan analisa kebolehpercayaan, kebolehsenggaraan dan ketersediaan keatas system pemprosesan gas semasa fasa operasi dalam meningkatkan pencapaian system operasi and penyelengaraan. Disamping itu, kajian in menfokus kepada cara untuk mengaplikasikan pendekatan statistik sedia ada dan memasukkan pengetahuan pakar medan dalam membuat jangkaan bagi pengiraan berkaitan kebolehcayaan. Selain itu, kajian ini meneroka dan menengahkan isu utama dalam perlaksanaan analisa RAM di industri minyak dan gas dan mencadangkan jalan penyelesaian.

Di dalam penyelidikan ini sistematik analisa bagi setiap komponen RAM dicadangkan dan peranan mereka sebagai alat yang strategik dalam proses penambahbaikan and membuat keputusan dibincang dan didemontrasikan melalui kajian kes berkaitan dua sistem di kilang. Di dalam analisa kebolehpercayaan dan kebolehsenggaraan (R&M), dua langkah utama; eksploratori dan inferensi diusulkan. Teknik seperti Pareto, *plot trend* dan fungsi risiko; *Kaplan Meier* (KM) dan model risiko berkadar (PHM), digunakan di fasa eksploratori untuk mengenalpasti elemen kritikal kepada prestasi R&M sistem. Untuk analisa inferensi, kaedah sistematik

dibentangkan bagi menentukan pengukuran berkaitan R&M. Pengunaan pengetahuan pakar medan juga di ekplorasi sebagai jalan alternatif dalam proses penganggaran apabila data sedia ada tidak mencukupi. Di sini, kerangka kaedah untuk elisitasi pakar medan dalam menilai distribusi dicadang and didemontrasikan. Untuk analisa ketersediaan, pendekatan simulasi *Monte-Carlo* di kemukakan dalam menilai sistem ketersediaan dan senario apa-jika bagi pelbagai pilihan untuk membantu pengurusan membuat keputusan and tindakan yang strategik..

Hasil penyelidikan ini menunjukkan kerangka analisa yang dicadangkan untuk mengaplikasikan analisa kebolehpercayaan, kebolehsenggaraan dan ketersediaan adalah efektif dan praktikal dalam menganalisa system pemprosesan gas disamping boleh digunakan sebagai alat strategik bagi meningkatkan pencapaian sistem operasi dan penyelengaraan.

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AGRU	Acid gas removal unit
AVS	Anti-surge valve system
CCO	Compressor change-out
CDF	Cumulative density function
CM	Corrective maintenance
CMMS	Computerised maintenance management system
ECO	Engine change-out
ESD	Emergency shutdown
EW	Engine wash
FMEA	Failure mode effect analysis
FS	Fuel system
FTA	Fault tree analysis
GB	Gear box system
GC	Gas compressor
GCT	Gas compression train
GT	Gas turbine
GPP	Gas processing plant
IID	Independent and identically distributed
HPP	Homogeneous Poisson process
KM	Kaplan Meier
K-S	Kolmogorov-Smirnov
LDA	Life data analysis
LOS	Lube oil system
MC	Monte Carlo
MDT	Mean downtime
MLE	Maximum likelihood estimation
MMSCFD	Millions standard cubic feet per day
MTBF	Mean time between failures

MTBM	Mean time between maintenance
MTTR	Mean time to repair
NHPP	Non-homogeneous Poisson process
OREDA	Offshore reliability data
PDF	Probability density function
PFD	Process flow diagram
PHM	Proportional hazards model
PM	Preventive maintenance
PRO	Process and utilities
PSD	Planned shutdown
P&ID	Piping and instrumentation diagram
RAM	Reliability, availability and maintainability
RBD	Reliability block diagram
ROCOF	Rate of occurrence of failures
R&M	Reliability and maintenance
STS	Starter system
TA	Turn-around
TBF	Time between failures
TCS	Turbine control system
TTF	Timeto failure
USD	Unplanned shutdown
VMS	Vibration monitoring system

CHAPTER 1

INTRODUCTION

1.1 The Challenging Business Operation

Petrochemical plants nowadays are under increasingly pressure to drive improvement in operating margins and profitability due to internal and external factors. The management of plant is getting more challenges due to increasingly high expectation to operate with higher revenue and minimum loss. Issues such as escalating capital and operation cost, intense competition, tighter budget, narrower profit margin, stricter environmental regulation, depletion in world's oil and gas reserve, and instability in world economy, all put immense pressure on plant management to make sure that the plants are running reliably, safely, efficiently and profitably. It is paramount that plant equipment operates with high reliability, safety and minimum downtime with the optimum operation cost and at the same time meeting high demand of production, safety and environmental goals. Recent incident of oil spills in Gulf of Mexico that caused an estimated of USD 23 Billion loss to British Petroleum (Macalister, 2010) was an excellent example where equipment reliability has high impact on organization's profitability. It was reported that the disaster was partly due to the failure of blow out preventer equipment which fails to activate during the event ("BP Releases Report on Causes of Gulf of Mexico Tragedy", 2010).

Table 1.1: Main processes for production assurance and reliability improvement at Operation phase (ISO 20815:2008)

Processes	Objectives
1. Reliability assurance	Perform planning, reporting and follow up of the production assurance activities to manage and demonstrate production assurance.
2. Project risk management	Ensure that all risk elements that could jeopardise a successful execution and completion of the project are identified and controlled in a timely manner
3. Performance tracking and analysis	Collect and analyse operational performance data to identify potential improvement potentials and to improve the data basis for future production assurance and reliability management activities.
4. Management of change	Ensure that no changes compromise the reliability performance requirements.
5. Reliability improvement and risk reduction	1. Identify the need for improved system reliability performance or reduced risk is a project to ensure that performance goals are not compromised 2. Identify and communicate potentials for improved equipment or system reliability or risk reduction to the system or equipment manufacturers based on tracking and analysis of performance data
6. Organisational learning	Ensure that product and process failures of the past are not repeated.

With all of these challenges occurring, many organizations are urgently seeking for an effective and innovative approach to continuously drive improvement in plant's reliability and performance in order to keep profitable, even for a stable and considered high performance plant. A general approach for achieving such improvement at each phase of plant lifecycle has been proposed and outlined in the ISO 20815 (2008). Table 1.1 describes six key means that management should focus on to drive improvement at operation phase. To drive profitability, an organization needs to strive for continuous improvement through utilization of effective tools and techniques that can identify and quantify potential areas for saving and be part of the decision making process. Several improvement programs have been rolled out as part of strategic initiatives by management to propel plant's performances, which include Total preventive maintenance (TPM); Reliability centred management (RCM); bad actors management; Root cause failure analysis (RCFA) and Reliability, availability and maintainability (RAM) analysis. Among them, RAM is increasingly getting popular and becoming a standard tool in process industry since it focuses directly on asset optimization and reduction in maintenance cost (Shaikh and Mettas, 2010). According to William (2001) RAM is considered the main area for plant profitability improvement besides yield. With regards to six important areas for reliability improvement, RAM approach specifically addresses key items no 3; performance tracking and analysis and no 5; reliability improvement and risk reduction.

1.2 Why Need RAM?

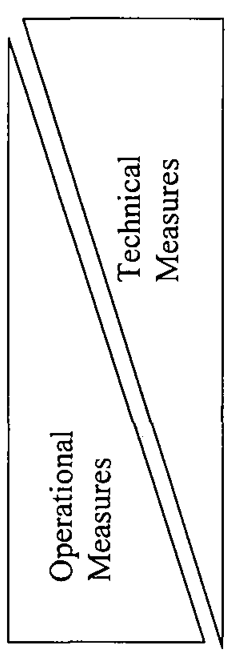
RAM study has been applied throughout the oil and gas industry to serve as a quantified mean to assess plant operational issues and a strategic tool for management to increase plant availability and performances. Improvement in availability, even small, as is turn out is a significant variable for maximizing plant profitability. As pointed out by Sutton (2010), an increase of availability by mere 1% (i.e. 95-96%) will eventually drive higher profitability since normally the 90% of availability covers all the production cost, whereas profit normally in range of 90 -100% availability. In improving plant operational performances, RAM plays these critical roles:

- RAM analysis identifies, measures and ranks plant weak points with respect to failure and downtime that affect plant availability, leading to a basis for making effective solutions and actions to enhance plant availability.
- RAM analysis can estimate system availability and assess various alternatives and configurations on the basis of quantitative benefits in order to achieve the best option or action for improving system availability. Some of these options include equipment capacity/reliability, upgrading, redundancy, maintenance

strategy, spare part allocation policy, manpower strategy and competing solutions.

- RAM approach provides a decision support tool for management to effectively align operational decisions with organization's objective. These decisions are based on technical and operational measures which could be applied by management to increase plant performances based on recommendations of RAM study. A list of these measures is shown in Figure 1.1.
- RAM analysis presents a systematic approach of effectively analysing plant failure and maintenance data, which are abundant but usually not fully exploited, as a vital source for monitoring plant performance and driving continuous improvement activities.

The financial benefits gained from effective RAM analysis projects are tremendous. William (2001) estimates that the opportunity for RAM contribution to refinery profitability improvement without additional capital investment is 0.10-0.20 USD/bbl, where for poorer performance can even reach 1-2 USD/bbl. Other examples of reported financial gains from RAM study are highlighted in Table 1.2, which cover a wide spectrum of industrial sectors, applications and values.



Choices of technology
Redundancy at system level
Redundancy at equipment or component level
Functional dependencies
Capacities
Instrumentation / automation philosophy
Material selection
Selection of make
Protection from environment
Reliability testing
Self-diagnosis
Buffer and standby storage
Bypass
Spare parts
Maintenance strategy
Maintenance support

Figure 1.1: Different degrees of measure for plant improvement (adapted from ISO 20815:2008)

Table 1.2: Reported RAM benefits

Plant	Reported improvement
1. Ethylene plant in US	Development of availability modeling successfully pinpointed improvement areas to increase the plant's on-stream factor, hence assisted the plant in increasing its annual revenue by $1 million (ARINC, n.d.).
2. Petrochemical plant in Thailand	RAM program had identified opportunities in increasing plant reliability from 93% (2003) to 95.4% (2004) and reducing maintenance cost by 10% throughout the program to assist the plant to achieve $2 million profit improvement goal by 2005 (KBC, 2005).
3. LNG plant in Egypt	RAM modeling had assisted the plant to increase production of LNG export and domestic gas supplies by 7% through quantification of critical system contributors to production loss (GL Noble Denton, n.d.).
4. Angostura oil and gas facilities, offshore Trinidad	RAM study on improved gas availability due to the dedicated gas processing platform and provision of additional compression capacity indicated that significant cost-benefit of approximately $46 MM and 5 bcf deferred gas savings could be realized through the purchase of a spare compressor bundle (IRC, 2009).
5. Nuclear power plant in Ontario, Canada	RAM analysis to improve turbine generator availability successfully saves an estimated maintenance cost of USD 3.5 million annually through more effective plant maintenance program (Cockerill, 2005).

1.3 Challenges and Issues of RAM studies at Operation Phase

Based on literature review and industrial feedback, several challenges are identified and should be considered when planning and executing RAM study for any system or plant in oil and gas industries. Getting sufficient, consistent, high quality and integrity plant reliability data is quite difficult and challenging task, and has always been a major concern in many reliability studies at operation phase (Madu, 2005). The success of any plant reliability study depends highly on quality and availability of failure data and on suitability and accuracy of the various assumptions that will be used (Rossedi, 2006, Scully and Choy, 1993). Insufficient data leads to many assumptions being adopted in the reliability study, which in turn increases degree of uncertainties in the analysis results. Alternatively other sources of data such as generic industrial standard, handbook and database are being used widely to fill in missing data. Important concern related to this application is on compatibility of such data to represent actual system under studied. OREDA handbook for example, is limited to offshore applications (Vinnem, 2007) where its data come mainly from offshore installations in the UK and Norwegian sectors of North Sea yet it has been applied widely for study of chemical and refinery plants, and offshore platform systems in other regions.

Another issue is related to the complexity and dynamic nature of system. Many problems related to plant system nowadays are complex due to high and increased degree of complexity in the system with its multi-systems and network system which consist of hardware, software, organizational and human components and their interrelationships (Zio, 2009). The representation and modelling of the complexity of such system poses a challenge to RAM study due to possibly increase in uncertainties associated with system characteristics and their modelling. Uncertainties also derive from lack of knowledge about system failures and causes, and understanding of system dynamic performance as a result of system aging or improvement.

Despite various benefits associated with RAM, the adoption of this approach as a strategic tool for plant management particularly in the maintenance section, is far from satisfactory. Numerous research papers have been published related to reliability theory and model and have claimed their roles in resolving various issues related to real system in industrial. Nevertheless, many of them fall short in providing the practical solutions to the real problem faced and attracting industrial people to use RAM for driving improvement in plant performances. The reasons can be traced back to the nature of the RAM approach used in the research. From the literature, the following issues have been identified as key factors:

1. *Focus too much on modelling* – Scraf (1997) cites that many research papers put less emphasis on the practicality and worthiness of the technique in the real applications. Instead, the focus are more on model development and then find the applicability of the model rather than the effort on solving real problem in the plant. Michelsen (1998) stresses that much of the effort has been made to develop system models to perform overall assessment of system instead of a simple and practical approach to solve specific problem experienced by industry, which is more needed. Bazu and Bajenescu (2011) point out that many mathematical approaches on reliability issues are restrictive and producing cryptic results since they are developed mainly by statisticians. There is a vast tendency among researchers to apply complicated mathematical model even when it can be solved with a fairly simple model (Ansell and Philips, 1994). According to Scarf (1997), the development of more and more complex model are done generally for the sake of novelty, which ends up making the model more obscure instead of striving for clarity and simplicity. Many mathematical models developed stay only at theoretical and are not being used in the industries due to difficulty to find real problem suitable for the models (Dekker, 1996). Researchers should avoid over-parameterization of the models which often are too detailed for their application to be practically feasible (Zio, 2009). Furthermore, the use of complicated model is not going to attract much interest in industry since they normally prefer more tractable and simpler model and approach.

2. *Less focus on data gathering process* – many studies are also found not paying much attention on proper plant data gathering and analysis methodology, a critical step in RAM study. Substantial improvement in reliability can only be realised when an appropriate system to collect actual failure data and repair times exist (Barringer, 2004). This raise issues such as quality, adequacy and

integrity related to data which make it rather difficult to develop plausible model and validate it. As a result, flawed assumption such as constant failure rate is made without first conducting sufficient analysis on maintenance data, even though it is in reality not necessarily true.

3. *Pessimistic estimation results* – finding on some of RAM results studies shows that they tend to be too pessimistic compared to the actual plant performance due to the use of conservative data and assumptions in the analysis (Michelsen, 1998). This pessimistic result does not reflect the existing performance thus cannot be effectively integrated with decision making process.

RAM poor acceptance is also contributed by plant personnel attitude towards reliability based studies. Reliability is always hard to sell to plant management and maintenance since they generally have weak tradition in reliability application, skills and competency, doubt of cost-effective strategy for maintenance optimisation, and tendency to discard the validity of generic type information to evaluate their specific equipment (Michelsen, 1998). The implementation of reliability studies can also be impeded by other constraints such as cost, policy, schedule and certain problems related to the existing system inherent reliability (Keller-McNutty and Wilson, 2003). Many organizations, due to lack of internal expertise, will have to resort to employing external consultants for conducting such analysis, which sometimes can be quite expensive.

To conclude, the pertinent issues relating to existing approach of reliability, maintainability and availability analysis at operation phase are:

1. It suffers from limited practical applicability mainly due to the use of complicated mathematical model and impractical methodology. Consequently, many industrial practitioners shy away from the approach and hence fail to realize and capitalize its full potential as a strategic analysis tool for driving improvement in plant performance.

2. Generally, it has fairly limited involvement of expert personnel during analysis process. The role of expert is basically secluded only on data gathering and verification processes.

3. There is still a lack of case studies on analysis on real problems against myriad of issues faced by oil and gas industries. In many case studies, generally the approach is not presented in details and uses inaccurate assumption such as constant failure and repair rate.

1.4 Motivation of the Study

To increase the applications and decision tool roles of RAM related analysis in industry, the identified issues above have to be addressed and the gap between theory and industrial practicality need to be reduced. Research studies should be more focus on solving real and specific problem faced by industry using more practical approach (Michelsen, 1998). In doing so, more research based on cases studies are much needed in which collaboration can be made with industry by engaging plant management and engineers to work together such that more details and effective data collection, realistic model and practical results can be achieved. The existing literatures are still exhaustive to present all kind of issues in plant due to increasing complexity and dynamic nature of today's system. There is no single technique can sufficiently cover all plausible conditions, problems and complexity of the real world system (Ansell and Philips, 1990), hence more case studies based on real industrial experience is deem necessary to explore other issues untouched and render appropriate approach to tackle these issues.

The use of tractable and non-complicated models, yet sufficiently capable of resolving problem should be pursued since they can be applied widely even by non-experts in industry. As for industrial people, more open-minded attitude is needed with regards to resources (investments and manpower) allocation for reliability studies and managing proper maintenance data (Zio, 2009), taking into consideration benefits gained from the analysis. More exposure to RAM techniques and its potentials should be given to plant management to change their mindset on RAM analysis role as a strategic management decision tool. Another important point is on the need to analyse existing maintenance data more effectively and realise their significant roles in supporting plant improvement plan.

1.5 Research Objective

The following are the objectives of this research:

1. To develop a framework for applying reliability analysis of gas processing system at operation phase to improve system operational and maintenance performances

2. To develop a framework for applying maintainability analysis of gas processing system at operation phase to improve system operational and maintenance performances

3. To develop a framework for applying availability analysis of gas processing system at operation phase to improve system operational and maintenance performances

To address the existing issues with RAM analysis, the proposed frameworks will incorporate the following main elements:

- *Effective and intensive utilization of plant reliability and maintenance data* – Highly abundance data exist in the plant should be used as the prime source of RAM study and critical information on system performance.

- *Applications of practical, non-complex yet tractable method to achieve the objective of analysis* – The use of simple and practical method will attract more interest from industrial practitioners leading to increase in its applications in industry.

- *Exploitation of expert opinion as an important data input* – Expert opinions can play significant roles in strengthening data analysis process making the results more relevant and realistic.

- *Applications of simulation method to achieve best options of system configurations* – Simulation method has been found to provide the best approach to analyse complex system with stochastic equipment and evaluate performance of the existing system with various conditions.

- *Applications of statistical techniques for analysis and decision making process* – The use of statistical-based decision making will increase management and engineers' competency in solving problems and driving plant improvement activities.

This research contributes to the general knowledge in reliability field by presenting a general framework for conducting RAM analysis at operation phase. This framework adds to and enhances the existing approaches by providing feasible and detailed means for analysing plant maintenance field data. It also provides plant engineers and management with the essential tools for continuous improvement and decision making strategies.This research also highlights some real issues faced during the study such as lack of field data and offers innovative solutions to overcome them. The roles of field experts in the analysis process have also been enhanced particularly in the maintainability study for eliciting downtime measures.

1.6 Research Scope

The research work covers the analysis of failure and maintenance data of system at gas processing system. The scope of the study was limited to assessment at system level primarily due to the limitation of related field data at component level. Furthermore, the application of the analysis is also limited to the operation phase.

1.7 Thesis Outline

A brief description on applications, approach and techniques of RAM analysis at operation phase is presented in Chapter 2. Apart from that, this chapter discusses the reliability and statistical theory related to RAM analysis, to serve as a foundation for subsequent case studies analysis. Chapter 3 discusses proposed frameworks for applying RAM analysis used in the research. In this research, a RAM analysis is broken down into three component of studies; reliability, maintainability and availability. Reliability and maintainability studies can be done separately and on their own, whereas availability calculation requires combination of reliability and maintainability parameters as its inputs.

The following three chapters (Chapters 4, 5 and 6) present detailed analysis on real industrial problems based on the proposed frameworks for each RAM study component. Chapter 4 describes reliability analysis approach used for an analysis of a gas compression train system at offshore platform. The maintainability analysis approach of the same system is addressed in Chapter 5. In this analysis, both planned and unplanned system downtime are investigated. In Chapter 6, the availability simulation studies of the similar system and an acid gas removal unit (AGRU) system in gas processing plant are discussed. Finally, the conclusions and recommendations of this thesis are presented in Chapter 7.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter provides an overview of various techniques applied in RAM study of plant system at operation phase. Basic concepts of reliability, maintainability and availability, and general approaches to system analysis are also discussed to provide the basis for the proposed analysis methodology applied in this research.

2.2 RAM Application in Operation Phase

Numerous researches on RAM related studies during operation phase of petrochemical and power plants have been reported in literatures covering a wide range of applications, objectives, and areas i.e. systems, subsystems and equipment. The availability of a natural gas plant was studied by Bosman (1985) to determine the optimum cost configurations of number of compressors. Rotab Khan and Zohrul Kabir (1995) estimated improvement in ammonia plant's availability through some modifications in plant design and changes in overhaul interval. Reliability data analysis and modelling approach was applied by Wang and Majid (2000) to model an offshore oil platform plant and investigate the effectiveness of preventive maintenance interval. Rajee *et al.* (2000) discussed applications of availability analysis on a critical pumping system in the crude distillation unit (CDU) of a refinery to assist maintenance in deciding on optimum repair strategy. AlSalamah *et al.* (2005) modelled and examined the reliability and availability of the cooling sea water pumping which supply sea water to refineries and petrochemical plants. Sikos and

Klemes (2010) conducted a study on effective modelling and optimisation of heat exchanger network maintenance and reliability. Shaikh and Mettas (2010) demonstrated the application of RAM analysis on a natural gas plant. The study on reliability of boiler feed system of a large power plant was presented by Sculli and Choy (1993). Arora and Kumar (1997) performed availability study to identify critical components of steam and power generating systems in a thermal power plant. Equipment criticality of heat recovery steam generator (HRSG) installed in combined cycled power plant was evaluated by Carazas *et al.* (2010).

2.3 RAM Modelling Approach

For analysis of a system, there are various methods that can be applied to achieve the objective as described in Figure 2.1. For petrochemical plant it is neither economical nor feasible to conduct real experiment on the physical system after the plant has been commissioned to avoid unnecessary issue with the plant operation. The construction of physical model will usually incur high cost thus also is not a good option. Hence, the best option for RAM analysis involves utilization of mathematical model of the system under studied.

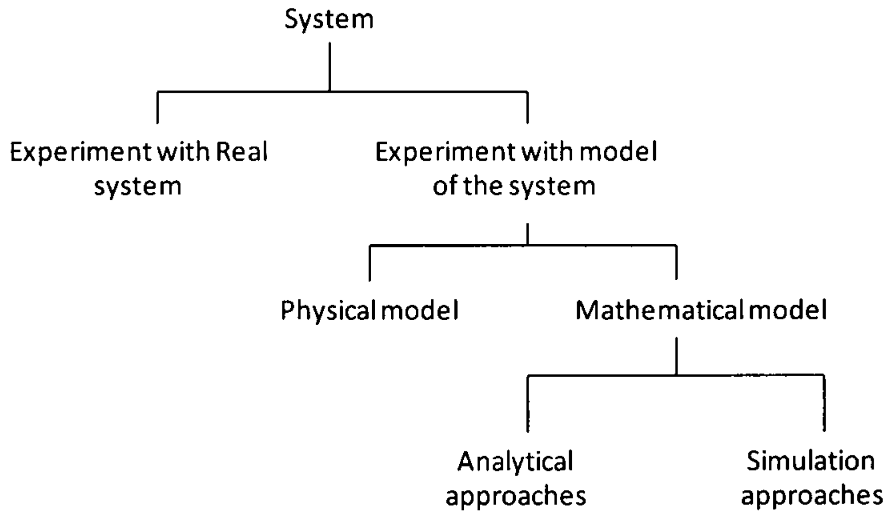


Fig. 2.1: Various methods of analyzing system (Law and Kelton, 2000)

Mathematical model can be those of analytical or simulation techniques. Sathaye *et al.*(2000) expand this classification to include hybrid approaches, a combination of analytical and simulation parts. In analytical approach, the system characteristic is modelled by set of equations. The evaluation is performed by solving these equations either based on closed-form or numerical solutions. Example of analytical techniques include event tree, fault tree, reliability block diagram (RBD), Markov and Petri-net analysis. Simulation approach uses discrete-event simulation technique such as Monte Carlo to describe more details of system conditions, simulate system dynamic behaviour and evaluate the required performance measures (Sathaye *et al.*, 2000).

2.3.1 RAM Techniques at Operation Phase

ISO 201815 (2008) describes various methods and techniques that can be applied to assess the reliability and availability of the operating system. These techniques are briefly described below.

2.3.1.1 Failure Mode and Effects Analysis (FMEA)

FMEA is a systematic methodology of evaluating inherent reliability of a system by considering potential failure modes of each component comprising a system and evaluate their effects on the system's reliability. Based on the effects, the criticality of each of the failure mode can be assigned and appropriate corrective actions can be taken to reduce the chances of failure (Davidson, 1994). FMEA is a 'bottom up' analysis and can be performed at any level of assembly. The analysis can be based on a hardware and functional approach (O'Connors, 2002). In the hardware approach, the hardware failure modes are considered, while in the functional approach the functional failures such as 'lost of memory' is used. FMEA can also be used as inputs to FTA (Fault tree analysis) and RBD, and vice-versa. While it is usually applied in early stage of system design, FMEA can also be applied on existing system to focus on problem areas related to system reliability, safety, availability, maintainability, or logistics support (Rausand and Hoyland, 2004, ISO 20815, 2008).

2.3.1.2 Fault Tree Analysis (FTA)

FTA is one of the most widely used tools for risk and reliability assessment nowadays (Rausand and Hoyland, 2004). It was first introduced by H.A. Watson of Bell Telephone Laboratories in early 1960s to conduct analysis on the Air Force Minuteman Missile Launch Control System and later enhanced and adopted by other industrial sectors such as aviation, nuclear, petrochemical and computer software (Ericson, 1999). FTA is used to identify all possible causes of a particular system failure mode and provides a basis for determining the probability of occurrence for each system failure mode (Davidson, 1994). In the FTAa failure event of the system is first specified and then the system is analyzed in the context of its environment and operation to identify all plausible ways in which the failure can occur (Vesely *et al.*, 1981). Graphically, FTA displays the logical relationship between the top event (a specified system failure mode) and the basics events (basic failure causes) via various gate symbols (Rausand and Hoyland, 2004). Besides providing a qualitative or quantitative mean of analyzing system reliability, FTA offers the following advantages to the analyst (Davidson, 1994):

- assist in identifying the failure or parts of system which have high influence on system's reliability and performances
- enable the analyst to focus on one system failure mode at a time
- provide a clear and concise means of presenting reliability information to management
- allow failures related to human and no-hardware factors to be evaluated

Although FTA is usually best used during the design and configuration stages of a project where changes for improvements can easily made (Barringer, 1996), it is also being applied widely at operation phase in availability assessment purpose. FTA also has some practical limitations. To be successful, the analysis need to followa strict methodology approach which normally demands more time and efforts. At operation phase, where field data is preferred, missed and unrecorded causes on certain failure modes may bias the calculated likelihood resulting in inaccurate estimation (Bichou, 2010). Other issues include the assumption that the failure is random, statistically independent and not caused by a sequence of events, which are not true in some applications (Lazzaroni *et al.*, 2011). For example, some common causes may not be independent hence might exaggerate the chances of system's failure. Similarly, the occurrence of failures sometimes can be induced by sequence of events.

2.3.1.3 Reliability Block Diagram (RBD)

RBD is a success-oriented network describing the logical reliability-wise connections of functioning components required to meet a specified system function (Rausand and Hoyland, 2004). When a system has many functions, separate RBD has to be built for each function. RBD consists of blocks that are connected through two basic topologies namely series and parallel, which represent the logical relationship between blocks from a reliability standpoint (DOD, 2005). Based on these logic connections, more complicated system configurations such as series-parallel and k-out-of-n voting system can be generated and analysed (Yang, 2007). A block, depending on the analysis purpose, may represent a component, a module, or a system. Since it physical details are not shown, a block is considered as a black box where the reliability of item that a block represents is the only inputs that matters the evaluation of system's reliability (Yang, 2007). In a series arrangement, any block failure will cause the system to fail. In a parallel configuration, however, the system will not fail as long as a given number of alternatives path are functioning. For a complex system, the represented RBD is normally consists of many blocks with combinations of series and parallel configurations. The constructed RBD is not the same as the physical layout of the system since it's based on logic diagram describing the function of the system (Rausand and Hoyland, 2004). Generally, RBD is primarily used for reliability prediction of non-repairable system. The approach has limitations when it is used to analyze system having different failure modes, external events i.e. human factors and priority of events (Verma *et al.*, 2010). Nevertheless, recent comparative study indicates that RBD technique has been the most intuitive approach for RAM analysis among industrial practitioners (Shaikh and Mettas, 2010).

2.3.1.4 Markov Analysis

Markov analysis has been used widely for reliability and availability assessment of large, multi-states and dynamic systems. The reasons are mainly due to its simplicity and the quality of existing data which is commonly available in mean lifetimes of components and mean repair time (Ansell and Phillips, 1994). Markov can analyze system behaviour thoroughly and incorporate details such as repair strategies, capacity loss and partial failures, hence suitable for analysis of complex and repairable system (Bauer *et al.*, 2009). Markov analysis steps in principle can be summarized as follow (Pintelon and Puyvelde, 2006):

1. Identify of all system possible states
2. Determine and quantify all possible transitions between these states
3. Establish appropriate system of differential equations or transition matrix
4. Compute the probability of respective state by solving the difference equations or multiplying the relevant probabilities
5. Determine the limiting conditions of the probabilities

Ericson (2005) argued that Markov technique is not that simple since it involves rather detailed mathematical model of the system failure, transition and timing states hence its application requires analyst to have good understanding of technique's methodology and assumptions. Other limitations on Markov analysis include:

- The probabilities of changing from one state to another is assumed constant, hence indicating that the technique can only be applied when a constant failure rate situation is justified (O'Connors *et al.*, 2002)

- The future states of the system is also assumed independence of all past states excluding the immediate preceding state. For repairable system, it means that the system is assumed to be in 'as good as new' condition after each repair action (O'Connors *et al.*, 2002)

- The assumption of stationary transitions probability used in Markov process means that the technique is not suitable for modelling a system where the transition probabilities are influenced by long-term trends (Rausand and Hoyland, 2004)

For large systems, Markov model can be complicated, hard to construct, compute and validate. It is also may be exceedingly large leading to a state space explosion problem (Buckl *et al.*, 2007). The number of states in Markov modelling increases exponentially with the number of state variables hence make it difficult to solve analytically even with the advanced in computer technology (Grassman, 2000).

2.3.1.5 Monte Carlo Simulation

Monte Carlo (MC) simulation, first developed in 1940s at Los Alamos National Laboratory for investigation of US atom bomb, is a numerical technique based on a probabilistic interpretation of quantities obtained from algorithmically generated random variables (Birolini, 2010). This technique has been applied in a wide range of disciplines such as applied mathematics, economics, science and engineering. MC simulation is found extremely useful in reliability and availability prediction and analysis since it provide means and flexibility to evaluate complex system, describe realistic aspects of system behaviour and consider various significant factors affecting system performances, which can be difficult or impossible to be captured and evaluated using analytical approach (Marquez *et al.*, 2005, Zio *et al.*, 2006). These factors include redundancy, K-out-of-N, maintenance actions with stochastic or deterministic characteristics, equipment degradation and aging, repair groups and priorities. MC simulation approach utilizes randomly generated samples of the input variables for each deterministic analysis, and estimates response statistics after several repetitions of deterministic analysis (Haldar and Mahadevan, 2000). In general, this process involves four main steps (Sokolowski, 2010):

i. Define a distribution of possible inputs for each input variable

ii. Generate inputs randomly from those distributions using random number generator

iii. Conduct a deterministic computation using that sets of inputs

iv. Aggregate the results of the individual computations into the final result

Despite having numerous advantages, MC simulation technique also has few limitations. The analysis process may consume longer time, effort and money, and over simplification can result in simulation or result not sufficient for the task (Banks *et al.*, 2010). Additionally, the simulation is highly dependent on computer simulation program, where the program itself may set certain limitations (Rausand and Hoyland, 2004). Nevertheless, with the advances in computer hardware and software technology, faster simulation can be performed and more advanced simulation packages can be developed that permit rapid running of more complex scenarios (Banks *et al.*, 2010).

With various advantages of simulation approach, there is a great tendency to combine analytical techniques with Monte Carlo simulation method in the study of reliability and availability. Some the related studies include those by Wang and Pham (1997), Ejlali and Miremadi (2004), Zio *et al.* (2006) and Herder *et al.* (2008).

2.4 Basic Definitions

2.4.1 Reliability

IEC 60050-191 (1990) defines reliability of an item as the ability to perform under given conditions for a given time interval. Qualitatively, reliability means the ability of the item to remain functional. As a quantitative performance measure, reliability can be expressed as the probability that the item will perform its required function under given conditions for the stated time interval. In other words, reliability specifies the probability that no operational interruptions will happen during a stated time interval, including for a system with redundant parts where each part can fail and be repaired. Hence, the concept of reliability can be applied for both non-repairable and repairable items (Birolini, 2007).

Mathematically, the reliability function $R(t)$ is the probability that an item or system will be successfully operating without failure in the interval from time 0 to time t and can be expressed as

$$R(t) = \Pr [T \geq t], \qquad t \geq 0 \tag{2.1}$$

where

$R(t)$ = a non increasing reliability function, where $R(t) \geq 0$ and $R(0) = 1$

T = a continuous random variable of the time of occurrence of a failure, where $T \geq 0$

t= time period

Thus, for a given value of t, $R(t)$ is the probability of the time to failure, T, is greater or equal to t. The unreliability or probability of a failure will occur before time t can be denoted as $F(t)$, and defined as

$$F(t) = 1 - R(t) = \Pr [T < t], \ F(0) = 0 \text{ and } \lim_{t \to \infty} F(t) = 1 \tag{2.2}$$

The failure probability, $F(t)$ is also known as the cumulative distribution function (CDF) of the time to failure distribution. If the time to failure, T, has a probability density function (PDF) of $f(t)$, then

$$f(t) = \frac{dF(t)}{dt} = -\frac{dR(t)}{dt} \tag{2.3}$$

Hence, given the $f(t)$, the relationship with $F(t)$ and $R(t)$ are given by

$$F(t) = \int_0^t f(x)d(x) \tag{2.4}$$

$$R(t) = \int_t^\infty f(x)d(x) \tag{2.5}$$

Both unreliability, $F(t)$ and reliability, $R(t)$ functions actually represent the area under curve of the function $f(t)$. Since $R(t)$, $F(t)$ and $f(t)$ are inter-related, knowing any one of the functions is sufficient to determine the others. $F(t)$ is usually used to compute failure probabilities and $f(t)$ is generally applied to understand the failure distribution shape (Ebeling,1997).

2.4.1.1 Failure Rate

Failure rate is the conditional probability that a component fails in a small time interval given that it has survived from time zero until the beginning of the time interval. Failure rate function, $h(t)$, can be estimated by dividing the probability density function over the reliability function

$$h(t) = \frac{f(t)}{R(t)} \tag{2.6}$$

Failure rate term has been widely used to describe reliability of both non-repairable components and repairable system leading to some confusion in the definition and applications (Ascher and Feingold, 1984, Davidson, 1995, Wasson, 2006 and Trindale and Nathan, 2008). The more appropriate term for non-repairable is the hazard rate, and for repairable is the rate of occurrence of failure (ROCOF).

2.4.1.2 Bathtub Curve

The reliability characteristics of a component over it lifetime can be hypothetically modelled by a bathtub curve. A bathtub curve concept is also used to describe a system with many non-repairable components where the failure of each component is statistically identical and independent (Birolini, 2007) as well as a repairable system with ROCOF as the Y-axis (NIST/SEMATECH, 2011). Bathtub curve can be divided into three phases as depicted in Figure 2.2, where each phase can be characterized by Weibull and exponential distributions. The first phase is early failures, also known as infant mortality and burn-in period. Here, the failure rate is initially higher due to issues such as improper manufacturing, installation and poor materials, but is later gradually decreasing and level off as those problems are identified, solved and reduced and plant personnel's experience increased. In the useful life phase, the failure rate is approximately constant as the failures, assumed mostly stress-related occur at random. This flat-portion of bathtub is also referred as component's or system's 'normal operating life' where realistically many components or systems spend most of their lifetimes operating (Davidson, 1994). Due to its memory-less characteristic, it is easier to compute reliability in this phase as the failure process can be conveniently modelled by homogeneous Poisson process (HPP) (failure data follow exponential distribution). The wear out phase has increasing failure rate because of degradation phenomena due to wear out. Wear out is generally caused by fatigue, corrosion, creep, friction and other aging factors. Both infant and wear out phases can be generally modelled by Weibull distribution.

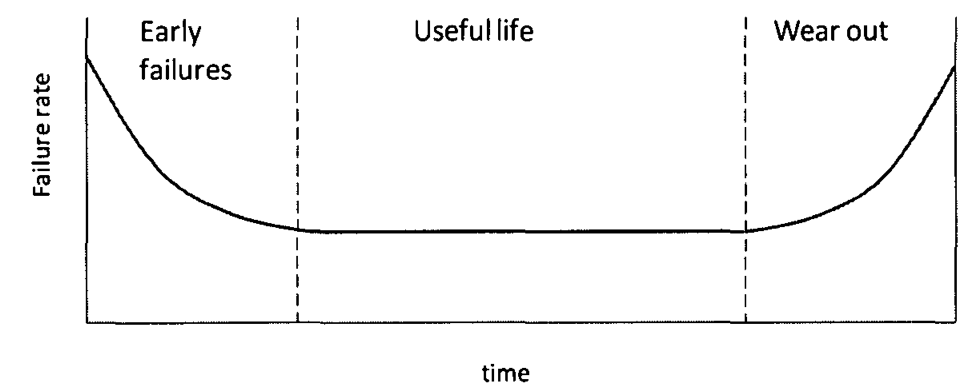


Figure 2.2: Bathtub curve

Many repairable systems have long useful life phase due to the impact of effective maintenance actions. Even though PM does not improve the system's inherent reliability, when implemented appropriately at specified operating intervals it will maintain the reliability performance in the useful life, keeping the low failure rate leading to a delay in the onset of wear hence extending the length of useful life phase (Benbow and Broome, 2009). Effective and timely corrective and preventive maintenance actions together with proactive improvement program may minimize the effects of degradation and reduce the failure rate over time (Wasson, 2006). This phenomenon is illustrated in Figure 2.3.

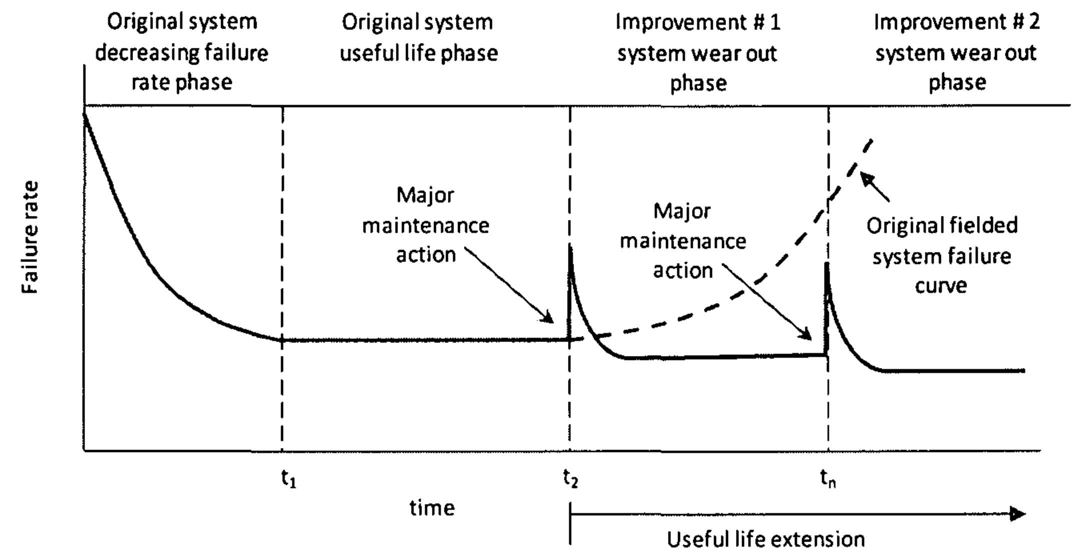


Figure 2.3: Equipment / system useful life phase extension (Wasson, 2006)

2.4.2 Maintainability

Maintainability can be defined as "the measure of the ability of an item to be retained in or restored to specified condition when maintenance is performed by personnel having specified skill levels, using prescribed procedures and resources, at each prescribed level of maintenance and repair"(MIL-STD-721C, 1981). Maintainability can be expressed either as a probability to restore the system following a failure to operational status within a period of time or a measure of the time required to repair a certain percentage of all system failures(MIL-HDBK-338B, 1998). At the highest level, maintainability can be seen as a product of overall support programme in the system where high maintainability reflects the effectiveness of in the design approach, manpower allocations, training delivery and supply chain management (Knezevic, 1997). Several common maintainability measures include the probability of task completion, success of task completion, percentual duration of restoration or downtime and mean duration of maintenance task or downtime (Knezevic, 1997).

Downtime is the time interval for which the system is unable to perform as required due to fault or maintenance activity (IEC 60050-191, 1990). A formal definition is difficult to establish since it varies from one system to another based on the operating conditions and elements of downtime, however, it is necessary to define the downtime as required for the system under studied (Smith, 2005). During operation of a plant, there are many incidents that can cause downtime to the system. Hence, clear understanding of which events relate to the calculation of the system downtime need to be established and well defined.Downtime is not the same as repair time, since the latter is a subset of the downtime. The system downtime consists of three main elements; active maintenance time (repair time), logistics delay time and administrative delay time (Blanchard and Fabrycky, 2006). The quantification of repair time during data collection for system operating stage has been always an issue due to scarce of information (OREDA, 2002). Many plants have a good record of downtime history but not repair time. Another reason is because the exact measurement of each downtime element is difficult to obtain from the data. The logistics and administrative delay time may occur at several times with no particular sequence during the downtime period thus making it difficult to quantify the exact repair time (Smith, 2005). The complexity in segregating downtime elements is depicted in Figure 2.4.

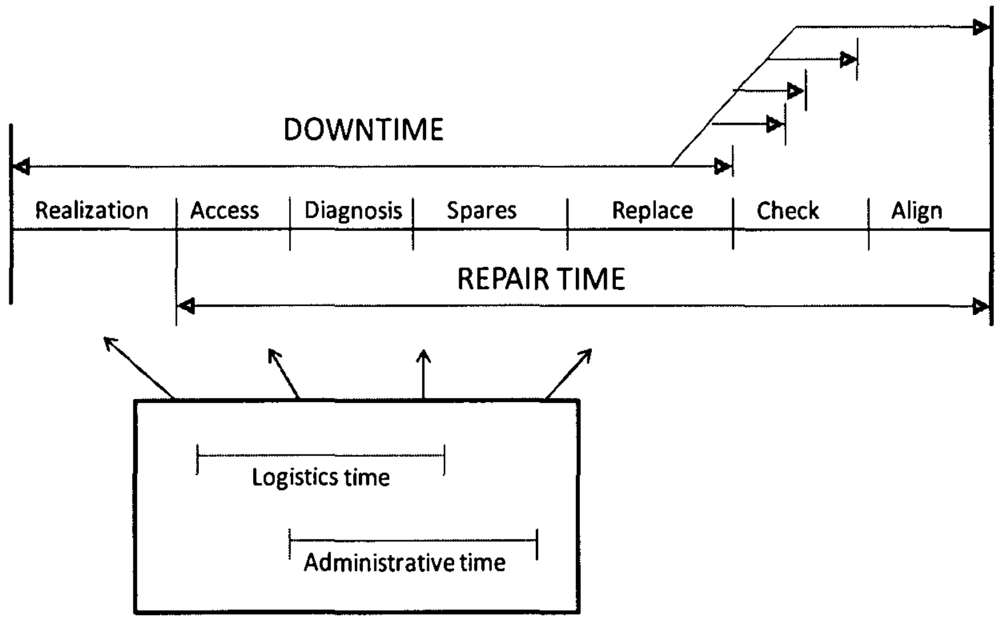


Figure 2.4: Downtime main elements which include repair time, logistic and administrative delay time (Smith, 2005)

At the operationphase, the measurement and analysis of system downtime are of interest of management since they represent the operational characteristics which include the operational availability, effectiveness of the current maintenance scheme and logistic support system, and improvement actions. The operational unavailability is simply the total downtime over the total operating time.

2.4.2.1 Maintainability Analysis at Operation Phase

Many large and complex systems experience high maintenance and support activities costs in order to have sustainable operating condition. According to Blanchard and Fabrycky (2006), these costs could account for up to 75 percent of the total system life cycle cost. High maintenance expenditure is normally due to poor decision making and planning when determining the maintainability requirements of the operating system in the early phase of system life cycle. Thus, to reduce this cost, appropriate maintainability factors and requirement must be considered, defined and firmly established in the early part of the system conceptual design phase as well as on every subsequent phase of the system life cycle (Blanchard *et al.*, 1995). Figure 2.5 shows the maintainability requirements (specified in qualitative and quantitative terms) required throughout the system's life cycle. These requirements are generated from the outcomes of feasibility analysis, operational requirement and maintenance concepts development, and identification of technical performance measure such as mean time to failure (MTBF), mean time to repair (MTTR) and mean downtime (MDT) (Blanchard *et al.*, 1995). Maintainability requirements should be built-in into each system phase and integrated with other important design factors such as reliability, safety, supportability, quality, human factors and producibility, to ensure that the system meet its operational and performance objectives (Blanchard and Fabrycky, 2006). Appropriate maintainability analysis and tools are used to measure the effectiveness of these requirements. The results are then feedback to the design team to improvise future system development.

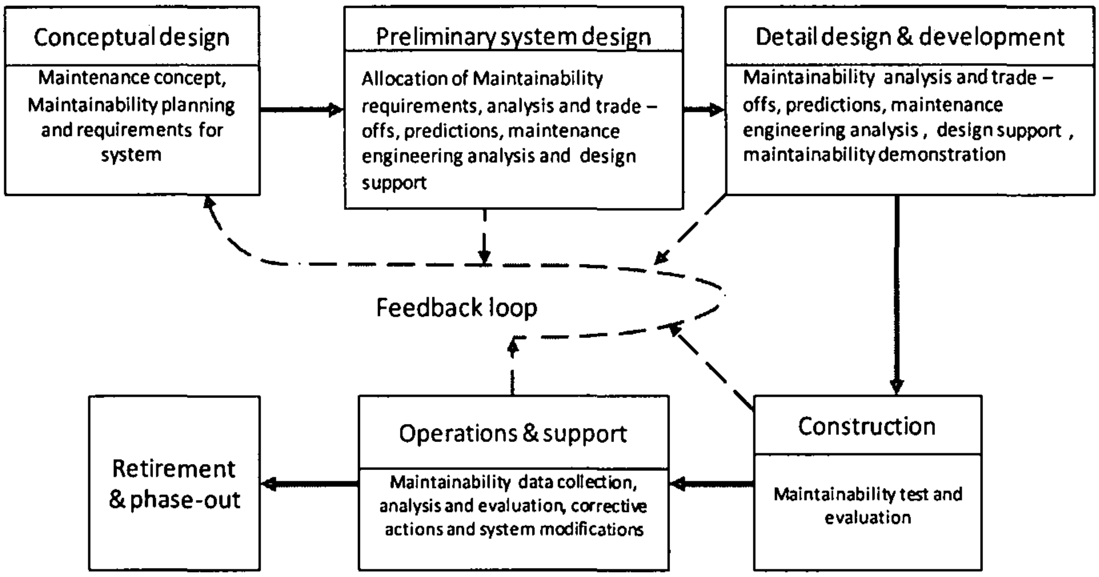


Figure 2.5: Maintainability requirements in system life-cycle (Blanchard *et al.*, 1995)

At the operation and support phase, the on-going maintainability analysis provides quantifiable assessment of the performance and effectiveness of the maintenance and support system, identification of equipment, system and process high cost and downtime drivers, and evaluation of maintainability measures and prediction. The results of the analysis are then used as valuable information for operation, maintenance and design personnel to make maintenance system more effective, plan logistic support requirement (i.e workers, tools and materials), carry out improvement actions to reduce operation costs, and achieve operational targets, which willconstantly change as a result of plant decreasing profit margin and escalating operation cost.

2.4.3 Availability

IEC 60050-191 (1990) defines availability as the ability of an item to be in a state to perform a required function under given conditions at a given instant of time or over a given time interval, assuming that the required external resources are provided. The availability of equipment or system basically is the function of its reliability and maintainability performances; hence both aspects should be focussed when considering system's availability improvement actions. High availability can be achieved when the system has high reliability during start and operation. High maintainability in terms of the completion of maintenance actions within the specified duration will also result in high availability. There are three types of availability and they are being applied for different purposes: i) inherent availability, ii) achieved availability and iii) operational availability.

Inherent availability (A_i), is solely based on corrective maintenance events (failure and CM repair time distribution) and can be expressed as

$$A_i = \frac{MTBF}{MTBF + MTTR} \tag{2.7}$$

This definition is generally used at design stage when designing for equipment parameters, where reliability-maintainability trade-offs can be determined based on that expression (Ebeling, 1997).

Achieved availability (A_a) takes into consideration both corrective and preventive maintenance features. It is defined as

$$A_a = \frac{MTBM}{MTBM + \bar{M}} \tag{2.8}$$

MTBM is the mean time between maintenance and $\bar{M}$ is the mean active maintenance timefor all corrective and preventive maintenance actions. More detailed definition and formula can be found in Wasson (2006) and Ebeling (1997). Achieved availability is used by system developer who has no control over plant's support system factors such as logistics and administrative delay time (Wasson, 2006).

Operational availability (A_o) is a measure of .availability which includes all maintenance downtime and delay factors. Mathematically it is defined as

$$A_o = \frac{MTBM}{MTBM + MDT} \tag{2.9}$$

MDT is the mean maintenance downtime which includes active maintenance, administrative delay and logistics delay downtime for all corrective and preventive maintenance actions. Achieved availability is basically the actual availability experience by a plant and can also be expressed as the ratio of the total system uptime to total cycle time (Reliasoft, 2007).

$$A_o = \frac{Uptime}{Operating\ cycle} \tag{2.10}$$

The operating cycle is the overall observation period which includes the total time of system uptime and downtime. For illustration consider a system having the uptime and downtime profiles as in Figure 2.6. Based on Equation 2.10, A_o can be calculated as

$$A_o = \frac{Total\ Uptime}{Total\ Uptime + Total\ Downtime} \tag{2.11}$$

$$A_o = \frac{U1 + U2 + U3}{(U1 + U2 + U3) + (D1 + D2)} \tag{2.12}$$

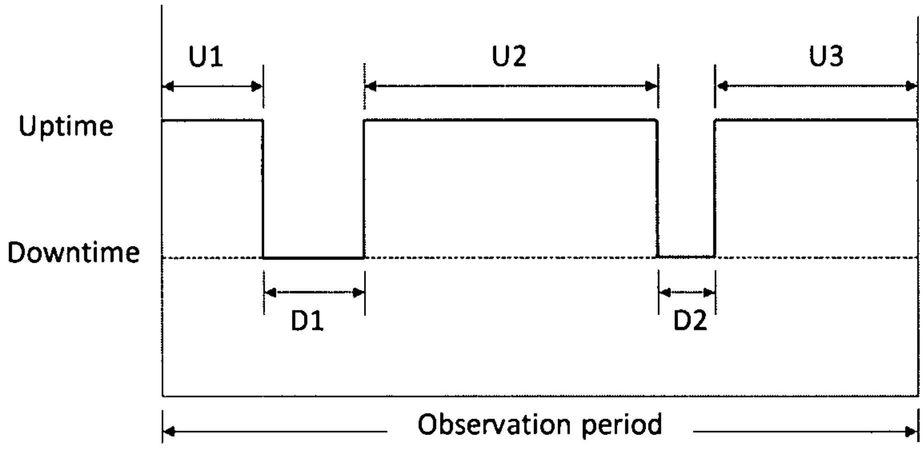


Figure 2.6: An example of system's profile having uptime and downtime states

2.4.3.1 Availability Analysis at Operation Phase

Availability analysis, a last component of RAM study, can become an important and strategic tool for management in improving plant operation bottom line and aligning plant performance with the organizational objective. Availability analysis presents a means to understand the impact of existing maintenance system and maintenance resources to the overall system operational availability. Apart from that, more importantly this analysis can be used as a management strategic decision tool to make right decisions based on sound statistical analysis rather than one's gut feeling or experience. Availability analysis can assist management to quantitatively assess various improvement actions such as redundancy, reduction in preventive maintenance frequency and utilization of new equipment. It also can be used to evaluate how much improvement in terms of failure rate and repair time is needed to achieve specific operational goal. Identification of potential issues when a system is under different operating conditions can also be assessed.

As explained in Chapter 2, with the increasingly complex characteristics of plant system nowadays, a simulation approach has become a preferred method of performing availability analysis for evaluating system availability accurately. In the study of system maintenance, availability modelling simulation offers the following benefits:

- Identification of critical equipments or components to system's availability
- Practical and fast mean to evaluate and estimate system performance since collecting sufficient actual observation data is time consuming and difficult
- Systematic analysis of "what if" scenarios to assess impacts of different maintenance strategies (e.g. PM action), operation options (e.g. redundancy) and R&M performances to overall system availability, hence more effective decision making and actions can be made

Literature on practical application of availability analysis in the oil and gas industry is relatively limited. Nevertheless, several attempts to conduct practical availability analysis at operation phase of various plants have been made by various researchers. Despite these efforts, the adoption of this technique as a strategic tool for decision making among industry practitioners is still relatively low. The problem is mainly due to the lack of awareness among management on the capability of the analysis in solving current issues and maximising plant production potential. Therefore, wider exposure among plant management is needed on the practicality and capability of this technique as well as broader involvement of plant personnel in the analysis activities. Another issue is, as pointed out by Herder *et al.* (2008), most research papers do not present detailed steps and problems faced while implementing the analysis. Moreover, some of them are not practical, too theoretical and highly mathematical for practitioners to comprehend and implement (Dekker, 1996). Approach to conduct more case studies based on real industrial application will definitely promote this tool among industry and explore more practical issues related to the implementation of the analysis.

2.5 General Approach to System Reliability Study

An important aspect of reliability analysis of a real plant system is the development of model to understand about the behaviour of the system so that prediction of system's future condition can be made. Reliability modelling concerns with model development to achieve solutions to problems pertaining to estimating, predicting and optimizing the performance of the system, assess the impact of various factors to the system and corrective actions to mitigate the impact (Blischke and Murthy, 2000). Real world system consists of various attributes in which each one has its own characteristics and conditions, which requires adequate model to represent them. Wasson (2006) defined a system as "an integrated set of operable elements, each with explicitly specified and bounded capabilities, working synergically to perform value-added processing to enable a user to satisfy mission-oriented needs in a prescribed environment with a specified outcome and probability of success". Modelling process can be quite a challenge when the system under study has high level of complexity. In reliability study, modelling of system can be made either by using graphical or mathematical model (Rausand and Hoyland, 2004). Graphical models comprise of symbol, diagram and schematic representation of important features of a system (Satzinger *et al.* ,2007). They are used to represent abstract aspects of a system such as processes, data and connections and make it easier to understand complex relationship within the system. An example of a graphical model is a system reliability block diagram. A mathematical model is an abstract, simplified, mathematical construct related to a reality of system or part of it and developed for the purpose of analyzing the system (Bender, 2000). It generally consists of various mathematical structure and concepts such as functions, variables, equations, constant, graph and relation (Meyer, 2004). Rausand and Hoyland (2004) stressed two important aspects of modelling that need to be considered. First, it should be simple enough for mathematical model to deal with, and second, it should be realistic enough such that the deducted conclusions are practically relevant. General approach in constructing a mathematical model for understanding real world system is given by Giordano *et al.* (2009) and it generally involves observation of real system's behaviours and identification of factors associated with them, making conjecture about relationship between factors, application of mathematical analysis on the model developed and interpretation of mathematical conclusions in term of real world issues.

In reliability analysis, mathematical model is applied to estimate reliability, risk, safety parameters and performances measures using relevant statistical and reliability theory. It is also used to describe how different components within a system are inter-connected and affecting the overall system performance.The most appropriate methodology in conducting a reliability analysis of a real-world system is through a systems approach (Murthy *et al.*,2008, Blanchard, 2004), which presents an integrated framework for solving various issues related to technical, operational, business and management (Blischke and Murthy, 2000). In the systems approach, an analytical model is developed and validated with the use of data and analyzed using appropriate techniques and tools. The analysis is an ongoing process of evaluating system performance and various alternatives, which is fundamental for supporting continuous improvement efforts.

The steps in systems approach was given by Blischke and Murthy (2000) and is illustrated in Figure 2.7. The first step is to clearly define the problem faced by the real world system that needs to be addressed. Simplification of the system characteristics and assumptions are required for feasibility of analytical analysis and because it's impossible to capture all the factors influencing to the defined problem. Generally this simplification can be accomplished by reducing the factors under consideration and assuming simple relationships between the factors to reduce the complexity of the problem (Giordano *et al.*, 2009). In the system characterization, the system details related to the problem under studied are made known and suitably modelled. A mathematical model then is developed for the system and checked whether it adequately represents the real-world system. In case it doesn't, changes are made to either in the mathematical formulation or simplification. Ansell and Phillips (1994) emphasized that the analysis should be conducted first by using a simple model before extending it into a more complex model. This is because many times most of the practical plant problems can be solved simply by using a fairly simple model. Once the adequate model is achieved, proper analysis of the model is done using various techniques based on reliability theory. Here, the analysis results should be interpreted appropriately to ensure that they adequately address the identified problem.

According to Blischke and Murthy (2000), reliability analysis can be divided into two categories: qualitative and quantitative. Nevertheless, generally both analysis are combined during system analysis to produce more comprehensive results (Billinton and Allan, 1992). In qualitative approach the main objective is to identify critical equipment, failure modes and causes that affect the reliability of the system. Various methods are applied in qualitative analysis and they include basic quality tools such as histogram, Pareto, scattered plot, and cause and effect diagram and more advanced technique such as Failure modes, effects, and criticality analysis (FMEA/FMECA), fault tree analysis, event tree analysis and reliability block diagram.

A quantitative approach concerns with formulation of mathematical model to produce quantitative estimates of system reliability. A generic flowchart for quantitative analysis of plant reliability data involving repairable items has been proposed by Ascher and Feingold (1984) in their important and famous book. Since then this model has been further elaborated by many researchers, see for example: Rausand and Hoyland (2003); Blischke and Murthy (2000); and Andrew and Moss (2002). Barabady and Kumar (2008) extended the method to be applicable for maintainability analysis. Similarly, Louit *et al.* (2009) enhanced the model by incorporating more statistical tests option to facilitate proper time to failure model selection. Ansell and Philips (1990), however, argued that ageneric flowchart is too rigid thus impractical for every type of analysis required in the industry since it is impossible to describe every eventuality of the problem and condition confronted.

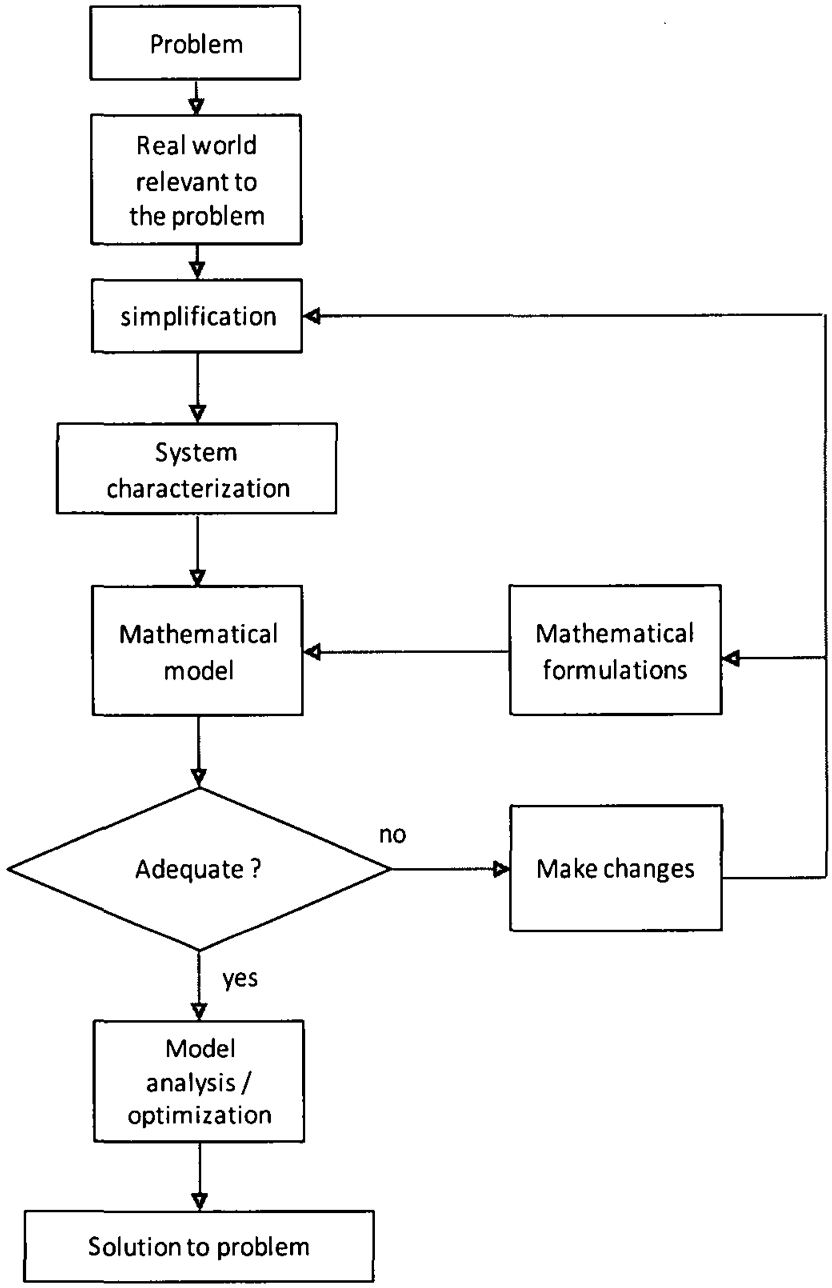


Figure 2.7: Systems approach to solve system reliability issues (Blischke and Murthy, 2000)

2.6 General Approach to Maintainability / Downtime Analysis

According to Knezevic (2009) two commonly used approaches for analysis of the empirical downtime data are the

i. parametric
ii. distribution

In the parametric approach, the main interest is to get the mean downtime, which is computed by dividing the sum of all downtime hours by the total number of downtime events. The interval of the mean based on certain confidence limits (i.e 90%) can be calculated using specific formula and referring to normal distribution table. Many reliability databases including OREDA (2002) use similar approach in their reporting format. In the distribution approach, the downtime is expressed in term of probability distributions, where the downtime is treated as random variable since every failure event will always result in different downtime duration due to different failure modes, components failure and skill level of maintenance people (Ebeling, 1996). Due to this, the distribution approach offers more information than the parametric approach (Knezevic, 2009), thus is the preferred method in evaluating maintainability measures. Besides that, having downtime data in the distribution form is fundamental for applications in Monte-Carlo simulation and Bayesian analysis, which are also widely used to predict the maintainability and availability of the system.

The most commonly used probability distributions to describe maintenance downtime are the exponential, normal and lognormal (Blanchard*et al.*, 1995). Other distributions may include gamma and Weibull (MIL-HDBK-338B, 1998). The exponential distribution is usually applied to electronics parts with build-in test capability and have fast remove and replace maintenance scheme (Blanchard and Fabrycky, 2006). It is however not realistic for many downtimes situations, except in the case where most part of the downtimes are attributed to failures searching actions (Rausand and Hoyland, 2004). Due to its constant downtime rate characteristics, many studies assume this distribution in the downtime model for the sake of convenience in modeling rather than practicality. In reality, this assumption is misleading since it presumes there are many failure events that have zero repair time (Blanchard*et al.*, 1995). The normal distribution is sometimes assumed for equipment having relatively simple removal and replacement tasks that usually can be completed within a fixed amount of time with little variations (Blanchard*et al.*, 1995). The lognormal distribution is the most common model for repair time or downtime distribution for both electronics and mechanical equipment. The shape of the lognormal is skewed to the right meaning that most of the downtimes are distributed about the center and few will be at the right-tail of the distribution. This characteristic seems logical in many downtime events since some downtime is very long due to the unavailability of spare parts at site or difficulty of maintenance crew to get access to or repair the failure (Rausand and Hoyland, 2004).

2.7 Non-repairable vs. RepairableSystem

Plant systems or equipment can be categorized into two; non-repairable and repairable, where each one requires different analysis approach. It is very important to understand the difference between these two since often industrial practitioners improperly use non-repairable technique to analyze data from repairable system (Trindale and Nathan, 2008). Non-repairable items are discarded or replaced with a new one upon failure. For example, light bulb, transistor and most components in plant equipment. The reliability of the item is based on the survival probability over its service life (Modarres, 1993).The time to failure is a continuous random variable assumed to be independent and identically distributed (IID) and is described by a single lifetime distribution. Typical lifetime distributions used in non-repairable items are exponential, Weibull, normal and lognormal. Exponential is the most commonly used distribution mainly due to its simplicity and memoryless property, in which the occurrence of failure is completely random. This characteristic is well suited to model the useful life phase (constant failure rate region of bathtub curve) of a component or system (Ebeling, 1997). Weibull has been extensively applied for component reliability analysis because of its flexibility to model various failure rate function; increasing, constant and decreasing, besides its mathematical simplicity (Davidson, 1994). Fitting a lifetime distribution to failure field data generally involves three steps: i) identifying candidate distribution; ii) estimating distribution's parameters; and iii) conducting goodness of fit (Ebeling, 1997).

Most systems in offshore facilities and petrochemical plant however are repairable. Repairable equipment means that upon failures the equipment are repaired and restored to the functional state. The probabilistic model for studying the occurrence of failures in the repairable system is based on stochastic point processes. The point process can be described as the occurrence of randomly distributed events in time with negligible events duration (Modarres *et al.*, 1999). The events here are the failure times (time between failures) of a repairable item. Several point process models for repairable system are proposed in the literature and they generally can be classified under three types of repair actions; perfect repair, minimal repair and imperfect repair (Rausand and Hoyland, 2004).

In the perfect repair model, the equipment upon failure is either repaired or restored to 'as good as new' condition. The distribution of time between failures is assumed to be independently and identically distributed (IID), hence it can possibly be fitted by a lifetime model. When the failure times exhibit exponential distribution (constant failure rate throughout the observation time) the process is called an homogeneous Poisson process (HPP). The HPP is the simplest model in the point process models where the expected cumulative number of failures for given interval of time follows Poisson process. If the distribution follows any arbitrary distribution, the process is called a renewal process.

A repairable system consists of components with renewal process may be modelled by a perfect repair based on Drenick's theorem, where at the system level the superimposition of equilibrium renewal processes tends to be an HPP as the number of processes increase (Ansell and Phillips, 1994, Trindale and Nathan, 2008). In other words, the system's time to failure distribution is exponential regardless of the nature of component's lifetime distribution (Kececioglu, 2002). Nevertheless, this assumption must be first verified for IID condition of the time to failure data before it can be validly applied (Ascher and Feingold, 1984, Ansell and Phillips, 1994, Rausand and Hoyland, 2004)

The minimal repair model refers to the condition where a repair done on a system resulted in the system in exactly the same condition as it was ('as bad as old') just before the failure (Rigdon and Basu, 2000). The inter-arrival time distribution here is not IID and the process is modelled by a non-homogeneous Poisson process (NHPP). Two models commonly used for NHPP are the power law (Crow model) and log-linear model (Cox-Lewis model). Finally, the imperfect repair model is applied when the repair action results in the equipment condition between the 'as good as new' and 'as bad as old'. The proportional age reduction and proportional intensity variation models are examples of two point processes that can be used to describe the imperfect repair model (Muralidhan, 2008).

A general flow for analysing plant maintenance data will be presented in the next chapter.

2.8 Applications of Expert Opinion in R&M Analysis

In many cases, the data are limited and in poor quality thus make them inappropriate for reliability modelling purpose. An alternative way is to use expert opinion. Expert is a skilful person who has extensive training and knowledge on the specific area. Expert opinion can be defined as the expert's formal judgment on the matter in which the expert's opinion is sought (Ayub, 2001).The application of expert opinion has been found in various studies covering a wide spectrum of disciplines such as nuclear, chemical, aerospace, health and banking industries (Goossens *et al.*, 2008). In the areas of reliability and maintenance analysis particularly in the decision making and prediction processes, this application is gaining widespread attention mainly due to unavailability of sufficiently good quality maintenance record as well as uncertainties in the data(Bedford *et al.*, 2006).

Coolen *et al.* (1992) used expert inputs to estimate the prior distribution of the mean life of heat exchangers. Oien (1998) elicited maintenance engineers' knowledge to predict a "naked" failure rate (failure rate if no PM actions were being carried out) in light of corrupted maintenance data. The elicitation results are used later to estimate the mean time to failure (MTTF) of shutdown valves. Horkstad *et al.* (1998)

discussedthe elicitation process for acquiring failure rate of an offshore umbilical where there is no previous lifetime data exists. The inputs from experts are used in the Fault Tree Analysis (FTA) to predict the probability of the umbilical being tensioned. The application of expert judgments in estimation of delay time distribution for extrusion press failures was presented by Wang (1997). The delay time is the time interval between the first time faults is detected and the time of failure. Kudak and Ercan (2009) studied the maintenance time of a jet engine aircraft ignition system failure during the wartime with inputs from military experts.

2.8.1 An Overview of Method for Elicitation of Expert Opinion

The details on elicitation process can be found in Ayub (2001) and Cooke (1991). In general, the elicitation process consists of three stages (Oien, 1998);

- Preparation
- Elicitation
- Calculation

In the preparation stage, the following main activities are done; setting the problem description and objectives, identification of expert(s), formulation of appropriate questionnaire and calculation method. The right design of questionnaires is critical for the elicitation process to be successful (Wang, 1997). The question should be set and asked with simplicity yet able to extract the required information from the actual knowledge of expert (Oien, 1998).

The number of experts involved in the process varies depending on the elicitation technique used, the scope of problem and availability of experts (Fink *et al.*, 1984). Generally, multi and diverse experts are preferable so that the problem will be thoroughly considered from many viewpoints hence minimizing the influence of a single individual(Meyer and Brooke, 2001). In a face-to-face interview approach,Meyer and Brooke(2001) recommended five to nine experts in order to increase chance to provide adequate diversity or information to make inferences.

Nevertheless, in reality in some critical industries and specialised operations, it is very difficult to get many experts available for elicitation session that typically take a great of time, since they can be sparse or tied up with day-to-day tasks. For example, the US Nuclear Regulatory Commission recommends no fewer than two but preferably three experts should be consulted in the Accident Sequence Precursor (ASP) analysis, and allows the use of a single expert where time constraints prevent use of multiple experts in the analysis of Significance Determination Process (SDP) (Boring *et al.*, 2005). Horkstad *et al.* (1998) asserted that the use of one expert when there is no other option, when implemented through systematic approach is better than none or can be as valuable as having many experts particularly when they indicate strong dependent or biased. The elicitation of expert opinions using one to three experts has been demonstrated and discussed in various reliability analysis applications in (Campodonico and Singpurwalla, 1992, Horkstad et, 1998, Booker and McNamara, 2004).

The elicitation stage involves elicitation exercises with the expert. It is normally conducted via an interview and discussion format where the assessor plays critical role in asking the right questions and minimizing expert's bias (Walls and Quigley, 2001). Two types of elicitation method are commonly employed; direct and indirect (Oien, 1998). The direct method involves a direct estimate of the experts believe on a certain issue. The indirect method is applied when seeking the probabilities estimate from the probability-illiterate expert. The interview process should not be too long and it is recommended to be less than half day, since fatigue will normally start to develop after two hours of the session (Cooke and Goossens, 2008).

In the final stage, calculation of inputs from expert is performed to get the results in the required format (e.g., failure rate, lifetime, downtime etc.). Aggregation method is applied when to combine data from more than one expert to establish a single overall output. Generally, the aggregation methods can be dichotomized into two; mathematical and behaviour, although sometimes in reality it may involve combination of both (Clemens and Winkler, 1999). In mathematical aggregation individual probability distributions are processed using analytical models to produce a single probability distribution. On the other hand, behavioural method aims at generating some type of agreement among experts through group consensus and interactions among them with the help of facilitator(s). Some well-known behavioural approaches include Delphi and nominal group method. In Delphi method the experts respond individually to sets of questionnaires, where the results are then combined, summarized and returned for experts to revise. This process is repeated until consensus is achieved (Al-Fares and Duffuaa, 2009). Nominal group method involves a process in which experts are allowed to discuss their opinion directly with others to reach consensus results in a controlled environment, is usually a more preferred method (Ouchi, 2004). Example of application of nominal group approaches can be found in (Forester *et al.*, 2004, and Booker and McNamara, 2004)

2.8.2 Eliciting Probability Distribution

Eliciting probability distribution from expert has always been a challenging and not an easy task, particularly when expert has very little knowledge on statistics and probability distribution model (Van der Gaag *et al.*, 1999). Furthermore, the process should be done as short as possible due to the expert time constraint (Mazzuchi *et al.*, 1991) where he is normally busy and has a tight schedule.Most experts find it difficult if not impossible to state what would be a proper distribution model and its parameters. Elicitation of inputs in a form of discrete distribution (histogram) instead of a continuous distribution has been found to be effective to overcome this problem. Experts usually feel this process more comfortable and easy to comprehend since the concept of probability of failures is being used instead of probability density (Mazzuchi *et al.*, 1991). In addition, the calculation involved in the discrete model is much simpler than the continuous model (Van Noortwijk *et al.*, 1992). The resulting histogram can later be converted into probability density function (pdf) easily using a computer software. Another elicitation format which is more effective and popular than a discrete is a quantiles or fractiles format (Cooke and Goossens, 2008). In this method, expert is required to propose pre-defined fractiles on the subjective uncertainty distribution, which are normally set at 5, 50 and 95%. The fractile technique has been widely used for eliciting prior distribution in Bayesian inference study (Kadane and Wolfson, 1998). In their modelling of prior distribution for reliability growth model, Walls and Quigley (2001) used histogram and fractile techniques to develop a Cumulative Distribution Function (CDF). Here, expert was asked to give input on specified distribution percentiles which represent the expert belief on the certain concerns. The percentile distribution was later enhanced by adding more interval data to form a smooth discrete (histogram) distribution which is later converted into a cdf. The corresponding pdf can be later estimated from the cdf.

It is noted that the literatures on applications of expert opinion in the maintenance and reliability field focus primarily on the estimation of failure rate or lifetime distribution. Very little attention has been given on the maintenance downtime estimation. Hence,in Chapter 5 a practical way of incorporating expert opinion in the modelling of maintenance downtime distribution is proposed and demonstrated to fill in that knowledge gap.

2.9 Chapter Summary

General framework for RAM related study on system at operation phase has been discussed in this chapter. Various methods either qualitative or quantitative can be utilised to analyse the reliability, maintainability and availability of a system. Depending on the study objectives and system conditions, sometimes the methods are combined to produce more comprehensive results. While analytical techniques are still preferred, the application of simulation techniques is rising due to the increasing complexity of system and capability of computing technology. In the analysis of plant system, equipment are categorized into non-repairable and repairable. The analysis approach will differ based on this distinction. Fitting statistical distribution into repairable data, as it is applied for non-repairable, should be avoided unless the repairable data is statistically independent and identically distributed (IID). The use of expert opinion is increasingly important because of the prevailing poor conditions of plant field data. Despite its widespread attention in reliability study, the application of expert opinion is found rather limited in maintainability analysis.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter presents the methodology applied in conducting reliability, maintainability and availability analysis of two systems under study: a gas compression train of an offshore platform and an acid gas removal unit (AGRU) in a gas processing plant. The study focuses on systematic and practical aspects of conducting analysis using mainly operating and maintenance data of those systems which have been in operation for several years. In this chapter a general approach used is discussed for each type of analysis, where the detailed and specific steps are left out and will be shown in case studies presented in the following chapters. The approach has been formulated in such a way that it provides where possible a simple yet practical mean for conducting RAM analysis. Several software are used in the analysis tasks and they include Reliasoft's Weibull ++ and Blocksim, SPSS, and Excel.

3.2 Research Approach Overview

The approach of this research is mainly centredaround several case studies based on real industrial data and problem analysis. This approach is in line with the need to focus on real plant issues in research studies pertaining to plant maintenance. There are, however, few challenges worth mentioning in performing case studies: it is time consuming; requires in-depth research; constant communication with plant personnel;

great patient particularly when dealing with "raw" plant data; and high care when drawing generalized conclusion from a few case studies. Nevertheless, this approach can potentially generate new and creative insights, and more importantly through collaboration can have high validity with industrial practitioners, the ultimate target users of the research (Voss, 2009). Furthermore, case studies can help researchers to retain the holistic and meaningful characteristics of real-life events which are fundamentally important for understanding complex phenomena (Yin, 2003). Consequently, itcan open up possibility of generating new ideas in dealing with proper method to handle and solve real industrial issues. The finding of case studies can be generalized to form a generic theoretical hypothesis or methodology framework which can be practically applied in other similar analysis for other system (Voss *et al.*, 2002).

The focus of this research is on the practical applications of each of the RAM study components, namely reliability, maintainability and availability analysis. For each of the component, a practical approach of analysis is discussed and demonstrated via relevant case studies related to real problems and systems in plant. The analysis on reliability and maintainability can be conducted separately for any particular system of interest. For availability analysis, however, it requires input from both reliability and maintainability analysis results in term of failure and repair distribution characteristics on every equipment or subsystem in the system under studied. The analysis results from each of the RAM component can be used directly to improve plant operational and maintenance performance. Figure 3.1 illustrates the overview of the RAM analysis approach used in this research and the relationship between its three study components.

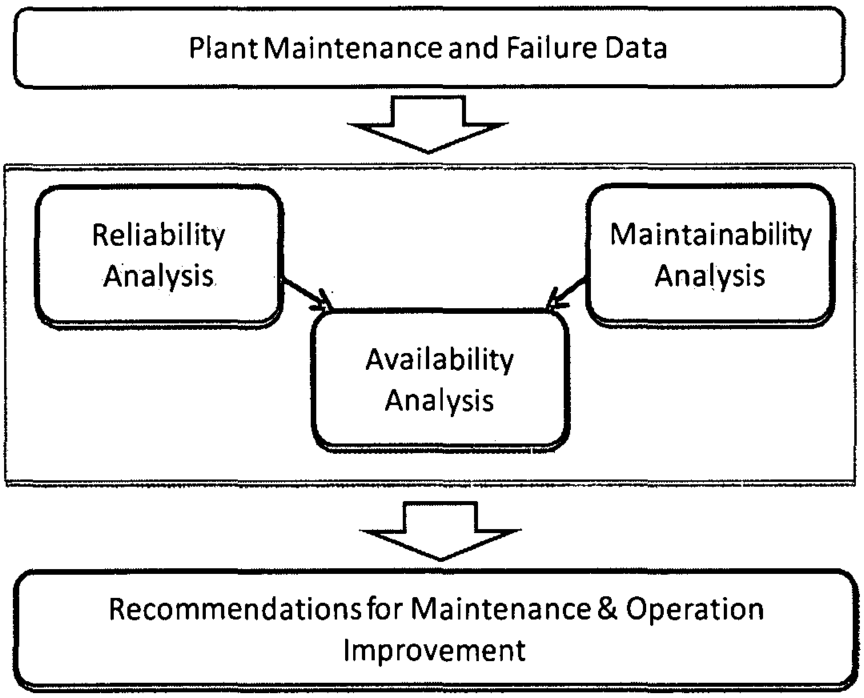


Figure 3.1: Overview on reliability, maintainability and availability analysis of a system in plant

3.3 Approach Used in System Reliability and Maintainability Analysis

In this thesis, the proposed approach to reliability and maintainability (R&M) analysis of a system in plant can be illustrated using a generic framework in Figure 3.2. In general, it involves six major steps, which will be elaborated afterwards. Reliability analysis basically focuses on the analysis of system failure data and frequency, whereas maintainability analysis looks at the downtime characteristics of the system. In this framework, the study of plant maintenance data will be based on qualitative and quantitative analysis to determine major factors affecting system reliability and maintainability performances so that appropriate actions can be recommended. The applications of this proposed R&M analysis approach will be demonstrated in great detail in Chapters 4 and 5.

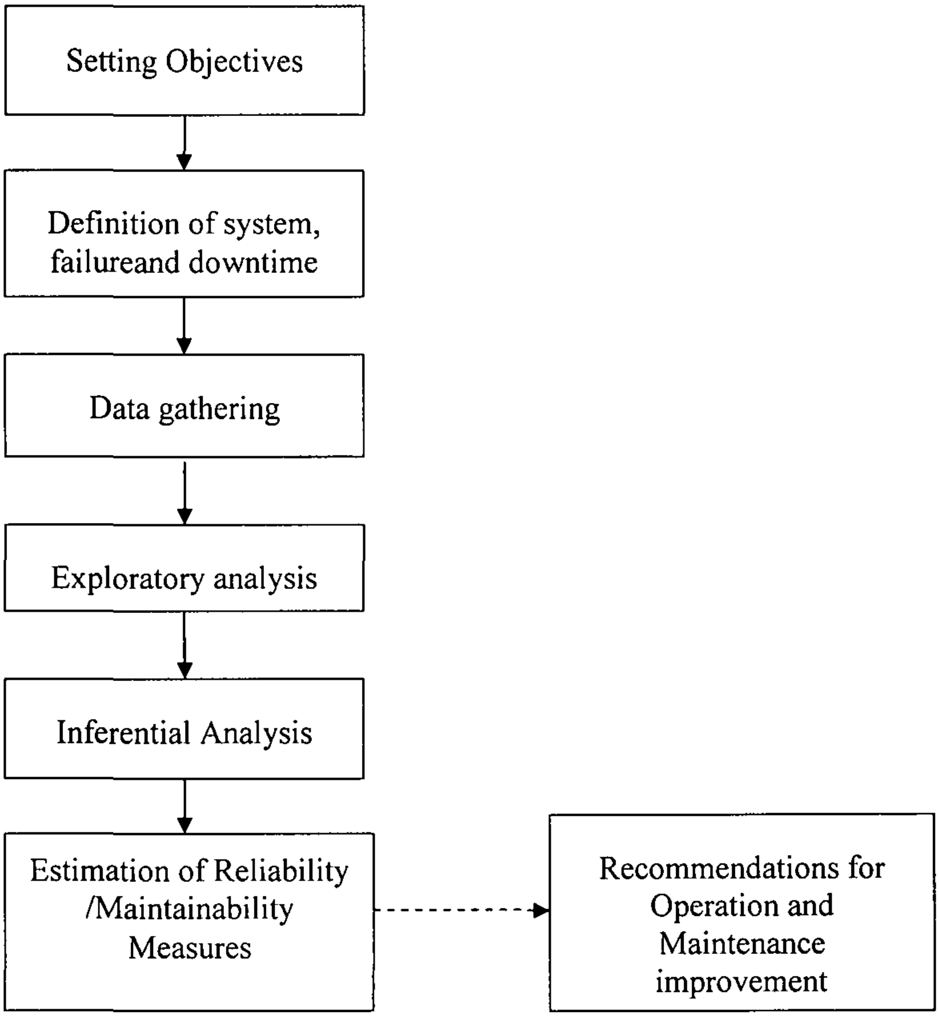


Figure 3.2: Proposed generic framework for reliability and maintainability analysis of a plant system

3.3.1 Setting Objectives

The most important factor for successful reliability study is having clear definition of the specific purpose to be achieved at the end of the analysis (Denson, 2006). Only by having unambiguous objectives in the beginning and consistently sticking to it throughout the whole analysis process, can a proper and effective analysis be accomplished (Ansell and Philips, 1989). The objective of the reliability study has high influence on the approach and method of modelling and analysis used (Aven and

Jensen, 2009). For example, the choice of computational methods (i.e analytical vs. simulation) and performance measures and factors to be analyzed. The nature of estimates derived also depends on the purpose to which the prediction will be used (O'Connor *et al.*, 2002). For instance, an optimistic figure should be applied when determining spare parts requirement, whereas it is more appropriate to use a pessimistic figure in a safety analysis. Precise objective will set proper conditions for appropriate collection of relevant maintenance data to be used in the analysis. Many inherent issues in reliability discipline with respect to selection and application of appropriate methodology can be related to the lack of clear objectives at the start of study (Bendell, 1988, Denson, 2006).

3.3.2 Definition of System, Failures and Downtime

The definition of system being studied, system boundary and operating states, failure event and modes need to be clearly specified to put the subsequent analysis steps in the right perspective and to minimize uncertainties associated with the data. A distinct system boundary shall identify what are components within the system and what are excluded from it. The boundary also defines what data are to be collected. Other system information such as its descriptions, applications, operating mode and environment conditions must also to be clearly specified. At this stage, it is also important to define all assumptions made in the reliability model and determine the hierarchical level (system, subsystem, component etc.) of which the data will be collected and analysis will be conducted.

Plant failure data can be classified under various failure modes, a description of the effect of failure on the equipment ability to perform, and it is critical to identify clearly different failure modes for further data analysis and better reliability estimation (Center for Chemical Process Safety, 1998). Similarly, there are many types of downtime which occur in the plant due to various reasons: failures; preventive maintenance; emergency shutdown; etc. Thus all relevant data must be clearly identified and segregated for subsequent analysis.

3.3.3 Data Gathering

The quality and accuracy of reliability analysis is highly related to the quality of the data collected. High quality data attributes include completeness of the data, compliance with data formats and reliable sources of data (ISO 14224, 1999). According to Patton (2005), besides quality, the collected data must be checked for:

- Reliability - data have high degree of consistency
- Validity - data are meaningful to the analysis's objective
- Relevancy – data are relevant to the study conducted
- Redundancy – data collected are all necessary and not redundant. Over-loaded of irrelevant information should be avoided.
- Sufficiency – data are complete with all required information
- Timeliness – up-to-date data are referred and used
- Cost – cost of gathering data is considered because more detailed information normally requires high investment.

The primary source of data in this research comes from in-house plant maintenance data. Data gathering step is usually the most time and effort consuming activity due to the nature of the data and their sources. There are many data available in a plant such as those from maintenance, engineering, vendor reports, SAP (CMMS) etc. Besides, the data also exist in various forms, thus choosing the relevant one and translating them into distribution and failure statistics can be a challenging task and normally requires considerable engineering judgment. Maintenance record usually has high degree of uncertainty. This is due to the nature of the record itself, which is primarily meant to support maintenance planning rather than for failure prediction (Davidson, 1994). The focus is more on capturing repair action instead of details on failure (causes, mode, time and downtime duration), equipment operating modes and environment. Moreover, since recording of failure data highly depends on human, it is subject to mistakes, omission and misinterpretation (Smith, 2005). To overcome these issues, good cooperation and constant feedback from plant personnel are required. Depending on the raw data conditions, some data need to be transformed to more meaningful, standardized and simplified format for easy analysis and thus further prolong the data collection process. In certain case, different source of information than maintenance data might be useful and relevant for the analysis. For instance, a flow rate reading can be used alternatively to track the operation conditions (i.e. operating, standby or shutdown) of a pump when there is no or incomplete record on pump operation states. In a situation where plant data is insufficient, other sources such as OREDA and expert opinion will be employed. The applications of expert opinion will be elaborated in the maintainability analysis in Chapter 5.

The main plant maintenance data used in this research are from three categories as outlined by Andrew and Moss (2002):

1. *Inventory data* – They consist of information of equipment related to its design, operational, functional and environmental characteristics. The data can be classified under equipment identification, manufacturing and design, maintenance and test, and engineering and process data. This information is important to support data analysis, for instance, to compare the particular equipment data with the data from same equipment category listed in the OREDA.

2. *Failure-event data* – This is the most important data and it comprises of the detailed record of failure incidents in terms of event date, duration, modes, causes, codes, severity and effect on system, repair modes, downtime date and duration, and plant or system operational state.

3. *Operating time data* – This data is needed for proper calculation of reliability measures based on the actual time under which the equipment or system is running. The required information includes the time and duration for each operating state such as operation, standby and downtime as defined in the previous step.

In some cases where necessary, costing and production data are also required in order to present analysis results in monetary terms. These data may include production output, product cost and maintenance cost (manpower, material etc.). A continuous data verification process with respective personnel is carried out throughout data gathering activity, to ensure that the required level of accuracy is attained.

3.3.4 Exploratory Data Analysis

This step marks the beginning of data analysis process. This approach is based on exploratory data analysis concept which was first introduced by Tukey (1977). Exploratory data analysis is the process of using statistical tools and techniques to investigate data sets in order to gain insight about the data, understand their important characteristics, identify outliers or errors, disclose underlying structure and extract important factors (NIST/SEMATECH, 2011) and assist in model formulation (Chatfield, 1985). Because of this apparent significance, many researchers propose the use of exploratory analysis at the beginning of any plant reliability data analysis process (Ansell and Philips, 1994, Blischke and Murthy, 2000, Andrew and Moss, 2002, O'Connor *et al.*, 2002 and Todinov, 2005). Chatfield (1985) stresses that overlooking exploratory analysis will lead to unnecessary adoption of complicated model in the study.

The purpose of exploratory analysis should be in tandem with the objective of study. Prior to performing analysis, the gathered data are normally subjected to further data manipulating processes such as categorization, classification, rearrangement and reordering of data. For reliability study, Ansell and Philips (1994) propose two levels of exploratory analysis: elementary and reliability analysis. In elementary analysis, simple plots like histogram, stem and leaf, box-whiskers, Pareto, scattered diagram and time series trend can be found useful to get a feel about the data, identifying key variables and possible errors in the data. Descriptive statistics such mean, median, standard deviation and fractile, are also commonly used to compare and rank factors. In the next level of exploratory analysis, more related reliability plots and analysis are conducted. These include rate of occurrence of failures (ROCOF), trend plot and hazard plots; Kaplan Meier and proportional hazard model. The main outcomes of analysis are the identification of key factors affecting system lifetimes and downtime, and assessment of trend in system's performance (i.e. improving, deteriorating or constant). Knowing these, management can take necessary actions to further improve the system performance.

3.3.4.1 Trend Analysis

To gain insight about the performance of the system, the graph of the cumulative number of failures against cumulative operating time between failures is plotted. This trend plot can provide a snapshot of how the system performance is heading to. When the inter-arrival time (time between failures) is getting shorter, the plot will tend to concave up signifies that the system is deteriorating. The opposite condition is observed when the system is improving. A linear plot is an indicator that that the system performance is constant. Ascher and Feingold (1984) referred these conditions as 'sad', 'happy' and 'non-committal' system respectively. Besides graphical analysis, these conditions can be assessed using analytical trend test which basically tests whether the process has a monotonic trend or not (stationary). Ascher and Feingold (1984) stressed the important of trend test as the first step of the reliability data analysis and model development and this is strongly supported by other researches (Lindqvist, 2006, Fu-rong *et al.*, 2008, Louit *et al.*, 2009). Several trend tests had been developed, but the most commonly used is the Laplace test. This test is used to statistically test for the null hypothesis that the failure distribution is stationary (homogeneous poison process (HPP)) against the alternative of a monotonic trend (non-homogenous poison process, NHPP). Other trend tests include MIL-HDBK-189 (HPP vs. non-HPP), Mann and Lewis-Robinson (renewable process, RP vs. a monotone trend) (Ascher and Feingold, 1984).

3.3.4.2 Laplace Trend Test

Consider the data consists of a series of n failures observed during the period of $(0,t_f)$. Let t_i denotes the time to failure of the i th event. The Laplace test statistics, U_L is defined by

$$U_L = \frac{\frac{\sum_{i=1}^{n} t_i}{n} - \frac{1}{2}(t_f)}{t_f \sqrt{\frac{1}{(12n)}}} \tag{3.1}$$

where:

t_i = the time of failure for i th event

n = total number of failures during the observation period $(0,t_f)$

t_f = observation end time (termination time). If the observation end time is a failure time at nth event (failure truncated), the above expression need to be modified by replacing n with $n-1$.

Under the null hypothesis, the test U_L approximately follows a standard normal distribution. Thus large positive or negative U_L values suggest that the process is not stationary (HPP). The null hypothesis is rejected if U_L is smaller or greater than the critical value read from the standard normal table for a given significance level. U_L value greater than 0 indicates degradation (concave up pattern) and less than 0 signifies improvement (concave down pattern) in the system performance.

3.3.4.3 Rate of Occurrence of Failure (ROCOF)

The changes in the pattern of failures can also be detected by examining the failure rate trend against the time. For repairable system, the failure rate, or commonly known as the failure intensity, can be estimated by calculating the rate of occurrence of failure (ROCOF). For a HPP process, the graphical plot of ROCOF over time should be constant (does not change over time) since HPP process has a constant failure rate. ROCOF for interval i can be estimated by the mean failure rate, v_i, which is the number of failures occurred in the evenly distributed time interval (t_i-t_{i-1}) divided by that time interval

$$v_i = \frac{\textit{number of failures in } (t_{i-1} - t_i)}{t_i - t_{i-1}} \tag{3.2}$$

3.3.4.4 Kaplan Meier Estimator

KM estimator (Kaplan and Meier, 1958) is a non-parametric method of estimating the reliability (survival) function from life-time data. It can be used for data with complete and censored events. The estimated reliability function, $\hat{R}(t)$, is a step function given by

$$\hat{R}(t) = \prod_{t_i \leq t} \left(1 - \frac{d_i}{n_i}\right) \tag{3.3}$$

Where $\hat{R}(t)$ is the estimated reliability for any particular point of time; n_i is the number of individual at risk just prior to time, t_i; and d_i is the number of individual that fails up during time period t_i. Thus, $\hat{R}(t)$ is based on the conditional probability that an individual survives at the end of interval provided that individual was existed at the start of the time period. $\hat{R}(t)$ is the product of these conditional probabilities and provides the point estimator for the reliability function at any particular time t. The variance of $\hat{R}(t)$ can be approximated using a Greenwood formula given by

$$\hat{Var}(\hat{R}(t)) = \hat{R}(t)^2 \sum_{t_i \leq t} \frac{d_i}{n_i(n_i - d_i)} \tag{3.4}$$

KM reliability (survival) function plot can be used to visually compare two different factors existed in the data for any difference in trend (which one is performing better). Statistical methods are used to test whether there is a significant between these two groups. Three statistical methods commonly used are Log-rank test, Breslow test and Tarone-Ware test.

3.3.4.5 Proportional Hazards Model

Another method of assessing effect of various factors to the system is the proportional hazard model (PHM) proposed by Cox (1972). In PHM analysis, these factors are also known as covariates, explanatory variables which can possibly affect the survival time (dependent variables). PHM or Cox regression model is the most important distribution-free regression model used for the analysis of censored data (Smith, 2002). According to Cox (1972) the hazard function of the equipment is composed of two parts; a baseline hazard function and a covariates dependent function. The model assumes a multiplicative effect of covariates to the baseline hazard function. The basic form of PHM is given by

$$h(t:z) = h_0(t)\psi(\beta^T z) \tag{3.5}$$

Where $h_0(t)$ is the baseline hazard function, ψ is the arbitrary function of the row vector covariates, z , and β is the column vector of unknown regression parameters. ψ can be represented in many functional forms, such as exponential, logistic and inverse linear and linear form. Cox (1972) proposed an exponential function due to its simplicity. Thus the PHM with k covariates can be expressed as

$$h(t:z) = h_0(t)\exp(\beta_1 z_1 + \beta_2 z_2 + \ldots\beta_k z_k) = h_0(t)\exp(\sum_{i=1}^{k}\beta_i z_i) \tag{3.6}$$

$h_0(t)$ is modelled as a non parametric thus making the PHM a semi-parametric model. The baseline hazard can also be fitted by a specific model such as Weibull, Gamma and lognormal thus transforming the hazard function into a parametric model. The advantage of having non-parametric model is that there is no need to make any assumption about the shape of the underlying failure distribution, thus eliminating the uncertainties about the model selection. The corresponding reliability function is given by

$$R(t:z) = R_0(t)^{\exp(\beta^T z)} \tag{3.7}$$

where $R_0(t)$ is the baseline reliability function. The regression parameter β can be estimated using partial likelihood method given by

$$L(\beta) = \prod_{i=1}^{n} \frac{\exp(\beta^T z_i)}{\sum_{k \in R_i} \exp(\beta^T z_k)} \tag{3.8}$$

where R_i is the risk set and z_i is the observed covariates at time failure time t_i. The calculation of the likelihood method is normally done using numerical method such as Newton-Raphson procedure. Test for significance of β is performed by analytical method such log-rank test, chi-square test and graphical methods.

For both KM and PHM approaches, the analysis is performed using SPSS statistical software. To fit into SPSS analysis, the data must be first prepared in appropriate format.

3.3.5 Inferential Analysis

The purpose of this step is to determine the best statistical model to represent the data. Figure 3.3 illustrates a general methodology used. Two major portions of works involved namely testing for independent and identically distributed (IID) data and fitting into lifetime distribution. For non-repairable items, the data is assumed IID, and hence can be directly assessed for lifetime distribution analysis (LDA). The data for repairable items, on the other hand, need to be arranged in chronological ordered before they can be tested for IID assumption. The importance of ensuring the data are IID before they can be used for prediction model cannot be emphasized enough. The existence of trend exhibits that the data are not in steady state thus cannot be fitted into any statistical lifetime probability distribution. In this case, a non-stationary model such as NHPP might be suitable. The predicted reliability and maintainability measures are highly influenced by the types of distribution and its parameters (Rausand and Hoyland, 2004), hence the use of inaccurate and poorly fitted distribution will definitely produce wrong results. Laplace's test has been widely used to test for identically distributed assumption (Ascher and Feingold, 1984) whereas serial correlation test is employed to determine independence condition (Ansell and Philips, 1994). Laplace test is also used to determine whether the data can be fitted into HPP distribution. Alternative method is based on a steady state trend of a ROCOF plot.

When the data exhibit IID characteristics, they will be fitting into a lifetime distribution model following a well established process. First, the distribution is selected then its parameters are estimated either using a least square (rank regression) or maximum likelihood estimation (MLE) method. Rank regression method is preferable when the data is complete and many (more than 30). When data consists of suspension data and is small, MLE is the better choice (ReliaSoft, 2005). Next, the goodness of fit test is carried out to assess if a hypothesized probability distribution for the data provides a good fit. Several types of test exist which include general test such as Chi-square, Kolmogorov–Smirnov and Anderson Darling which can fit multi-distribution. For more powerful test on specific distribution, there are specific type test that include Bartlett (Exponential), Mann (Weibull), Kolmogorov–Smirnov (normal and lognormal), and Cramer-Von Mises (NHPP) (Ebeling, 1997). Weibull ++ software uses correlation coefficient and log-likelihood value for goodness of fit when analyzing data with rank regression and MLE method respectively. When trying to find the best fitting lifetime distribution of reliability data sets, a common approach is to use general test to prioritize selection based on the smallest probability value (p-value) out of those hypothesized distributions. Alternatively, a combination of various statistical tests can be employed to propose the best distribution for the data. For example, in Weibull ++ software three factors namely Kolmogorov-Smirnov test, a normalized correlation coefficient and the likelihood value are analyzed based on statistical test values and assigned weights to rank distributions based on fit to the data.

3.3.6 Estimation of Reliability and Maintainability Measures

Based on the appropriate lifetime distribution selected and its associated parameters, the measures of reliability and maintainability can be determined. Reliability measures include reliability function, expected MTBF and percentual time to failure. Maintainability function, mean duration of maintenance task (MDMT), mean time to repair (MTTR) and percentage restoration time are the common measures for maintainability. The obtained measures are then to be interpreted accordingly to provide a basis for suitable recommendations for system improvement (e.g. which equipment is critical, hence should be focused on by management).

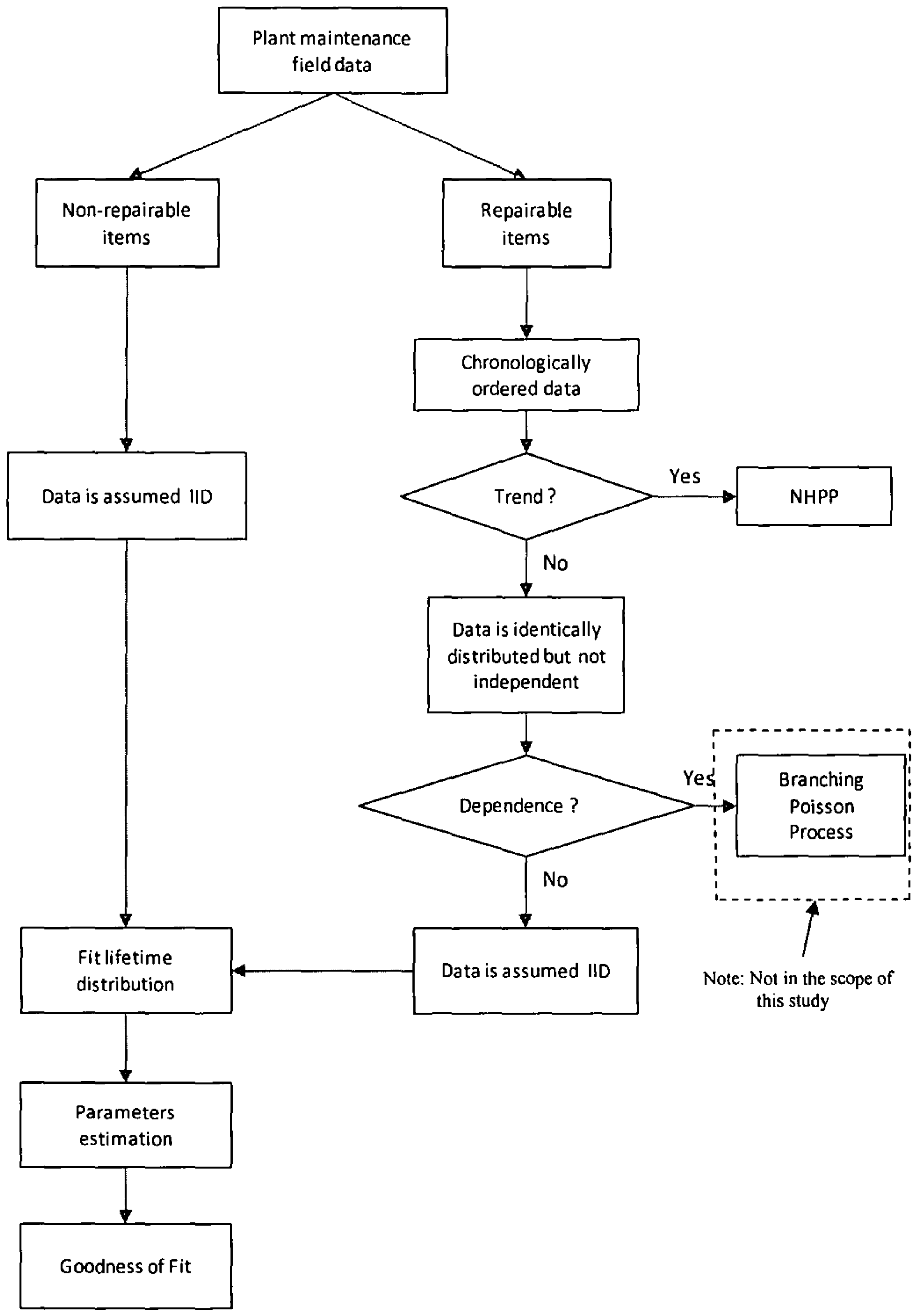


Figure 3.3: Proposed flow of inferential analysis in R&M studies of plant field data

3.4 Availability Analysis

A simulation-based approach is proposed in the availability analysis of a system, in contrast to analytical method used in reliability and maintainability measures. For simulation to be effective, great deal of efforts, systematic planning and organization are required (Mishra, 2006). General steps in performing simulation analysis can be found in Banks *et al.* (2010), Averill (2007) and ReliaSoft Corporation (2009). Marquez *et al.*, (2005) and Herder *et al* (2008) provide examples on how availability simulation can be approached in analysis of process industry data. The proposed approach used in this research is built on that of Bank *et al.* (2010) and is illustrated in Figure 3.4. The details of each step are discussed here:

i. *Define the problem, objective and system* - The problem and objective must be clearly defined at the beginning of the analysis. The objective will specify sets of questions to be answered by the study (Banks, 1998). The boundary, subsystems or equipment and their relationships, maintenance scheme, operating procedures and conditions of the system have also to be clearly specified.

ii. *Gather data* –Relevant process flow diagram and piping and instrumentation diagram (P&ID) within the boundary of the system under study are gathered and later used to develop the system conceptual reliability block diagram (RBD) model. Other vital information to be captured includes the reliability and maintainability (R & M) data related to failures and downtime, and the operation and maintenance characteristics such as equipment loading and maintenance schedule.

iii. *Make assumptions on model* - Various assumptions used need to be defined upfront together with specific measures for assessing the system's performances such as reliability, maintainability and availability. These assumptions include those related to failure and repair time definitions, maintenance operation, perfect switching condition, operation states and application of constant failure rate.

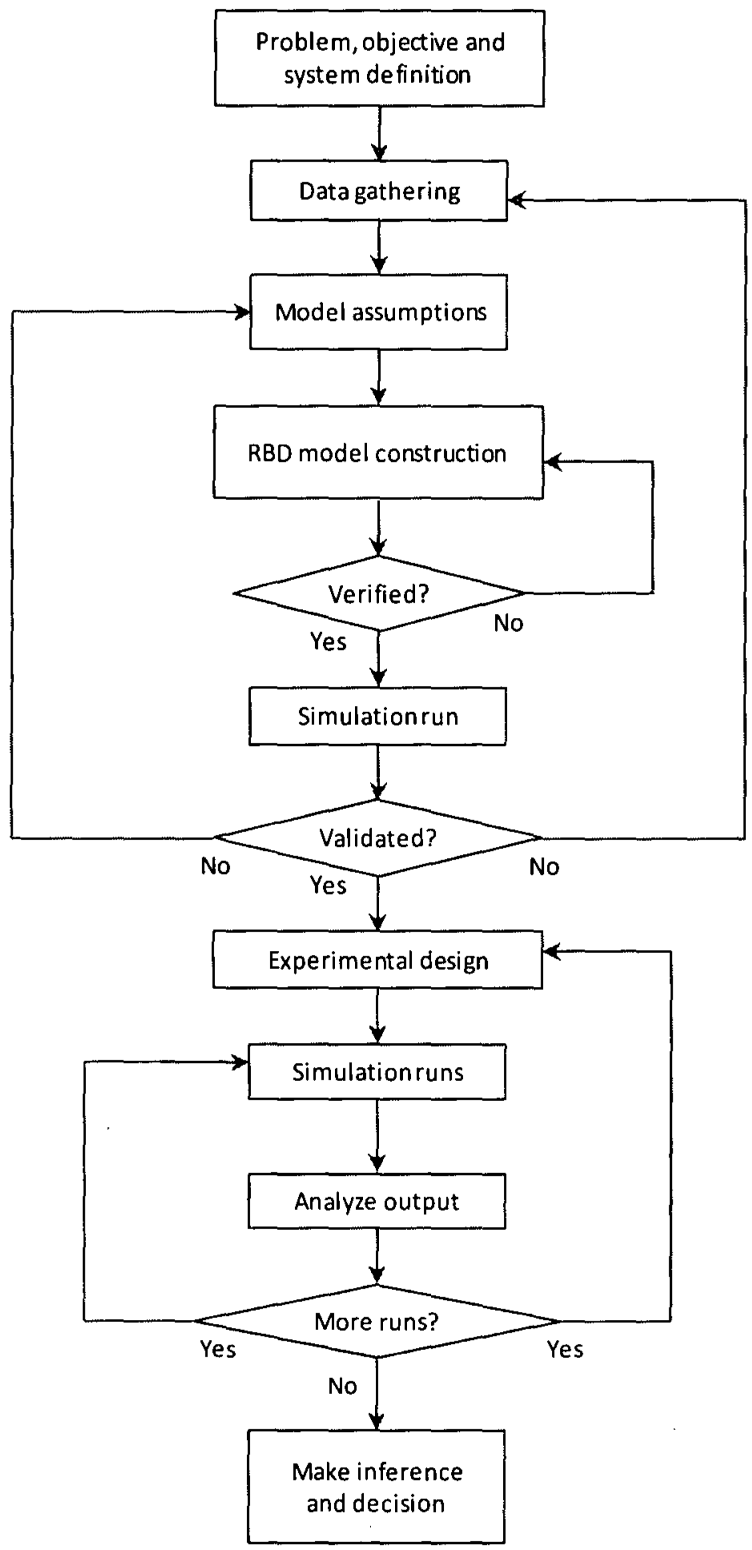


Figure 3.4: Proposed framework for analysis of system availability

iv. *Construct RBD model* -The aim here is to represent the actual system under study with a conceptual model which is adequate and capable of achieving the analysis goal. Normally a conceptual model starts with a simple model and allows for more complexity to be added on in later stage. RBD is used to represent the system configuration in which each block is used to represent a component or subsystem or function in the system. Plant personnel involvement and verification are needed throughout model development to ensure that the model is practically correct. The RBD based conceptual model is developed using computer simulation software named Blocksim. In Blocksim, RBD and its connecting lines are constructed to describe dependencies relationship. Inputs into the model are provided in the form of probability distribution of time to failure and repair time derived from the results of reliability and maintainability analysis done earlier (Figure 3.5). For repair time data, they comprise those of corrective (unplanned shutdown) and preventive maintenance (planned shutdown). Other important input is maintenance characteristics such as PM types and schedule, and depending on the study objective, may also include crew, spare parts logistics and costing.

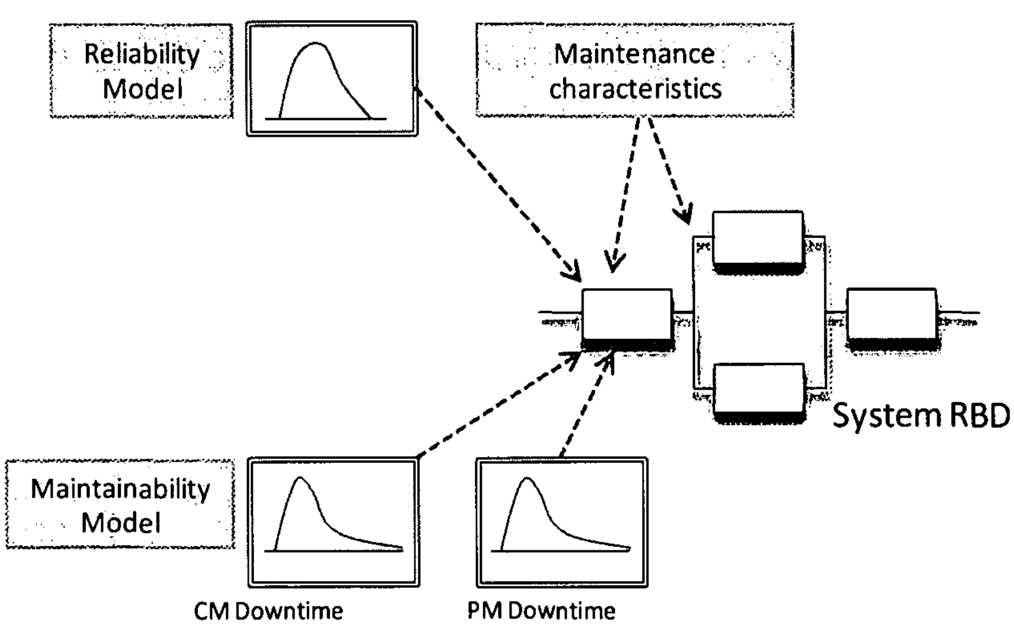


Figure 3.5: Data input requirement for RBD and each of its block in Blocksim

v. *Verified?* - Before a simulation is run, it is important to verify that the model is correct and ensure that plant personnel agree with the model. If this is not met, the model has to be reconstructed and re-verified.

vi. *Run simulation* - The model having inputs of existing system parameters, conditions and historical data is simulated to estimate the system availability for a specified duration. Simulation is performed using a Monte-Carlo technique by simulating system operation based on failure and downtime distributions. During simulation, random failure times and downtime duration from each component's distribution are generated. The results from each component are then combined according to RBD reliability-wise arrangement and analyzed to establish the overall availability of the system. Sensitivity analysis, a study on output variations by varying certain variables, can also be performed here to reduce model uncertainties.

vii. *Validated?* – The result of the simulation is then compared with the corresponding real system performance. This process refers to model input-output transformation validation, where the model obtains input parameters and transforms them into output of measures of performance of which they are validated against the actual system performances (Banks *et al.*, 2009). Changes in the model and its inputs are needed when the accuracy of the result is not satisfactory. This is an iterative process, where it is repeated until model accuracy is justified.

viii. *Experimental design* – In here "what if" scenarios or improvement options and their simulation design have to be determined. Simulation design also involves specifying the length, number of runs and mode of initialization for every scenario planned (Banks, 1998). Proper number of simulation and duration are necessary to produce stable output with minimum variation.

ix. *Simulation runs* - Once the experimental design is set, the simulation is conducted to estimate measures of performance relevance to the objective of the study for each scenario.

x. *Analyze output* - From the simulation output, the availability estimation for the system can be made. Other statistical analysis can also be performed based on the results of simulation such as criticality analysis of each block in terms of reliability, downtime and availability.

xi. *More runs?* – Based on the results obtained, decision can be made on whether additional runs are needed and what design of those additional runs should be. Additional runs are normally required for sensitivity analysis, a study on output variations by varying certain variables. It is also performed to understand the influence of various factors on the system overall performance.

xii. *Make inference and decision* - Based on the output results, appropriate conclusions can be made such as estimated system availability after certain years of operation based on existing performance, identification of the most critical equipment with respect to reliability and downtime, and quantification of the effect of redundancy, equipment, manpower and maintenance actions to the system's availability. From these findings, effective decisions can be formulated accordingly to improve the system.

3.5 Case Studies

In this research, two case studies are presented. The first is on a gas compression train system at the offshore platform and the second is on an acid gas removal unit system in a gas processing plant. The description on both systems is discussed below.

3.5.1 Gas Compression Train System

A gas compression train (GCT) system is an important section of gas compression system at a central processing offshore platform, which functions to transfer gas from all producing platforms in the field to onshore facilities. The availability of GCT is critical to ensure smooth and sufficient supply of gas as demanded by customer. The gas production from this field is significant since it is one of the main sources of gas and often acts as a buffer in case of supply shortages in other fields. With the increase in demand and declining trend in gas fields and capacity, the pressure to operate the system in high reliability and availability has increased more than ever. Even though there are new producing satellites that will temporary ease the tight supply condition, the overall production still depends on the aging GCT system reliability. Hence, in order to overcome these challenges, it is vital for the system performances to be continuously monitored and improved.

Figure 3.6 illustrates the gas production flow and gas compression system on the offshore platform with gas compressor as the main equipment together with other equipment such as separators, scrubbers, glycol contactor and heat exchangers. Natural gas produced from wells can be categorized into two; non associated gas and associated gas. Non associated gas (NAG) mainly contains pure gas at high pressure and flows out from reservoir that contains gas with no or very minimum oil, whereas associated gas (AG) refers to a gas that dissolved with oil at high pressure existing in reservoir and can also be present as a gas cap above the oil (Hyne, 2001). The NAG from a gas well has high temperature that needs to be cooled in by a wellhead cooler before being routed to the subsequent processes. The gas then passes a 2-phases gas production separator which separates crude and/or condensate from the gas before the gas is sent to glycol contactor. The AG comes from oil well is being processed at the low pressure (LP) system. After going thru a 3-phases oil production separator which separate crude oil, gas and oil water, LP gas is cooled in by a cooler before being routed to the gas separator. Here, the remaining crude and/or condensate are being separated from the gas.

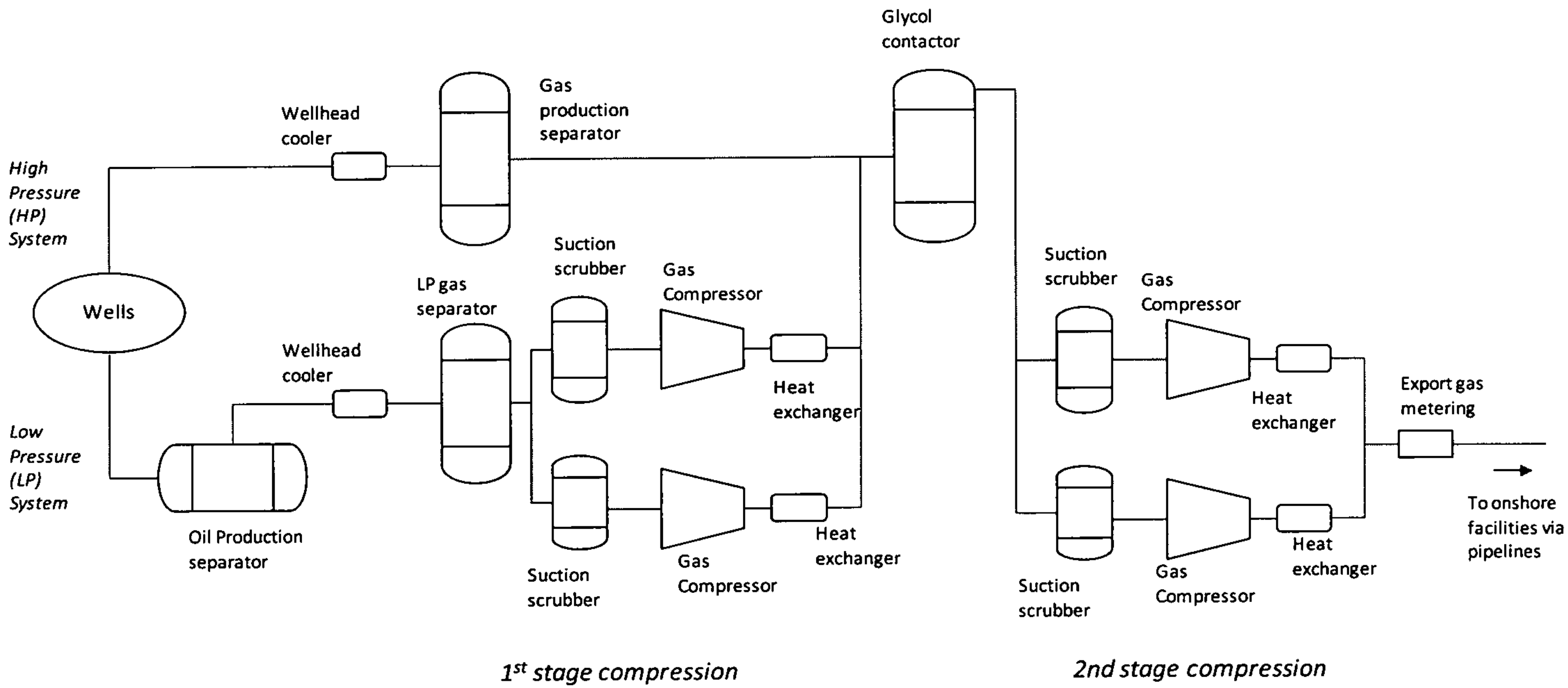


Figure 3.6: Schematic of gas compression system and simplified gas production flow

LP gas has to go thru 2 stages of gas compression compare to only 1 stage for HP gas to achieve the desired export discharged pressure. Before undergoing the first compression stage, LP gas is sent to suction scrubber to separate and dispose the remaining liquid in the gas. The compression process is done by a centrifugal compressor driven by a gas turbine. Next, the LP gas is cooled in before it joins HP gas into a glycol contactor for a dehydration process. Gas dehydration is a process of removing water vapour from a gas stream to lower temperature (dew point) at which water will start to condense from a gas stream. This will prevent hydrate formation and corrosion from condensed water (Arnold and Stewart, 1999).The gas enters the glycol contactor from the bottom contactor drum and flows upward. Glycol, a water absorption agent, is pumped into the upper part of the drum and it cascades down inside the drum coming into contact with the gas and absorbs any water in the gas. Next, the gas passes a suction scrubber and a centrifugal compressor for 2nd stage compression. After being cooled in by a heat exchanger, the gas is routed to gas metering skid before it is sent to onshore facilities via 32", 166 km pipeline.

3.5.1.1 GCT Description

The heart of gas compression system is a gas turbine compressor package consists of gas turbine, centrifugal compressor and support equipment. It is a common practice in the industry to regard this package as a single system for the purpose of design, safety, maintenance data collection and analysis (Wall *et al.*, 2006). In this study, for simplicity, this package is referred as a gas compressor train (GCT) system. There are two compressor trains; train 1 and 2, running in parallel to compress gas for export in the system. Each train consists of a 32,000 hp aero-derivative gas turbine which drives a single barrel casing two-staged inter-cooled centrifugal gas compressor. The operation philosophy is to run one train whilst another train is standby during low production, and run both trains when the production demand is high. During early years of production where the production was low, the plant always ran on one train configuration (single loading). However, beginning in 2005, when the production picked up, both trains were operated concurrently, except the time when either one of the trains was down due to failure or PM activities. The design capacity for each train is 225 mmscfd (million standard cubic feet per day) of gas, and with the combined two trains at 550 mmscfd. Figure 3.7 shows a schematic diagram of main components of a gas compressor train. Other important components not shown in the diagram are ancillary equipment such as lube oil and control systems. The system boundary of the GCT is defined and illustrated in Figure 3.8.

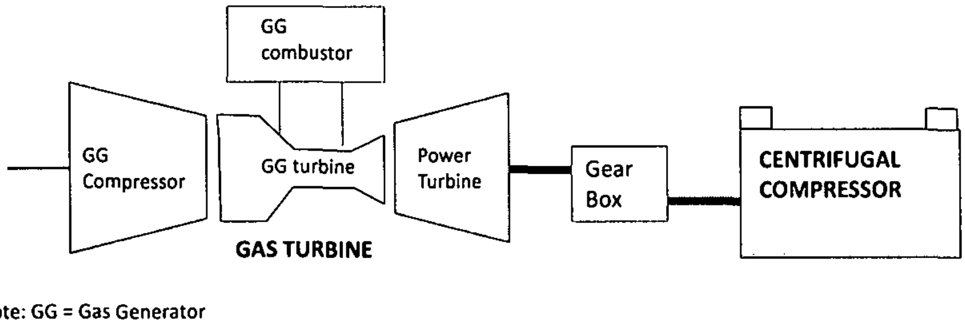


Figure 3.7: GCT diagram which shows a gas turbine drives a centrifugal compressor via a speed increaser gear box

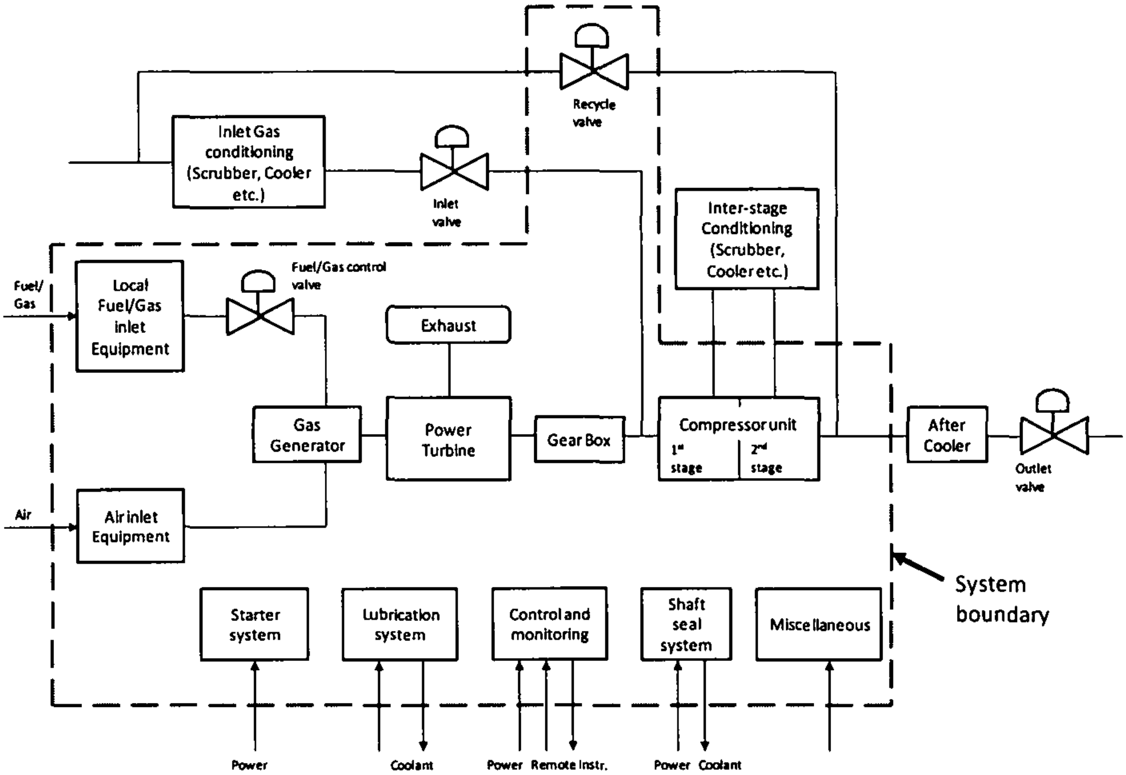


Figure 3.8: GCT system boundary (adapted from OREDA (2002))

3.5.2 Acid Gas Removal Unit (AGRU) system

The second case study is on an acid gas removal unit (AGRU) system, part of systems in a gas processing plant (GPP). There are four GPPs: GPP1; GPP2; GPP3; and GPP4, in operation in the petrochemical integrated complex. GPP treats and processes raw natural gas (NG) from gas fields offshore of the East Coast of Peninsular Malaysia and turns them into various products such as methane (sales gas), ethane, propane, butane, and condensate. A GPP's simplified process flow, its various systems and products are shown schematically in Figure 3.9. GPP can be operated in two operation modes; C_2 mode and C_3 mode. AGRU operation is running (on-line) when GPP is under C_2 operation mode, and by-passed in C_3 operation mode.

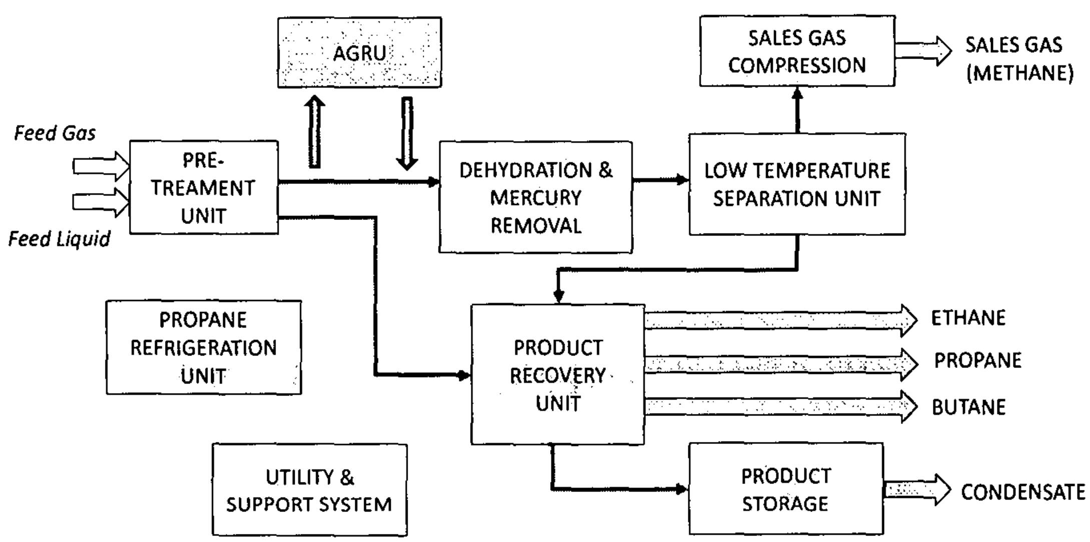


Figure 3.9: Simplified process flow of GPP

AGRU primary function is to remove H_2S (hydrogen sulfide) and CO_2 (carbon dioxide), which are corrosive and toxic contaminants, from NG. This process is also known as sweetening, in which the level of sulphur compounds concentration in NG is reduced from high (sour gas) to low (sweet gas). H_2S can form acid when reacting with water, hence can cause corrosive damage to gathering / boosting and transmission pipelines, compressors, pneumatic instruments, and distribution equipment. H_2S is also odor, poisonous and its total sulfur content is normally regulated. CO_2, on the other hand, is a greenhouse gas and its high content in NG can lower the production, transportation and storage efficiency. Beinfield process is used to remove these acidic gases from the gas stream by treating NG with Beinfield solution containing Potassium Carbonate (K2CO3), Vanadium Pentoxide (V2O5) and Diethanolamine (DEA).

In AGRU system, sour gas enters absorber A-201 at the bottom after passing thru heat exchangers. A lean Benfield solution is fed at the top section of the absorber to absorb H_2S and CO_2 from the up-flowing sour gas. The resulted sweet gas from the absorber is next cooled in heat exchangers and channelled into separator drum M202, to separate condensate, before further processing. A rich Beinfield solution containing the absorbed acidic gases is then routed to a regenerator (stripper A-202 with reboiler T204). Here, the gas is stripped to produce concentrated H_2S and CO_2 overhead gas. Lean Beinfield solution is regenerated in T204 reboiler and then fed into storage pump M203. From here, the lean solution is returned to the absorber via pumps (P202 and P201). The generator overhead is condensed in air cooler T206 and collected in regenerator accumulators (M204 and M205) before sending for regeneration (reboiler T205) and recycle. Acid gases remain uncondensed and exit accumulators for further processes (eg. vent out to atmosphere etc.).

3.6 Chapter Summary

In this chapter the methodologies used for conducting practical reliability, maintainability and availability analysis on plant system are presented. Here, the focus is on a realistic approach on how to effectively use and systematically analyse field maintenance data for improving system operation and maintenance performance. The proposed methods utilize modelling approach based on systems approach to model real system, analyse it using appropriate techniques and interpret the results accordingly. For reliability and maintainability analysis, a generic framework is presented. In this framework, the analysis process consists of six main steps namely: setting objectives, definition of system and failure, data gathering, exploratory analysis, inferential analysis and finally estimation of reliability and maintainability measures. The methodology presented for availability analysis is built upon RBD modelling and simulation techniques. To run a simulation, a computer simulation tool is needed. In this research, specialized reliability simulation software named Blocksim is utilized to achieve the objective.

CHAPTER 4

RELIABILITY ANALYSIS

4.1 Introduction

Reliability analysis as an important plant improvement tool for assessing the performance of existing operational system is discussed and demonstrated in this chapter. The analysis process is performed based on a systematic approach proposed in the previous chapter. The focus of the study is on real industrial data for a repairable system of gas compression train system (GCT) at an offshore platform.

4.2 Objectives of the Analysis

Maintenance data with proper statistical analysis techniques can help management to assess plant performance by giving insights on how well the performance of the existing or particular system and critical factors influencing the system performance (Ansell and Philips, 1994). From discussions with plant personnel, some of the common concerns about the plant performance include;

- How is the performance of the current system? Is it in improving or deteriorating or steady state?
- What are the critical factors that influence the system performance?
- How well is the current maintenance practice? Does it help to enhance the system lifetime and reduce the breakdown duration?
- What is the prediction of the future system performance in terms of failure rate, mean time to failure (MTBF), number of failures and availability?

A clear understanding of the above aspects about plant condition is fundamental for achieving high reliability and performance plant. Identification of the influential factors to system performance is crucial to plant operation so that appropriate actions can be rendered. To address those concerns, the following objectives have been set for the study of the gas compression train system:

i. To analyse maintenance data to gain insight into the existing and future system performance
ii. To identify dominant factors of system reliability in terms of subsystem and failure mode
iii. To assess the influence of other important factors such as preventive maintenance (PM) on the system lifetime
iv. To determine system reliability measures such as failure rate and mean time between failures (MTBF)

4.3 Maintenance Data

Sufficient, well formatted and quality maintenance data are fundamental for the success of reliability and availability analysis of gas compressor train. Field maintenance data are being recorded in the computerized maintenance management system (CMMS) database and turbo-machinery engineering availability tracking record. The latter is the main recording data for monitoring train's availability performance and hence, will be used as the prime data source for the reliability and availability analysis of the system in this research. CMMS is generally used for verification purpose. An example of the availability tracking report is described in Figure 4.1. This report contains details of critical failures (failures that cause train to shutdown) and maintenance activities. Turbo-machinery engineering group has started developing this data record since April 2002, when the system operation was handed over to the maintenance team even though the first commercial production of gas was in January 2002. Engineers use this report for their continuous monitoring and reporting of gas compressor train performance. The train operation data are captured on a daily basis and the time duration for each event is reported in hours. The events are broken down into four categories:

i. Utilization (UTIL) – normal operation states
ii. Standby (S.B) – standby mode due to low production demand and external events such as to emergency shutdown (ESD), plant shutdown and turnaround
iii. Planned shutdown (PSD) – shutdown caused by planned preventive maintenance (PM) activities
iv. Unplanned shutdown (USD) – shutdown as a result of corrective maintenance (CM) actions due to failures

From the report, the following important data for each train can be obtained:

- Failure frequency, time and downtime duration
- Failure modes, causes and corrective actions
- Causes of shutdown i.e. CM, PM, ESD, turn-around and plant shutdown
- Scheduled maintenance time and duration
- Train operation modes such as standby, down, single loading and shared loading
- Performance measures i.e. reliability, availability and utilization

The time between the successive failures data can also be established from the report. The time between failures is based on the actual operating days where it is calculated only when the train is running, and not counted when it is not in operation either due to failure, PM or standby. To facilitate the process, the data are rearranged in the special format to capture this critical information together with other important information such as start-up failure and operation loading mode. A sample of the formatted data can be seen in Appendix A.

The existing format used by field engineers in the availability tracking report is commendable since it keeps track on the exact timing of each event on hourly basis, hence make it easier to perform analysis on time between failures (TBF) based on operating days. Nevertheless, there are some issues with regard to the historical data.

In the early years of data recording, the event data was recorded either as a standby or a shutdown, regardless whether it was unplanned shutdown (USD) caused by failures, or planned shutdown (PSD) due to preventive maintenance actions. Starting from January 2005, a significant improvement had been made in the recording format, where the shutdown data were further divided into USD and PSD for better tracking. The data also suffer from common issues such as missing, incorrect and incomplete information, for example, the reasons for certain system downtime. Furthermore, some of the failure causes are unambiguous, for instance, failures related to compressor are not clearly specified whether they belong to turbine compressor or centrifugal compressor. To overcome these uncertainties and maintain the integrity of the data, clarification on failure and downtime data from respective engineers are highly critical. Throughout the study their active involvement and inputs are continuously sought to ensure the data and analysis are valid and relevance.

Besides these two records, other related reliability data can be found in monthly turbo-machinery performance reports by turbo-machinery engineering group, root cause failure analysis (RCFA) reports and vendor / supplier reports.

TURBO MACHINERY AVAILABILITY AND UTILIZATION										
AUGUST 2005										
DAY	HOURS									
	C-2420 (Train 1)					C-2450 (Train 2)				
	UTIL.	S.B	PSD	USD	TOTAL	UTIL.	S.B	PSD	USD	TOTAL
1	24				24	24				24
2	24				24	24				24
3	24				24	24				24
4	24				24	24				24
5	24				24	24				24
6	24				24	24				24
7	21.5	2.5			24	24				24
8		24			24	24				24
9		24			24	24				24
10		24			24	24				24
11	4	20			24	24				24
12	24				24	24				24
13	24				24	24				24
14	24				24	24				24
15	24				24	24				24
16	24				24	24				24
17	24				24	24				24
18	24				24	24				24
19	24				24	24				24
20			24		24	24				24
21			24		24	24				24
22			24		24	24				24
23			6	18	24	24				24
24	16			8	24	18		6		24
25	24				24	19		5		24
26	24				24	24				24
27	24				24	24				24
28	24				24	24				24
29	24				24	24				24
30	24				24	24				24
31	24				24	0.75			23.25	24
TOTAL	545.5	94.5	78	26	744	709.75	0	11	23.25	744
	UTILIZATION %				73.3	UTILIZATION %				95.4
	AVAILABILITY %				86.0	AVAILABILITY %				95.4
	RELIABILITY %				96.5	RELIABILITY %				96.9
	SHUTDOWN %				10.5	SHUTDOWN %				1.5

Note: UTIL = utilization, SB = standby, USD = unplanned shutdown, PSD = planned shutdown

Figure 4.1: Sample of availability tracking report

4.4 Exploratory Analysis

Based on plant engineers' recommendation, the failure data of gas compressor train can be categorized into 10 areas or subsystem for the purpose of data analysis. Table 4.1 depicts these subsystems and their respective coding. The field data used in the analysis are based on the data from 2002 till 2009.

Table 4.1: GCT subsystems and coding

No.	Subsystem	Code
1	Gas Turbine	GT
2	Centrifugal Gas Compressor	GC
3	Starter System	STS
4	Gearbox	GB
5	Fuel System	FS
6	Vibration Monitoring System	VMS
7	Anti-surge Valve System	AVS
8	Lube Oil System	LOS
9	Process and Utilities	PRO
10	Turbine Control System	TCS

4.4.1 Pareto Analysis

Figures 4.2 and 4.3 describe the failure breakdown charts according to subsystems for both trains. For train 1, major contributors to system failures are gas turbine (GT) and turbine control system (TCS) which both constitute two-thirds of total failures. Gas turbine, centrifugal gas compressor and process subsystem are the main causes for train 2 failures where together account for about two-thirds of the train failures. For the overall GCT (combination of train 1 and 2), gas turbine related failure is the highest contributor toward system breakdown followed by turbine control system as indicated in the Pareto chart in Figure 4.4. Further analysis on gas turbine failures reveals no dominant failure mode exists as the causes of failures are varied. The highest mode, about one-fifth of total failures (4 out of 21 failures), is a start-up failure after maintenance actions. This failure mode, however, mainly occurred in early years of train operation and has shown decreasing trend recently. The prime causes for turbine control system failures are related to faulty transmitter and programmable logic controller (PLC). Turbine control system failure has occurred more frequently lately as illustrated in Figure 4.5 and hence should be appropriately attended and resolved by turbo-machinery engineers.

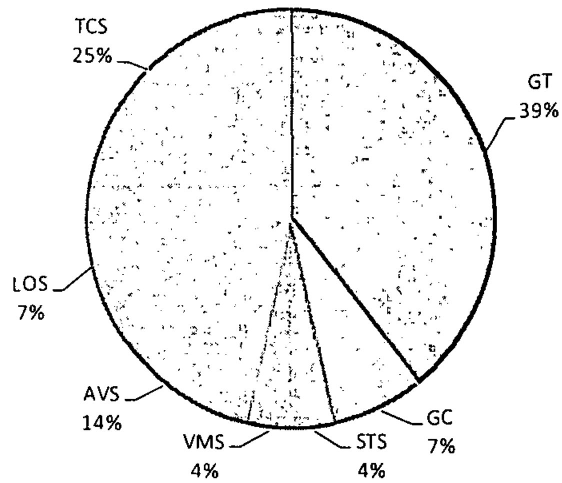


Figure 4.2: Train 1 CM breakdown by subsystems

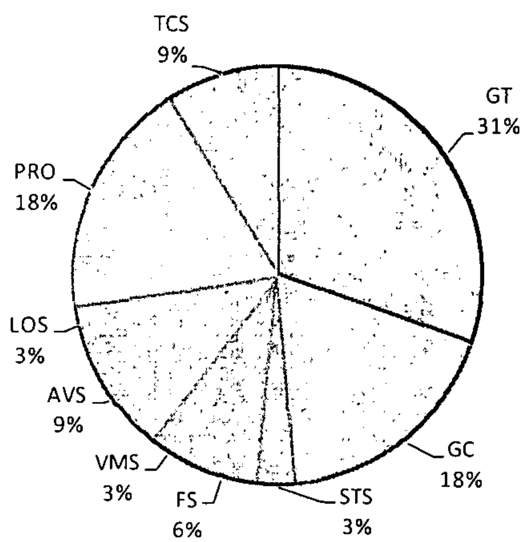


Figure 4.3: Train 2 CM breakdown by subsystems

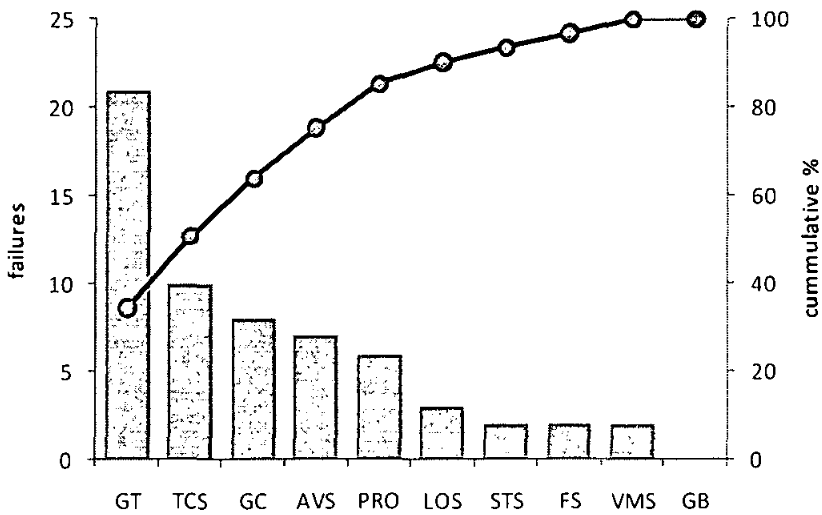


Figure 4.4: Overall GCT failure frequency by subsystem

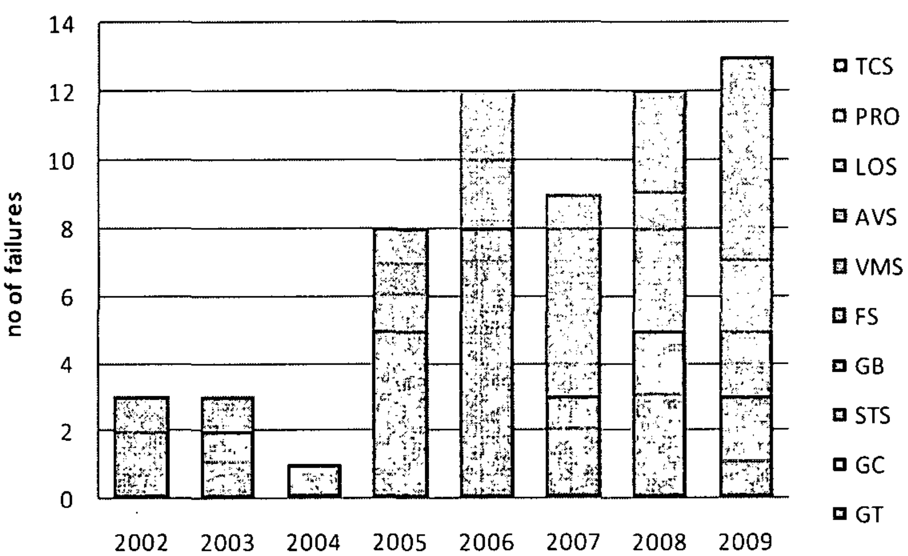


Figure 4.5: Overall GCT failure frequency trend

4.4.2 Trend Analysis

The processed operational data of time between failures for both trains is tabulated in Table 4.2. The resulted plots for train 1 and 2 are shown in Figures 4.6 and 4.7, respectively. The trend plots for both trains exhibit a linear pattern with no indication of monotonously increasing (concave up) or decreasing (concave down) pattern, hence signifies that the train performance in neither improving nor deteriorating. To test for this assumption, the statistical Laplace test based on Equation 3.1 with failure truncated is performed. The calculated Laplace statistics value, U_L, for train 1 and 2 is 1.409 and 0.484 respectively. These results are found not to be statistically significant at 95% confidence level (z = +/- 1.96). Thus the assumption based on the graphical method earlier is acceptable that the data do not exhibit any monotonic trend. This non-monotonic failure data trend suggests the failure process can be modelled by a simple homogeneous Poisson process (HPP) where the inter-arrival time between failures follows exponential distribution.

To look at how the failure rate change over time, the ROCOF based on time interval of 200 days is calculated. The plots of estimated ROCOF for respective train are shown in Figures 11 and 12. The plots indicate that there are no increasing or decreasing trends in failure rates for both trains. The failure rate for train 1 looks rather constant with little fluctuation throughout the observation time. For train 2, the plot also exhibits somewhat constant trend over the time period, however a slight increase in failure rate is noticeable near the midpoint of observation period. Based on the Equation 3.2, the estimated failure rates for train 1 and 2 are about 0.013 and 0.015, respectively.

Table 4.2: Time between failures based on operation days

	Train 1		Train 2	
Failure No	Time between failures (Days)	Cumulative operating time (Days)	Time between failures (Days)	Cumulative operating time (Days)
1	15	15	22	22
2	6	21	31	53
3	195	216	327	380
4	295	511	132	512
5	107	618	77	589
6	129	747	6	595
7	65	812	104	699
8	20	832	17	716
9	22	854	42	758
10	118	972	45	803
11	32	1004	208	1011
12	263	1267	22	1033
13	113	1380	28	1061
14	5	1385	8	1069
15	84	1469	56	1125
16	31	1500	22	1147
17	23	1523	7	1154
18	43	1566	30	1184
19	217	1783	151	1335
20	6	1789	17	1352
21	52	1841	64	1416
22	126	1967	89	1505
23	30	1997	100	1605
24	12	2009	80	1685
25	3	2012	4	1689
26	68	2080	91	1780
27	3	2083	124	1904
28	216	2299	62	1966
29	27	2326	7	1973
30	4	2330	26	1999
31	15	2345	3	2002
32	23	2368	103	2105
33	3	2371	3	2108
34	179	2550	119	2227
35	13	2563	26	2253
36			129	2382

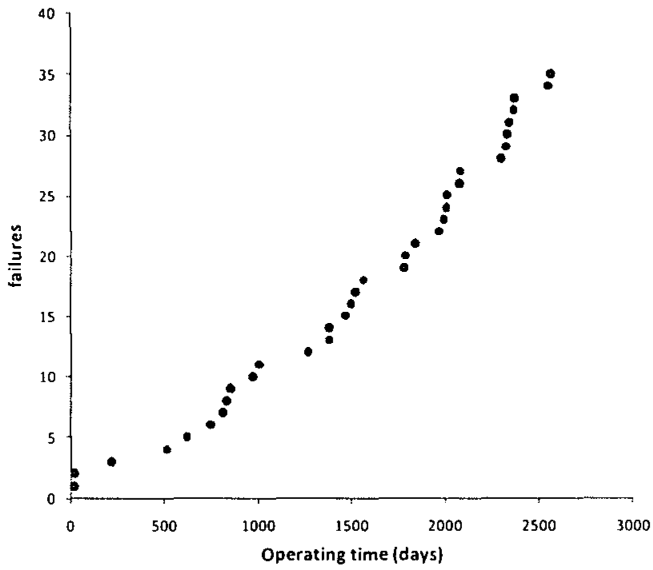


Figure 4.6: Cumulative failures versus cumulative operating days for train 1

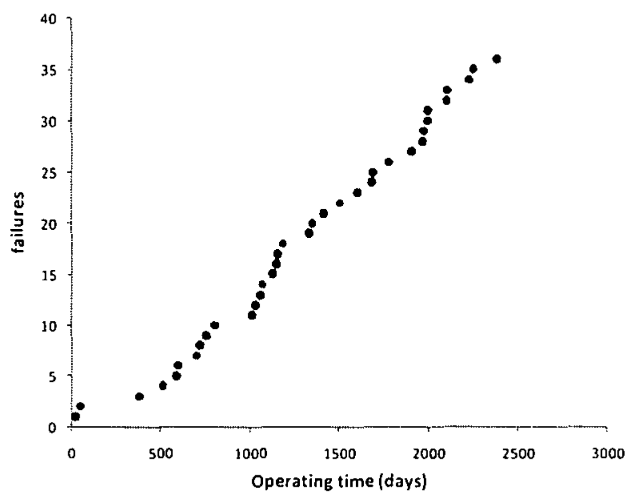


Figure 4.7: Cumulative failures versus cumulative operating days for train 2

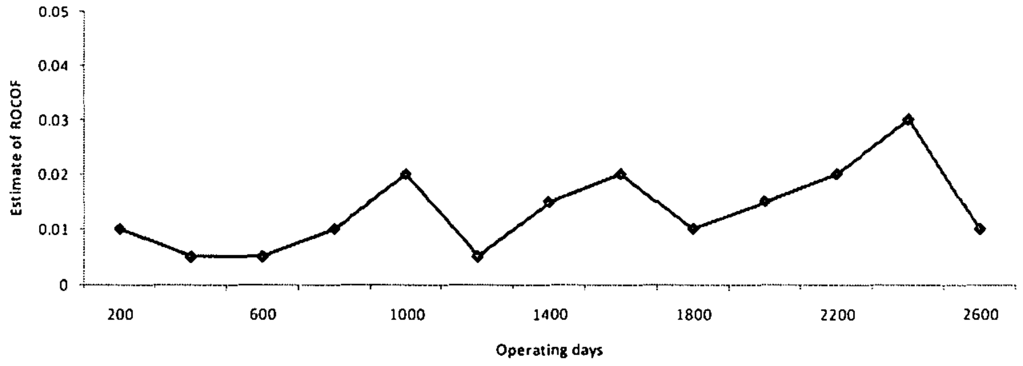


Figure 4.8: Estimated ROCOF for train 1

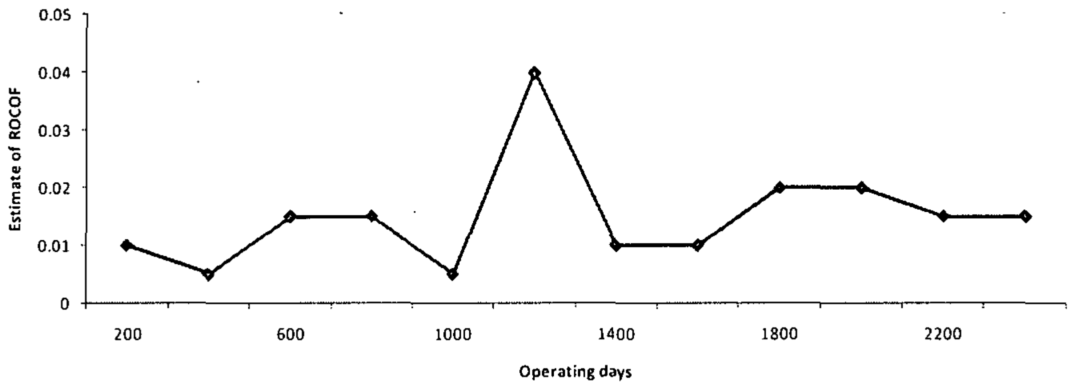


Figure 4.9: Estimated ROCOF for train 2

4.5 Analysis of Other Factors Influencing System Reliability

Besides subsystems, there are other factors that can possibly influence the train reliability performance, thus worth to be investigated. These possible factors sometimes may not be explicitly found in raw data, but can be identified by plant experts based on their extensive experience and detailed observation on the system. Any of these factors can be considered significant when it can shorten or lengthen mean time between failures. Based on discussions with plant personnel, the following factors or covariates are suspected to have some influence on the system reliability performance:

i. Train: Both trains are designed to produce the same performance, however based on the maintenance data, train 2 experiences longer shutdown duration than train 1.

ii. Operation loading mode: When both trains are in operation, the load is shared equally between them i.e. shared loading. When one train is down, another train has to take up the entire load i.e. single loading. This extra loading may increase stress on that running train.

iii. Subsystem: Almost 50% of the failures come from gas turbine and gas compressor. It is useful to understand the impact of these gas turbine and compressor related failures to the overall system failure frequencies.

iv. Failure after start-up: Frequent start up operation due to switching back of operation mode to operating state could be detrimental since it may induce stresses on the equipment which in turn leads to wear out problem. The occurrence of failures right after train being put up into action (including start-up failure) may be a symptom of this deterioration, hence could potentially shorten the elapsed time to the next failure. A switching operation is considered when train resumes normal operation after being in standby mode and shutdown due to failures and PM actions. In the case of standby mode as a result of low demand, a start up operation is assumed only when the equipment has been in standby for more than four hours.

v. Maintenance activities: Maintenance activities such as PM and engine wash are supposed to reduce number of failures and increase the time between failures of the system. Sometimes the maintenance impact can be insignificant or detrimental to the system performance.

4.5.1 Covariates Analysis

To test for the above assumptions and determine influential factor(s) affecting reliability, two approaches are used: Kaplan Meier (KM), and Proportional hazard model (PHM).

4.5.2 Modelling of Covariates

Let the time to failures of n number of failures be $t_0, t_1, t_2, t_3, \ldots, t_n$, with $t_0 < t_1 < t_2 < \ldots < t_n$. t_0 is the arbitrary time which mark the beginning of the observation period. The time between failures (inter-arrival) are denoted by X_i, where $X_i = t_i - t_{i-1}$. For illustration, let consider a PM as the covariate. Assume there is a PM activity being carried out in between t_1 and t_2 as illustrated in Figure 4.10. In this model the impact of that PM on the failure distribution is measured basically by the length of X_2; how effective is the PM to extend the X_2 period. For other covariates, except failure after start-up, the model follows the same notation. For example, let assume the 2nd failure occurs at time t_2 in the presence of a covariate, thus the effect of that covariates can be translated in the duration of X_2. In the case of failure after start-up covariate, however, the covariate's impact is measured based on X_3 instead of X_2. Here, we are interested to know the impact of failure after start-up to the next failure event and not prior to that.

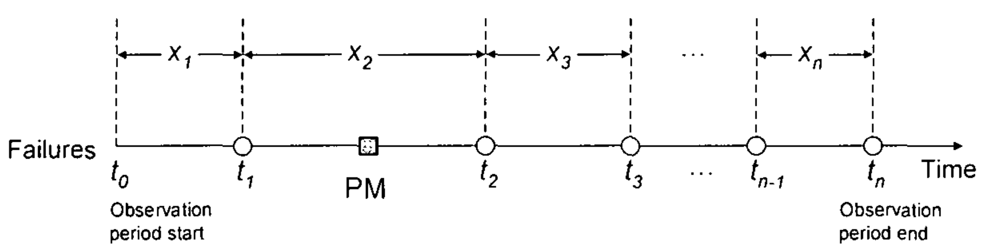


Figure 4.10: Modelling of failures for PM covariate

Once the model is determined, the manipulated data are then analysed for KM and PHM using SPSS software. Table 4.3 shows the grouping of covariates used in the analysis. Group 1 is assumed to have more significant effect on survival plot. The covariates consist of train, operation mode, sub-system, failure after start-up operation and maintenance activities. The maintenance activities, however, had been further broken down into two more covariates; PM and PM plus engine wash. The PM covariate only includes 4K and 8K ppm but not engine wash. This will enable separate assessment to be done on the effectiveness of PM action with and without engine wash. The complete formatted data for the analysis is given in Appendix B.

Table 4.3: Covariates and their grouping

Covariates	Group 0	Group 1
Train	Train 1	Train 2
Operation mode	Shared load	Single load
Subsystem	Other sub-systems	Gas Turbine + Compressor
Start-up	Other failures	Failures after start-up
PM	Other failures	Failures after PM
PM + wash	Other failures	Failures after PM + engine wash

4.5.3 Kaplan Meier (KM) Analysis Results

In this analysis, a statistical log-rank test is employed to test the null hypothesis that there is no significant difference between the survival data of group 0 and 1 for each covariate. The result of log-rank statistical tests is tabulated in Table 4.4. The result indicates that only a PM plus engine wash covariate has significant effect on the system failure distribution (P-value less than 0.05). The result also shows there is no significant difference between the two trains performance, thus it can be assumed that both trains have similar failure performance. Figure 4.11 describes the survival plot of PM plus wash covariate where it shows this covariate has a positive influence in extending the system inter-arrival failure time. The details of the analysis results can be found in Appendix B.

Table 4.4: Log-rank statistical test on covariates

Covariates	Train	Operation Mode	Subsystem	Start-up	PM	PM + Wash
Chi sq	0.186	0.031	3.34	0.017	2.41	8.52
Sig. (P value)	0.666	0.860	0.07	0.897	0.12	0.004

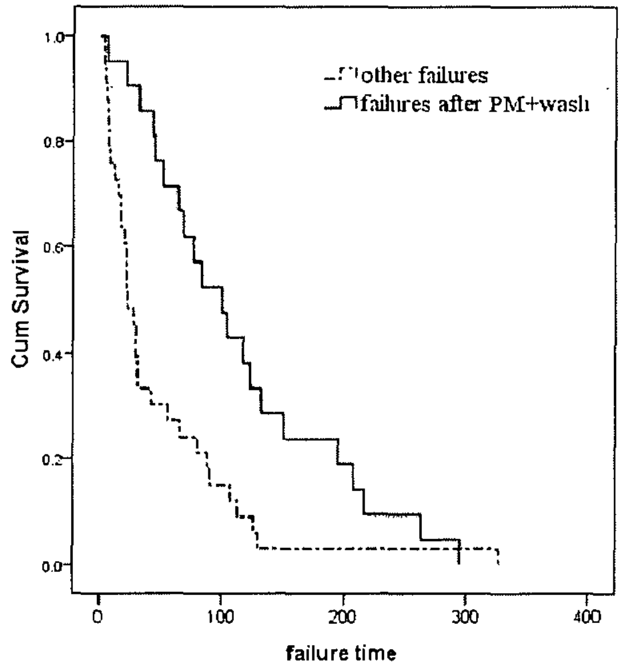


Figure 4.11: KM plot of cumulative survival for failures after PM plus engine wash vs. other failures

4.5.4 Proportional Hazard Model (PHM) Analysis Results

The result of PHM analysis on the covariates is tabulated in Table 4.5. For each covariate, the test of significance is done by comparing Wald statistic with a Chi square distribution with 1 degree of freedom. The Wald statistics is simply the square of z score (a value obtained by dividing the regression estimate, β, by its standard error). A Wald value greater than 3.84 will be significant at 5% level (p-value less than 0.05), thus indicates significant effect of that particular covariate. Based on the results, PM plus engine wash is the only influential factor with the statistical significant value (P value) of 0.044. This p-value is however higher than the one derived from KM log-rank test (0.004) since the PHM model includes the effects of all covariates in the analysis. A negative value of β indicates that the hazard is lower, thus the time between failure is better for covariates with lower β value. Hence, train, operation mode, subsystem, failure after start-up and PM plus wash covariates are associated with longer time between failures, whereas PM is associated with shorter time between failures. The impact of covariates to the hazard function can be determined by a hazard ratio, Exp (β). For PM plus engine wash, the estimated hazard is 0.567 lower than of another group (other failures). In other words, this covariate with reduce the hazard of failures by 56.7%. For other covariates, however, there are no significant differences in term of survival function since the p-values are not statistically significant at 95% confidence level. The estimated survival plot for PM plus engine wash covariate is shown in Figure 4.12 and the corresponding hazard plot is described in Figure 4.13. More details on the analysis results can be found in Appendix B.

Table 4.5: PHM analysis on covariates

Covariates	β	Std error	Wald	df	Sig. (P value)	Exp(β)
Train	-.045	.296	.024	1	.878	.956
Operation Mode	-.533	.557	.917	1	.338	.587
Subsystem	-.368	.323	1.302	1	.254	.692
Failure after start up	-.090	.405	.049	1	.824	.914
PM	.006	.466	.000	1	.989	1.006
PM + Engine Wash	-.837	.416	4.050	1	.044	.433

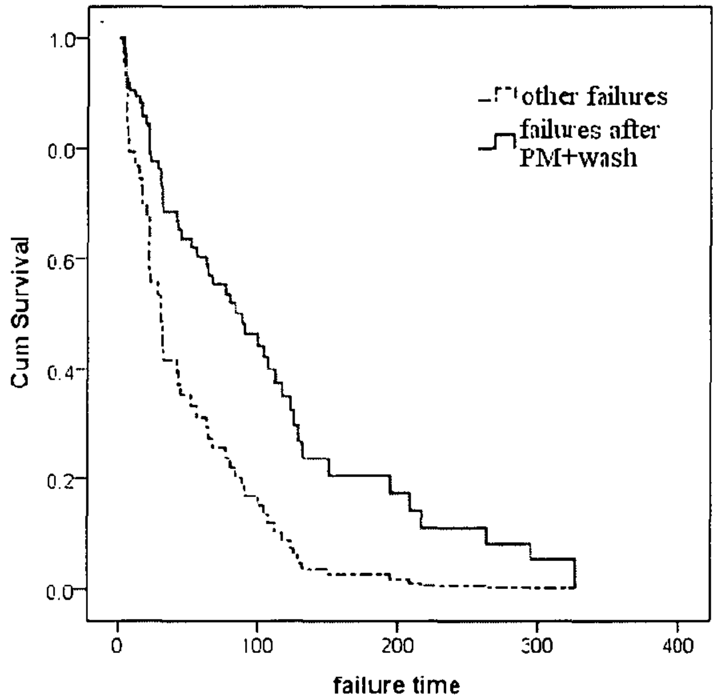


Figure 4.12: PHM plot of cumulative survival for failures after PM plus engine wash vs. other failures

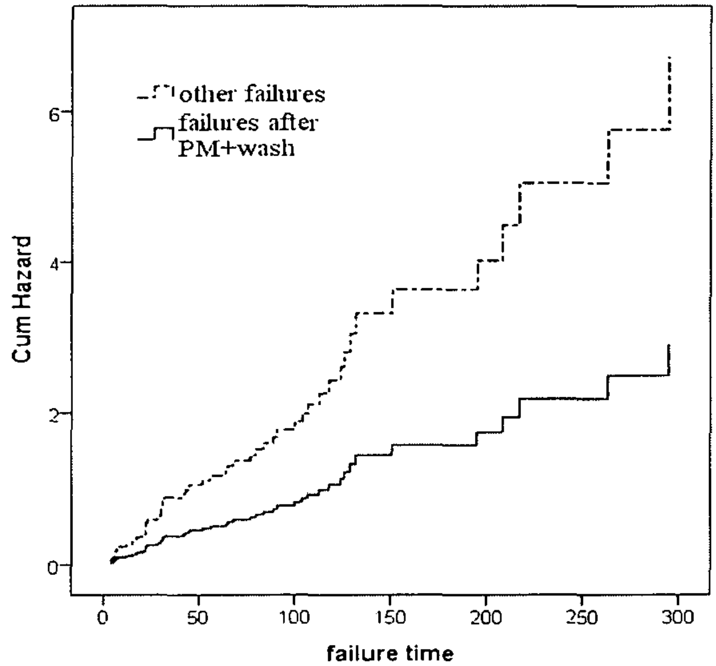


Figure 4.13: Hazard plot for PM plus engine wash covariate

Based on the findings of both KM and PHM analysis, the following conclusions can be made regarding the covariates:

I. There is no significant difference in term of reliability performance for both trains

II. There is no significant impact of single loading operation mode, failures after start-up operation and failures contributed by gas turbine and gas compressor on the time between failure distribution

III. The contribution of PM alone to increase the failure time interval is not that significant, however, when PM and engine wash are carried out, there is a significant improvement in system reliability.

4.6 Inferential Analysis

A rough estimation of failure rate has been given earlier for both trains based on the smooth characteristics of ROCOF plots. The plots of number of failures against cumulative time also suggest that the failure data can be modeled by Homogeneous Poisson Process (HPP). Nevertheless, before HPP model is assumed, it's necessary to ensure that the data are independent and identically distributed (IID). Whilst the assumption of identically distributed data has been validated by the trend plot and Laplace test, the independent assumption can be tested using a serial correlation test. This test is performed by plotting the *(i-1)*th time between failure (TBF) against the *i*th TBF data, where i = 1,2,..,n and n = the number of failure events. The serial correlation plots for both trains are shown in Figures 4.14 and 4.15. The graphs show the data plots are scattered randomly indicating the lacks of correlation. Hence, the IID assumption for the data is valid.

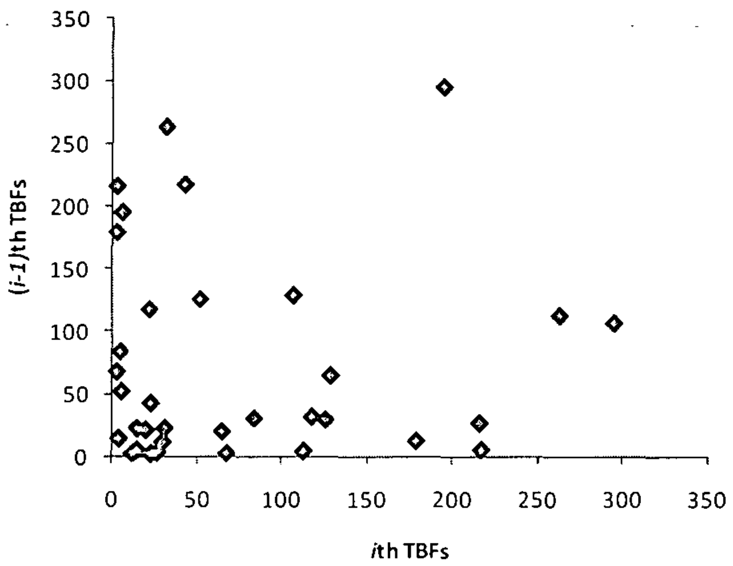


Figure 4.14: Dependency test for train 1 data

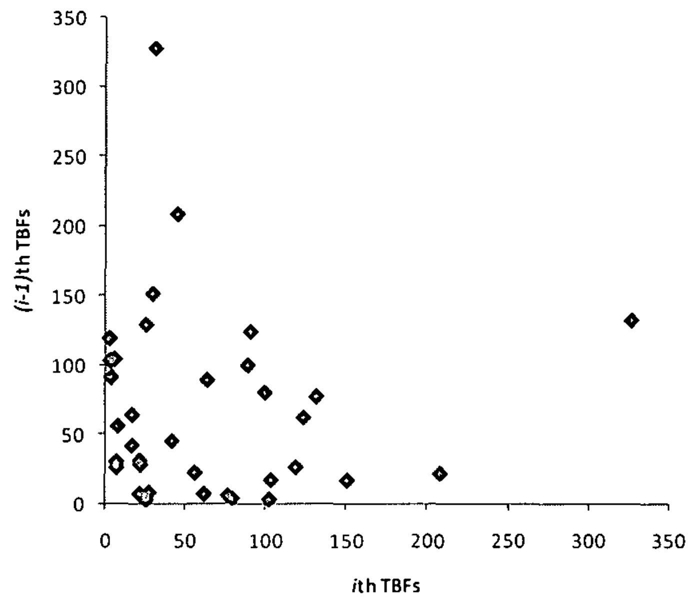


Figure 4.15: Dependency test for train 2 data

Using a Weibull ++ software, an exponential distribution is fitted into data for train 1, train 2 and combination of both and the corresponding probability plots are illustrated in Figures 4.16, 4.17, and 4.18, respectively. The goodness of fit statistical test using Kolmogorov-Smirnov (K-S) test indicates that the model fits the data sufficiently. The summary of the resulted reliability measures and their confidence bound are shown in Table 4.6. The estimated failure rates are close to those derived from ROCOF calculation. Train 2 shows slightly poorer reliability performance than train 1, however, they are not statistically different as it is shown in Kaplan Meier analysis.

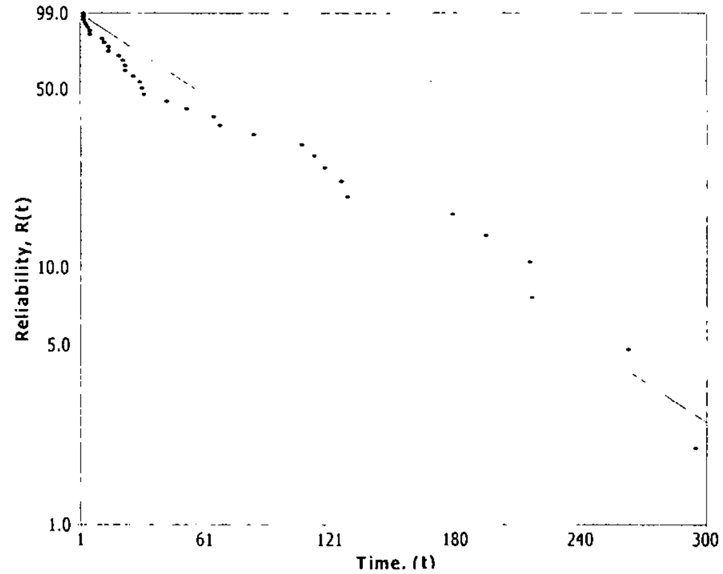


Figure 4.16: Probability plots for train 1

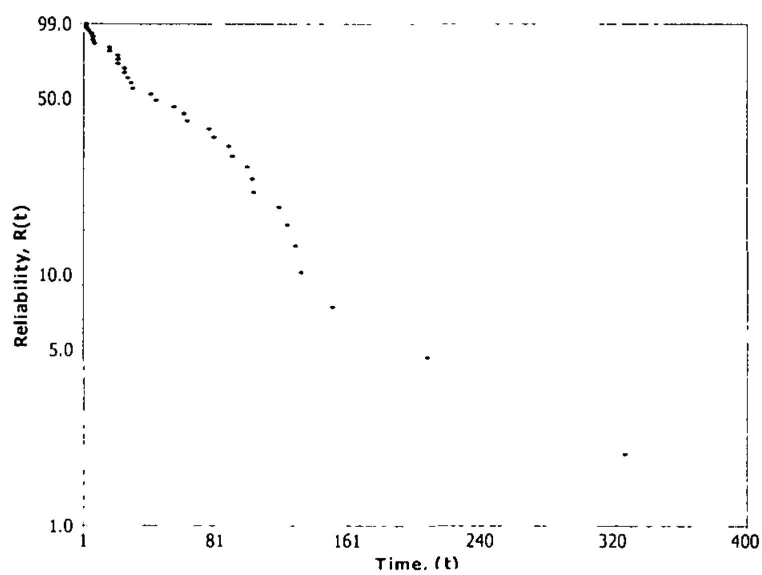


Figure 4.17: Probability plots for train 2

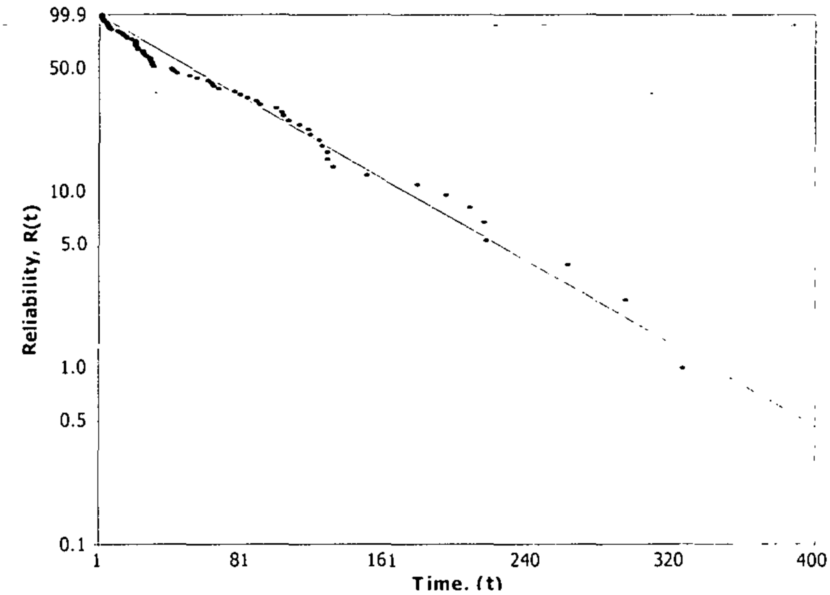


Figure 4.18: Probability plots for combination of data from both trains

Table 4.6: Goodness-of-fit for exponential distribution and reliability measures

Data	K-S value	Significant P-value*	Failure rate (λ) (per day)	95% confidence range	MTBF (days)	95% confidence range
Train 1	1.117	.165	0.0123	0.0088 – 0.0172	81.2	58.3 - 113
Train 2	.589	.879	0.0143	0.0103 – 0.0198	69.9	50.4 – 96.9
Combine	1.168	.130	0.0135	0.0107 – 0.0170	74.3	58.7 – 93.7

Note*: P value > 0.005 indicates good fit

4.7 Chapter Summary

In this chapter, the proposed reliability analysis approach has been demonstrated and found practical for investigating field maintenance data and providing useful insights on the present reliability performance of existing operational system. The study also describes the conditions and issues with plant data and highlights the importance of plant personnel involvement in the study to reduce many uncertainties in the data. Simple analysis such as trend plot and trend test can provide a snapshot of the system performance, hence should be performed in the early part of reliability analysis. Besides, they can help to determine whether the data can be modelled by a lifetime distribution. The analysis results show that for both trains the time between failures data can be sufficiently modelled by exponential distribution. This study also demonstrates the use of maintenance data for identifying critical factors to system reliability. Besides normal descriptive techniques such as Pareto analysis and trend chart to assess historical data and identify major contributors to system failures, this study employs methods based on hazard functions; KM and PHM, to evaluate the influence of other possible factors which are considered critical by engineers. These factors are not explicitly present in maintenance data, but largely derived from plant personnel inputs based on their experience and observation.

CHAPTER 5

MAINTAINABILITY ANALYSIS

5.1 Introduction

This chapter demonstrates the applications of the proposed maintainability analysis approach to assess the effectiveness of existing maintenance system in a plant and estimate maintainability measures. Here, maintainability analysis is carried out on two different types of maintenance actions; corrective maintenance (CM) and preventive maintenance (PM), using a gas compression train (GCT) system as a case study. The method used in performing those two studies varies in detail and scope depending on the analysis needs and existing data availability and condition. In the CM maintainability study, a systematic and simple method based on steady state trend and expert inputs for predicting system downtime is presented. For the case of PM, due to insufficient data, a novel approach using expert opinion has been proposed.

5.2 GCT Maintenance System and Practice

For the gas compressor train under studied, the following PM actions are implemented; planned PM (ppm) for every 4,000 (4K) and 8,000 (8K) operation hours, and off-line engine wash. There is also gas turbine engine change-out for every 24,000 (24K) operation hours. During all of these activities, the train system has to be shutdown and requires a proper start up process when resuming operation.

i) *4K and 8K ppm:* Based on the manufacturer's recommendation, gas compression train need to be serviced once every 4,000 operation hours or every 6 months. During this 4K ppm, various critical systems of gas turbine, ancillary and centrifugal compressor are checked. Appropriate maintenance repair and parts replacement are carried out to rejuvenate the system performance. More extensive and comprehensive tasks are performed during 8K ppm. Table 5.1 describes the main maintenance tasks undertaken during 4K and 8K ppm respectively.

Table 5.1: 4K and 8K ppm maintenance tasks

Type of PM	Area inspected
4K ppm	GT air intake, lube oil, fuel gas, gas compressor seal gas, GT compressor section, compressor rotor vibration system
8K ppm	GT air intake, lube oil, fuel gas, gas compressor seal gas, GT compressor section, GT and gas compressor vibration detection, fire and gas detection, pressure switches and transmitters, temperature switches and transmitters, over-speed protection system

ii) Engine wash: Regular gas turbine engine wash for the internal blades of the compressor section is a common practice in the industry (Forsthoffer, 2011). When a gas turbine is run, over time it becomes fouled with contaminants such as salt, soils and sooty hydrocarbon, which enter through air intake and encrust the compressor components. Engine wash is the most effective way of preventing and removing fouling deposits besides it restores the engine efficiency which leads to maximization of power output, fuel efficiency and extension of machine component lifetime (Emerson process management, 2005). Axial compressor deterioration has been known generally as the major source of gas turbine power and efficiency loss. An internal study on off-line crank / soak engine wash by the engineering team has also confirmed the effectiveness of engine wash in improving gas turbine efficiency (Hasnan *et* *al.*, 2004). During the off-line engine wash operation, which is normally a 6-hour task, a gas turbine is shutdown and then approved chemical and deionized water are injected through the intake with the machine cranking at starting speed. Based on the maintenance data, engine wash has been implemented since 2003 either as a separate PM event or incorporated with 4K and 8K ppm. Increased in production demand however, has caused reduction in the planned engine wash frequency, since production priority was on getting the highest utilization of the system with less downtime. There is a proposal by the engineering team to replace 4K ppm with bi-annual engine wash whilst maintaining a 8K ppm. This idea however is still pending, mainly due to production concern in meeting the output demand.

iii) ***Gas turbine engine and compressor bundle change-out:*** It is a standard industrial practice to overhaul GT engine in order to maintain its high operation efficiency after it has been in operation for certain period of time in view of component life and also induced stresses experienced by hot section components. In this compression train system, that time interval has been set at 24,000 hours. The removed engine will be sent for overhaul and replaced with a spare engine. There is also a centrifugal compressor overhaul operation, however with no fix time-based interval. The compressor will normally be planned for change-out when there is indication of performance deterioration such as incapability of producing the required head or discharged pressure. During this change-out, the compressor bundle is replaced with another spare, whilst the original one is sent for overhaul.

5.3 Maintainability Analysis

A generic approach for conducting a maintainability analysis has been presented in Figure 3.2 in Chapter 3. More detailed steps used for study on GCT will be discussed next. The flows are developed based on the objectives of the study and the conditions of plant maintenance data. The main objectives of the maintainability analysis are as follows:

- To demonstrate the application of proposed approach for effective maintainability analysis
- To identify the critical factors / subsystems affecting the system downtime so that appropriate actions can be taken to improve them
- To highlight key and effective downtime improvement activities related to the maintenance and logistics support system. These information can be feedback to design and operation engineers for further system improvement
- To assess the maintainability measures of the system which are useful for predicting future maintenance system and resources requirements

5.3.1 Maintenance Data

In a proper maintainability analysis, a precise definition of downtime events should be established according to the respective operating system. There are many factors which can cause downtime for the CGT system, and they should be clearly identified and categorized in the data. This is importance to ensure only appropriate data are being captured and used for the analysis. The downtime state of the gas compression train system is described in Figure 5.1.

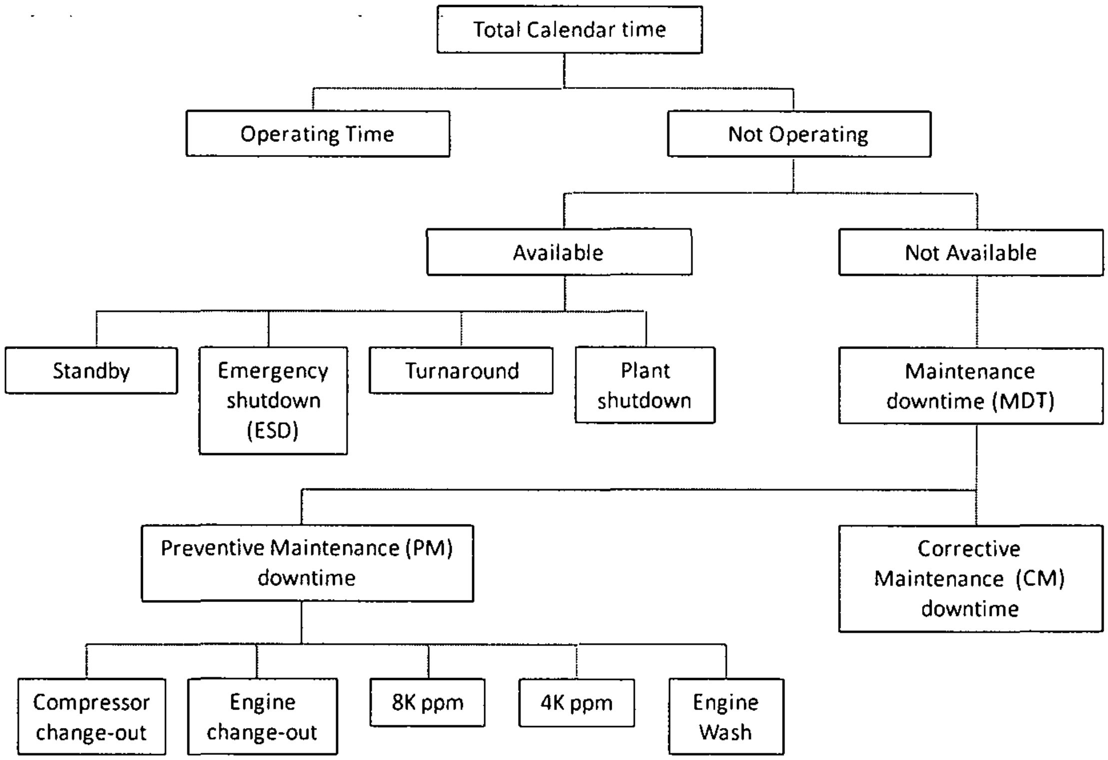


Figure 5.1: GCT operating states

5.3.2 Maintenance Downtime Impact on GCT Availability

Prior to conducting maintainability analysis, it is imperative to understand the influence of maintenance downtime to the availability performance of gas compression train. The availability of gas compression train is very critical for ensuring the platform plant meets its gas production demand. The availability is a function of CM and PM downtime duration. CM downtime depends on failure frequency and repair time, whereas PM downtime is related to number of PM actions and their time duration. Figures 5.2 to 5.5 show availability yearly figure since 2002 for train 1 and its corresponding plots on CM frequency, CM and PM breakdown trend. Similar graphs for train 2 are shown in Figures 5.6 to 5.9. Table 5.2 describes the code for PM type categories. The code for subsystems was given in Table 4.1.

Train 1 performance had shown a steady trend with the average availability of around 96%. There was, however, a slight drop in 2007 and 2008 where the availability was at 92.5% and 90.6% respectively. In 2007, the decrease was mainly due to CM for GT engine change-out because of turbine nozzle failure which occurred at the end of 2006. At the time of incident, the GT had been operated for more than 31,000 hours, which was beyond the recommended planned change-out of 24,000 hours. Planned compressor bundle overhaul which took more than 2 weeks to complete caused high downtime in 2008. Other causes of high downtime in 2008 were CM due to lube oil contaminated and flexi hose problem.

Train 2 started with high availability in 2002 but later deteriorated in 2003 before it recovered in 2006. Gas compressor bundle change-out due to broken tie rod bolts caused the availability to drop to 81% in 2003. In 2004, the availability trend further decreased to 54.6% mainly due to gas compressor high vibration issue which lead to another compressor bundle change-out. This time the downtime was much longer due to non-availability of spare compressor. Low availability in 2005 (79%) was caused by GT tripped on N2 speed pull away resulted in replacement of GT engine. Since 2006, the performance of train 2 has been encouraging with the availability average stood at 97.7%.

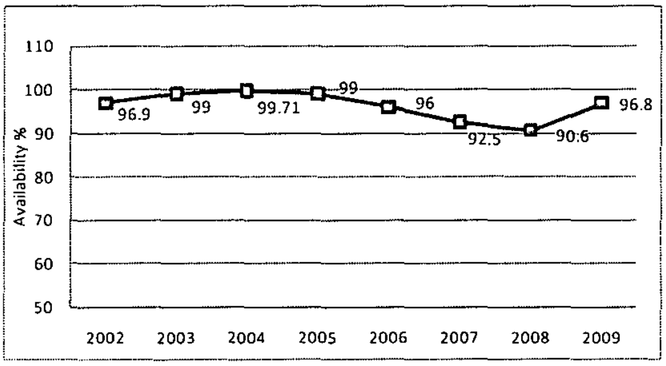


Figure 5.2: Availability trend for train 1

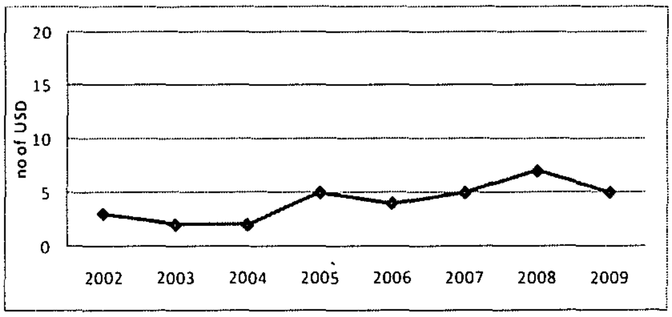


Figure 5.3: Number of CM by year for train 1

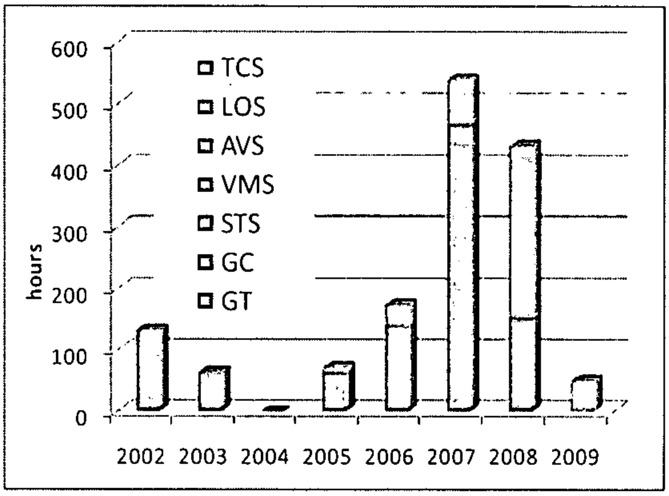


Figure 5.4: Train 1 CM breakdown by year

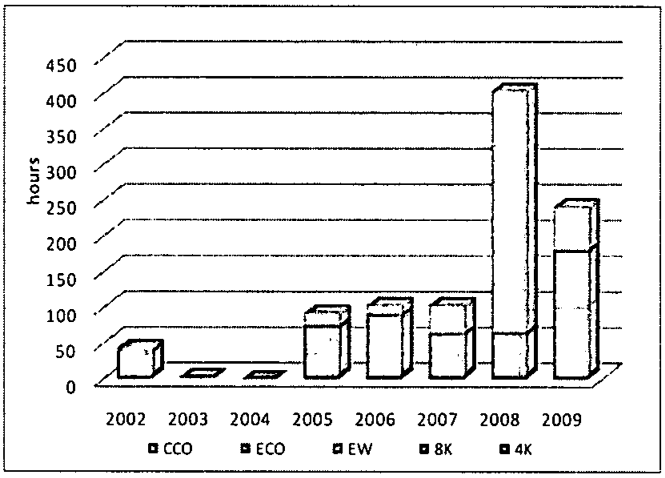


Figure 5.5: Train 1 PM breakdown by year

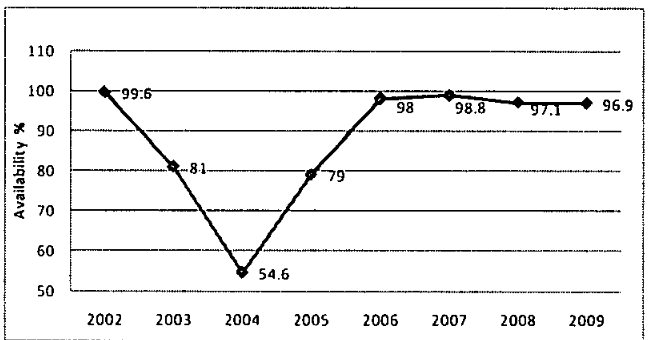


Figure 5.6: Availability trend for train 2

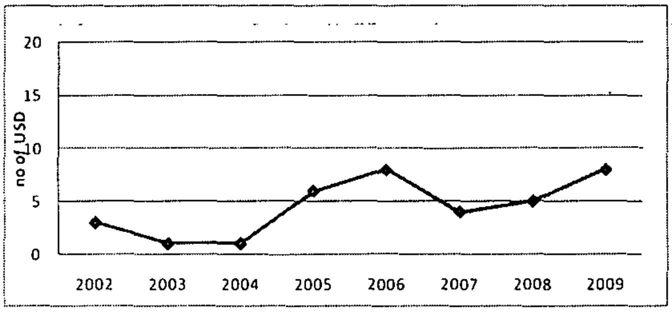


Figure 5.7: Number of CM by year for train 2

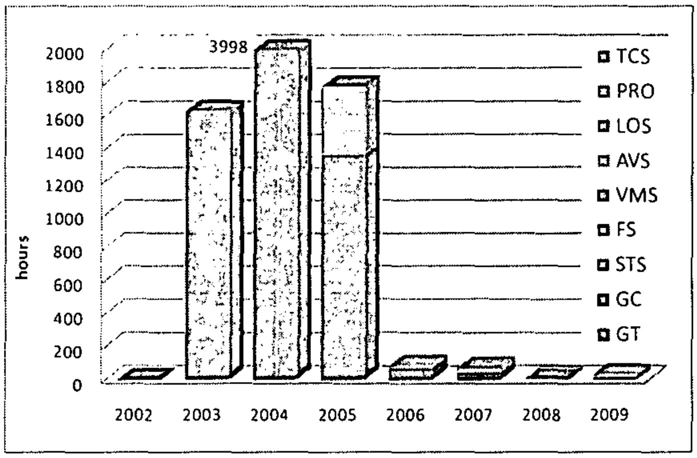


Figure 5.8: Train 2 CM breakdown by year

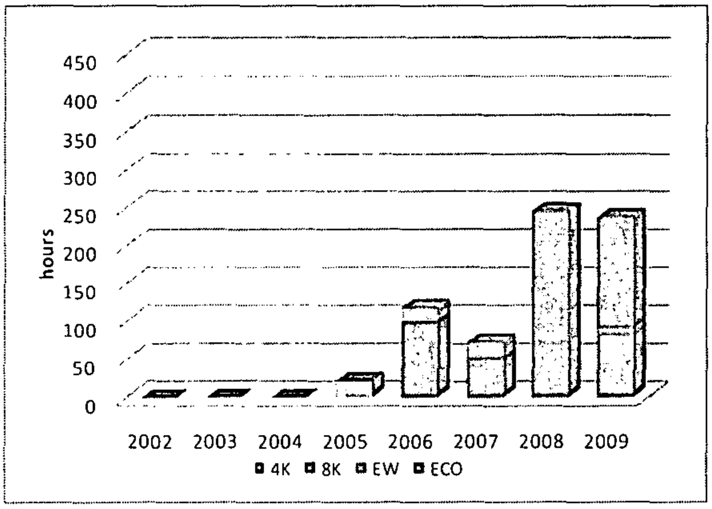


Figure 5.9: Train 2 PM breakdown by year

Table 5.2: Coding for PM types

PM types	Code
4K ppm	4K
8K ppm	8K
Engine wash	EW
Turbine engine change-out	ECO
Centrifugal compressor bundle change-out	CCO

From the graphs, it can be concluded that CM downtime has significant influence on the availability performance of both gas compressor trains compared to number of failures (failure frequency). As being discussed in previous chapter and shown in Figures 5.3 and 5.7, the plots of failure occurrence for both trains are rather flat and do not fluctuate as much as those of availability. The availability performance, on the other hand, is highly related to the USD downtime trend; the availability is low when CM downtime is high, and vice-versa. PM downtime also affects the availability trend, however the impact is relatively smaller. GT engine, centrifugal compressor bundle change-out and 8K planned maintenance are found to have some impact on GCT availability.

The improvement trend in availability is therefore predominantly due to the improvement (reduction) in maintenance downtime. Based on discussion with plant engineers, there are many factors that contribute to the trend but the most influential factor is the improvement actions carried out by the engineering, maintenance and production team in the plant which have resulted in continuous reduction in the amount of time to complete repair works, planned maintenance and put back equipment to operation mode. These important findings should be feedback and shared with designers and engineers working with similar system at different platforms. Some of those improvement initiatives are described as follows:

i. ***Spare part management:*** This effort is one of the main contributors to a significant reduction trend in the system downtime for both CM and PM. Several actions have been rolled out to reduce operation downtime particularly related to material and administrative delay. One of them is a 'Pit crew concept', which focuses on team efforts, early planning and streamlining work during shutdown (Hasnan *et al.*, 2004). The key steps are the identification of critical work path and segregation of jobs based on location and time they can be done i.e. before, during and after the shutdown. Since 2006, many of the critical spares had been placed at the sites, which were previously being stored at warehouse / supplier base on onshore or OEM vendors overseas. According to field engineer, this initiative has significantly reduced the material delay and maintenance downtime. Table 5.3 gives the estimated reduction in downtime due to critical spare parts relocation to sites.

Table 5.3: Estimated downtime due to critical failures of subsystem

Failures subsystem	Estimated downtime	
	Pre 2006 (months)	Post 2006 (days)
1. Gas turbine	6	7
2. Gas compressor	6	14
3. Starter system	4	2
4. Gear box	6	7
5. Fuel system	1	1
6. Vibration monitoring system	1	1
7. AVS	2	3
8. Lube oil system	1	1
9. Process	1	1
10. Turbine control system	2	2

ii. ***Supplier contract procedure improvement:*** In early 2008, a long term service agreement (LTSA) with major OEM suppliers such as Rolls Royce was implemented replacing the old bidding process. This initiative has resulted in improved maintenance services and part delivery by the suppliers which are importance for shortening downtime duration particularly involving spare parts logistics. High downtime in 2004 for train 2 was mainly due to logistics issues such as contracting delay, sourcing parts problem and OEM service delay.

iii. ***Technicians and operators skills upgrading:*** Various programs have been implemented to increase the plant workers skills. These include in-class and on sites training related to equipment operation, trouble shooting and maintenance. These training are conducted continuously for technicians and operators as part of on-going efforts to empower them and enhance their competencies.

iv. ***Engine and Compressor change-out policy***: It is highly suspected that the turbine engine and gas compressor failures which caused high downtime during 2003 to 2005 periods are caused by over utilization of the equipment. A prudent approach has been taken to ensure that the equipment change-out action will be carried effectively according to the standard industrial practice.

v. ***Technician logistics:*** A maintenance crew sparing policy is implemented in early 2009 in which turbo-machinery technician(s) is stationed at the platform to advise material personnel on the spare part requirement.

5.4 Corrective Maintenance (CM) Maintainability Analysis

5.4.1 Exploratory Analysis

For the purpose of maintainability analysis, the maintenance downtime data for both trains are combined since regardless of which train is under maintenance, the repair and maintenance works will be performed by the same pool of maintenance crews.

As shown earlier, the availability performance trend of each train is highly influenced by the duration of CM downtime and its improvement. To better assess the improvement trend of CM downtime, a plot of average CM downtime per CM event is used and is shown in Figure 5.10 together with the ROCOF. This plot clearly indicates that there is an improvement trend in the average downtime per CM which signifies the effectiveness of the improvement initiatives discussed previously. The average availability trend is also shown in Figure 5.11 for comparison.

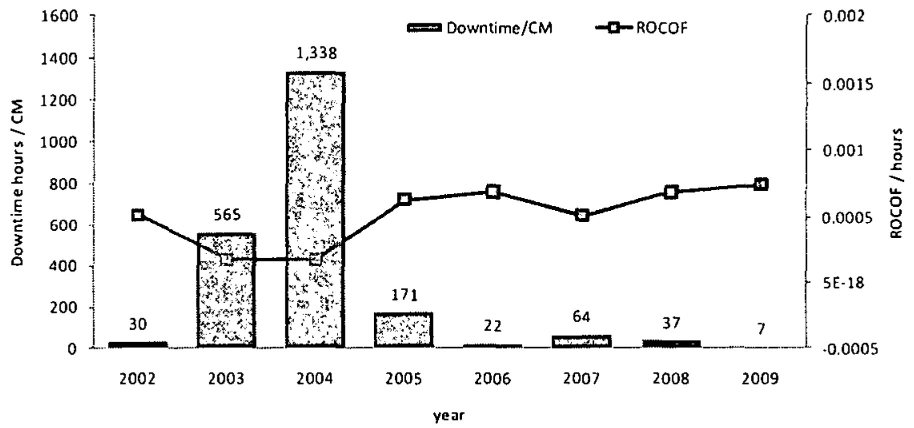


Figure 5.10: Overall GCT CM downtime event and ROCOF trend

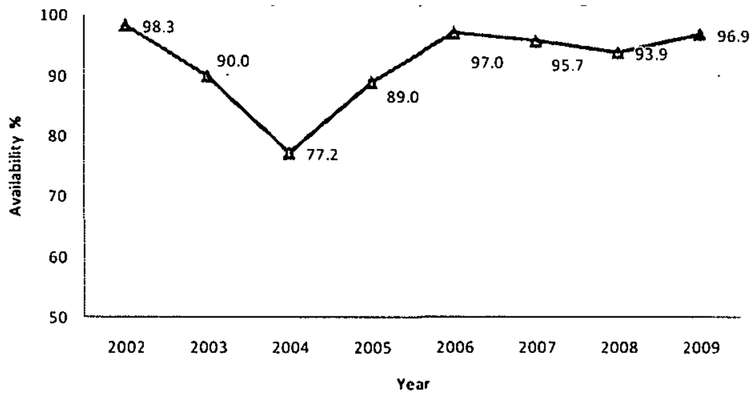


Figure 5.11: Overall GCT availability trend

5.4.1.1 Pareto Analysis

The Pareto of the total CM downtime hours according to subsystem is depicted in Figure 5.12. Major downtime contributors are gas compressor (65.6%), gas turbine (23.9%), starter system (5.2%) and lube oil system (3.1%). Since this chart represent the whole seven operation years, it is necessary to see the downtime breakdown over the operation years to find out whether the proportion is still valid in the recent operation years.

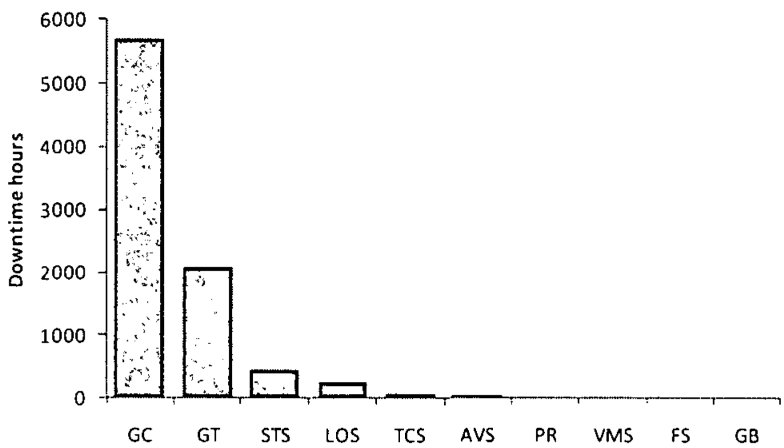
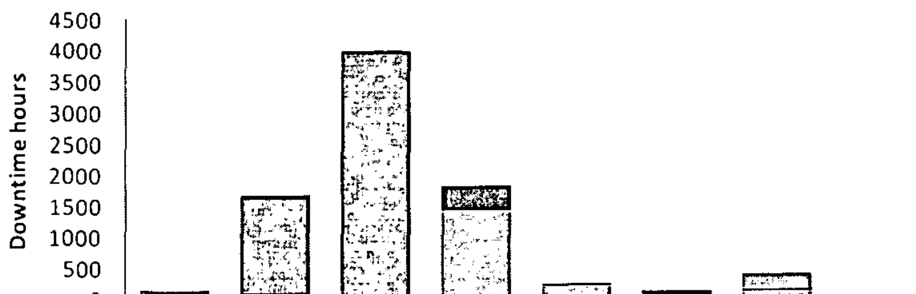


Figure 5.12: CM downtime hours by subsystem (year 2002-2009)

5.4.1.2 Downtime Breakdown Over-time

Figure 5.13 depicts the trend of downtime breakdown of those main subsystem contributors over years. As shown here, high gas compressor downtime occurred in 2003 and 2004. But since then, it has shown drastic reduction indicating the improvement activities carried out by the team paid off. However, downtime due to lube oil system has shown an increasing trend lately, which something that the management needs to investigate and focus on.



	2002	2003	2004	2005	2006	2007	2008	2009
LOS	0	0	0	0	0	13	257	1
STS	0	0	0	408	0	43	0	0
GC	0	1630	3998	0	1	38.05	4.5	12.5
GT	134.25	59	0	1438.75	221.75	57	152.5	8

Figure 5.13: CM breakdown trend of major contributors

5.4.2 Estimation of CM Downtime Measures

Table 5.4 shows the CM downtime data for both trains which are combined and arranged chronologically. Based on these data, the graph of cumulative number of downtime against cumulative downtime hours is plotted to determine if an upward or downward trend exists over time. As shown in Figure 5.14, there is an obvious improvement trend since 2006, as indicated by a concave up plot trend. The Laplace test value, U, calculated for this data is 6.04, which is larger than the critical value of 1.95 at 95% confidence level, also confirms the fact that the downtime is in an improving trend. The serial correlation test as shown in Figure 5.15, however, indicates that the data are independent since the data plot are randomly scattered.

Table 5.4: Downtime data in chronological order

no	Downtime (hrs)	Cumulative Downtime (hrs)	no	Downtime (hrs)	Cumulative Downtime (hrs)
1	10	10	29	8	7791.5
2	8.5	18.5	30	25	7816.5
3	16	34.5	31	23	7839.5
4	72	106.5	32	33	7872.5
5	62.25	168.75	33	5	7877.5
6	10	178.75	34	7	7884.5
7	6	184.75	35	144	8028.5
8	1630	1814.75	36	38.05	8066.55
9	59	1873.75	37	24	8090.55
10	10	1883.75	38	13	8103.55
11	3998	5881.75	39	14.5	8118.05
12	6	5887.75	40	1.5	8119.55
13	9.5	5897.25	41	3	8122.55
14	408	6305.25	42	3.7	8126.25
15	4	6309.25	43	1.5	8127.75
16	42	6351.25	44	43	8170.75
17	1.25	6352.5	45	3	8173.75
18	1	6353.5	46	37	8210.75
19	4.5	6358	47	2	8212.75
20	1.5	6359.5	48	0.75	8213.5
21	26	6385.5	49	4	8217.5
22	1368	7753.5	50	0.5	8218
23	11	7764.5	51	18.5	8236.5
24	0.5	7765	52	0.5	8237
25	7.25	7772.25	53	1	8238
26	1	7773.25	54	115	8353
27	3.5	7776.75	55	257	8610
28	6.75	7783.5	56	0.5	8610.5

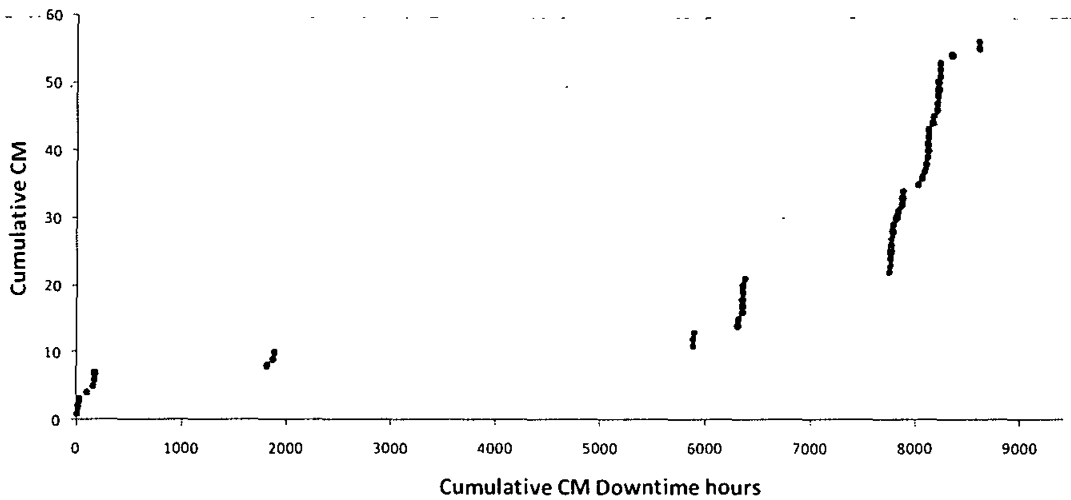


Figure 5.14: CM downtime data trend

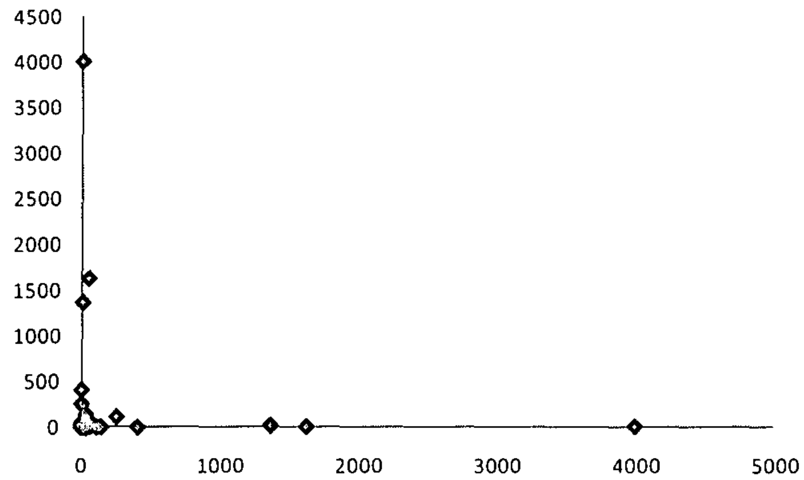


Figure 5.15: Test for dependency of CM downtime data

The decreasing trend in downtime duration also indicates that an approach based on assumption of constant repair rate could not be used to accurately estimate maintainability measures for the system. Besides, any attempt to model repair time using any lifetime model will be in serious flaw since the data are not identically distributed. A common approach for analysing data with trend is by modelling using NHPP model. This non-stationary model, however, is applicable when the trend is monotonic and produces result not in the form of the probability distribution but rather specific expected downtime duration within the certain given time. To determine the statistical distribution of the above data, two alternative methods namely steady-state pattern and expert input approaches are proposed.

5.4.2.1 Data Review for Steady State Pattern

The trend test has indicated that the existing data is not in a steady state (identically distributed), hence it is not appropriate to use either the distribution or parametric approach in the analysis. A closer look at the cumulative plot highlights that in the last four years of operation, the data seem to level off (Figure 5.16). This steady state region can be highlighted by constructing a simple linear regression line using a least-squares method on those data as illustrated in Figure 5.17. The resulted line has large value of coefficient of determination, R^2 at 0.903, which indicates a good measure of goodness of fit of the regression line to the data. To test whether the relationship is significant, a statistical test can be done using F test (Anderson *et al.*, 2002), with the null hypothesis that there is no significant relationship between two variables. A large value of F indicates the rejection of the null hypothesis. The F test calculation resulted in F value of 300 which is greater than the critical value of 7.5 for Type I error, α = .01, thus indicates that the null hypothesis can be rejected. Given this significance statistical relationship, we can confidently assume that the data in the recent four years of operation can be established as appropriate data for representing the actual current downtime performance and can be used as a basis for evaluating maintainability / downtime measures. The constant downtime rate predicted based on the slope of the linear line is 24.4 hours per downtime (slope = 0.0041 downtime/hours).

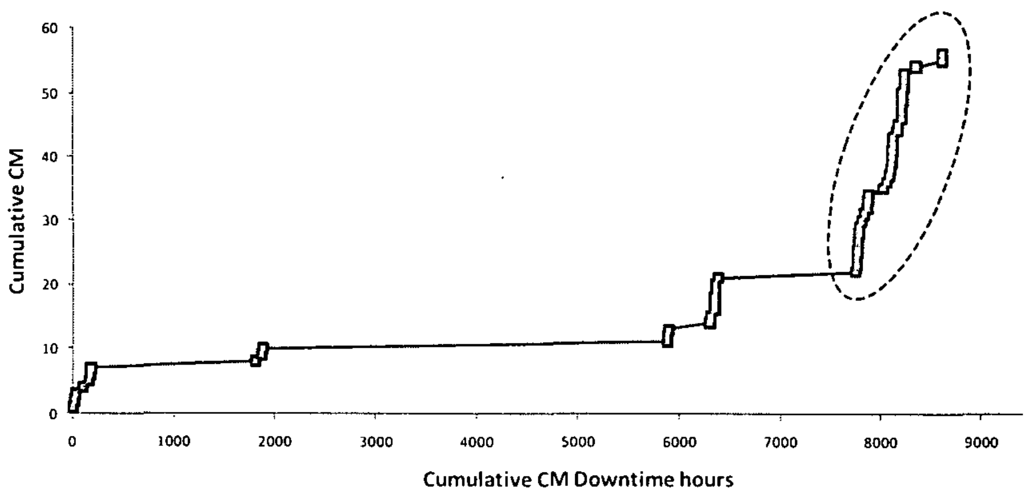


Figure 5.16: Steady state region in the data plot

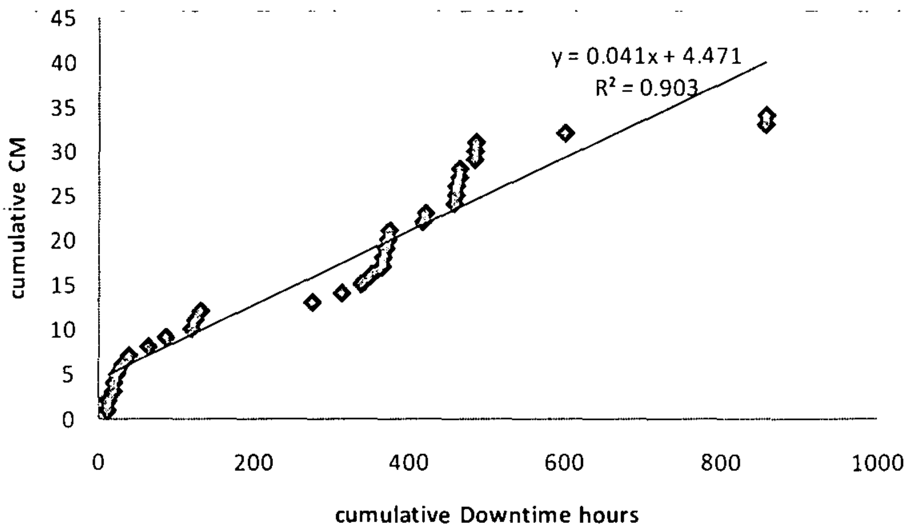


Figure 5.17: Plot of regression analysis of the steady state region

5.4.2.2 Expert Input (Censoring) Approach

Alternative method for getting practical and appropriate data is by seeking relevant inputs from field experts on the expected machinery failure frequency and downtime duration based on their assessment on the effectiveness of current maintenance system and improvement activities. The field experts are those with vast knowledge, skills and experience on the operating and maintenance system as well as improvement actions undertaken on the system under studied, thus their inputs should be considered valuable and reflective of the current performance. In this study, the field experts are the mechanical and maintenance engineers who have been involved in the operation of the system since its commencement. The experts were given all the failure events data and were asked to specify which events that have high probability will not re-occur in the future as the results of improvement initiatives in the system. The elicitation results, based on the consensus among the experts, indicate six events which are listed in Table 5 and include failures related to gas turbine (3), centrifugal compressor (2) and lube oil system (1).

Table 5.5: Downtime events considered one- off by experts

Downtime (hrs)	Cause	Corrective action
1630	Compressor bundle change-out due to broken tie bolts	Replaced compressor bundle with spare
3998	Rotor change out due to high vibration	Failed compressor bundle was removed and spare compressor bundle was installed
1368	Tripped on GG N2 pull away alarm sequence failure	Removed engine from skid and replaced GG module 3
144	Engine replacement due to eroded HPT nozzle	Replaced engine with newly overhauled engine
115	Flexible hose issue	Replaced the flexible hose
257	Lube oil contaminated	Replaced the lube oil

The experts believe that these issues are one-off events thus have very little possibility to happen again given effective corrective actions undertaken in the system, hence worthy to be excluded from the data. The remaining data are thus considered to be appropriately representing the downtime distributions of the system.

5.4.2.3 Distribution Analysis

Three commonly used statistical probability distributions (exponential, normal and lognormal) are chosen to model the downtime data based on the two proposed methods. The conventional method which uses all the data points is also being applied for comparison purpose. Table 5.6 shows the results of the calculated distributions' parameters using MLE and values of KS test. The calculations of MLE and KS test are done using statistical software; Weibull ++7 and SPSS. The KS test value represents the Z statistics which is the product of the largest absolute difference between the empirical and theoretical CDFs and the square root of the sample size. The significant value is derived by comparing the Z-statistics with the table of critical value. The specified distribution can be considered fit when the significant value is more than 0.005. Based on the results, the lognormal distribution is found to be the best fit distribution for all three methods.

Table 5.6: KS goodness-of-fit test for each data type

Distribution /Data types	Exponential			Normal			Lognormal		
	Param.	KS test	Sign.	Param.	KS test	Sign.	Param.	KS test	Sign.
All data	$\lambda = 0.0065$	4.321	0.000	$\mu = 153.76$ $\sigma = 595.12$	3.215	0.000	$\mu = 2.385$ $\sigma = 2.052$	0.654	0.77
Steady-state pattern	$\lambda = 0.0397$	1.844	0.002	$\mu = 25.21$ $\sigma = 51.36$	1.838	0.002	$\mu = 1.882$ $\sigma = 1.717$	0.407	0.99
Expert inputs	$\lambda = 0.0455$	1.94	0.001	$\mu = 21.97$ $\sigma = 58.34$	2.52	0.000	$\mu = 1.908$ $\sigma = 1.529$	0.545	0.93

Note: Sign. < 0.005 indicates not a good fit

5.4.2.4 Maintainability Measures Analysis

Table 5.7 lists the maintainability measures extracted from the lognormal distribution for all the three cases. Besides the mean downtime, the length of downtime at various percentages of probabilities (10, 50 and 90) of maintenance tasks to be completed can also be determined. This information is beneficial for management in maintenance system planning and for determining the costing, maintenance scheduling, technical and non-technical man-power planning, and availability projection. As seen from the table, the approach using all data points is rather pessimistic where the mean downtime is almost three-times higher than those of the other two methods. At 10 and 50 percent of maintenance tasks completion rate, the predicted downtime durations for all three cases do not differ much. However, they are distinctly varied at 90% completion rate where the expert inputs approach estimates the most optimistic length of downtime at 47.8 hours compared to 59.3 and 150.6 hours for steady-state and all-data approaches respectively. The maintainability plot for the three approaches is shown in Figure 5.18.

For comparison, a set of downtime data for 2009 and 2010 is examined and based on the lognormal distribution (was calculated to be the best fit distribution for the data) the mean downtime is 6.6 hours with standard deviation of 8.9 hours. This result is relatively closer to those of the two proposed methods than using the all-data approach, thus indicates that the two proposed methods are more practical to be applied for establishing the proper downtime distribution. Furthermore, the recorded average repair time in OREDA handbook (OREDA, 2002) for combination of both gas turbine and centrifugal compressor is 29.3, which is near to the estimation figures. The estimation using NHPP model results in higher mean downtime at 120 hours, due to poor data fitting. The adoption of all-data approach to determine the downtime duration for maintenance planning, on the other hand will produce a pessimistic prediction which is a longer downtime allocation than what it is supposed to be.

Table 5.7: Comparison of maintainability measures for all three approaches

Maintainability Measure	All Data	Steady State	Expert inputs
Distribution	Lognormal	Lognormal	Lognormal
Parameters	$\mu = 2.385$ $\sigma = 2.052$	$\mu = 1.882$ $\sigma = 1.717$	$\mu = 1.908$ $\sigma = 1.529$
Mean Downtime (MDT) (hrs)	89.1	28.7	21.7
Std	726.5	121.9	66.4
DT_{90}	150.6	59.3	47.8
DT_{50}	10.9	6.6	6.7
DT_{10}	0.78	0.73	0.95

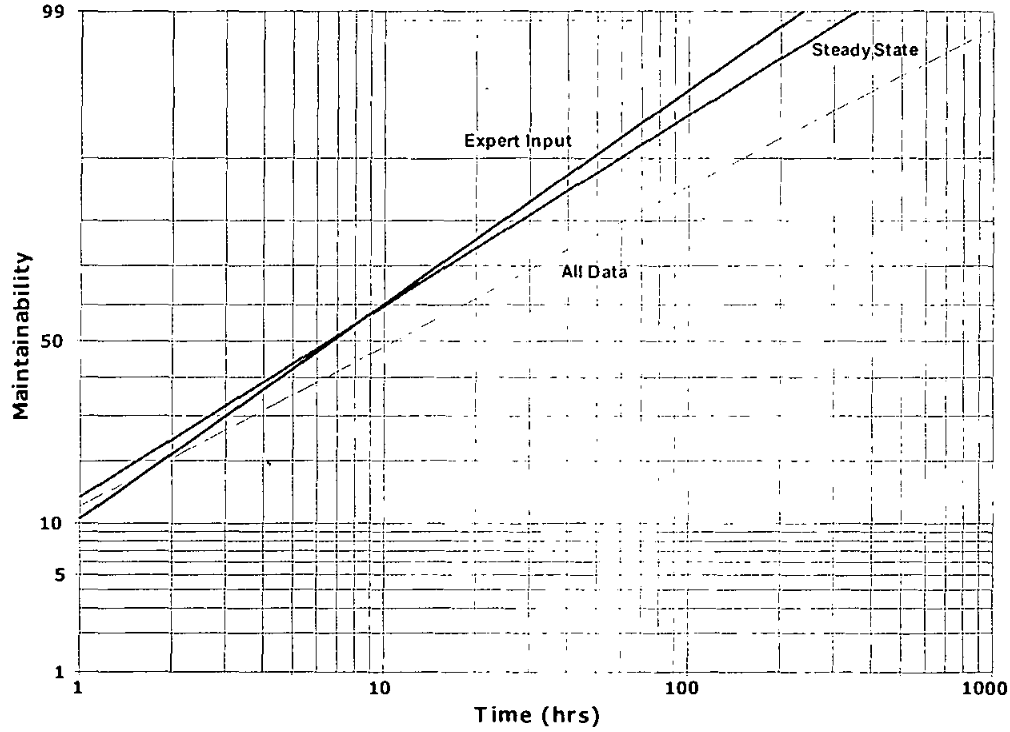


Figure 5.18: Maintainability over time based on the three approaches

5.4.3 Conclusion on CM Maintainability Analysis

In conclusion, the proposed framework for performing CM maintainability analysis of plant system maintenance data can be illustrated in Figure 5.19. This framework enhances Blanchard model (Figure 5.1) by providing detailed steps in achieving more effective way of giving feedback on system performance at operation phase to the design team as well as to other similar operational platform. Relevant feedback on the improvement initiatives and lesson learns is essential for ongoing improvement in the design and performance of other similar systems.

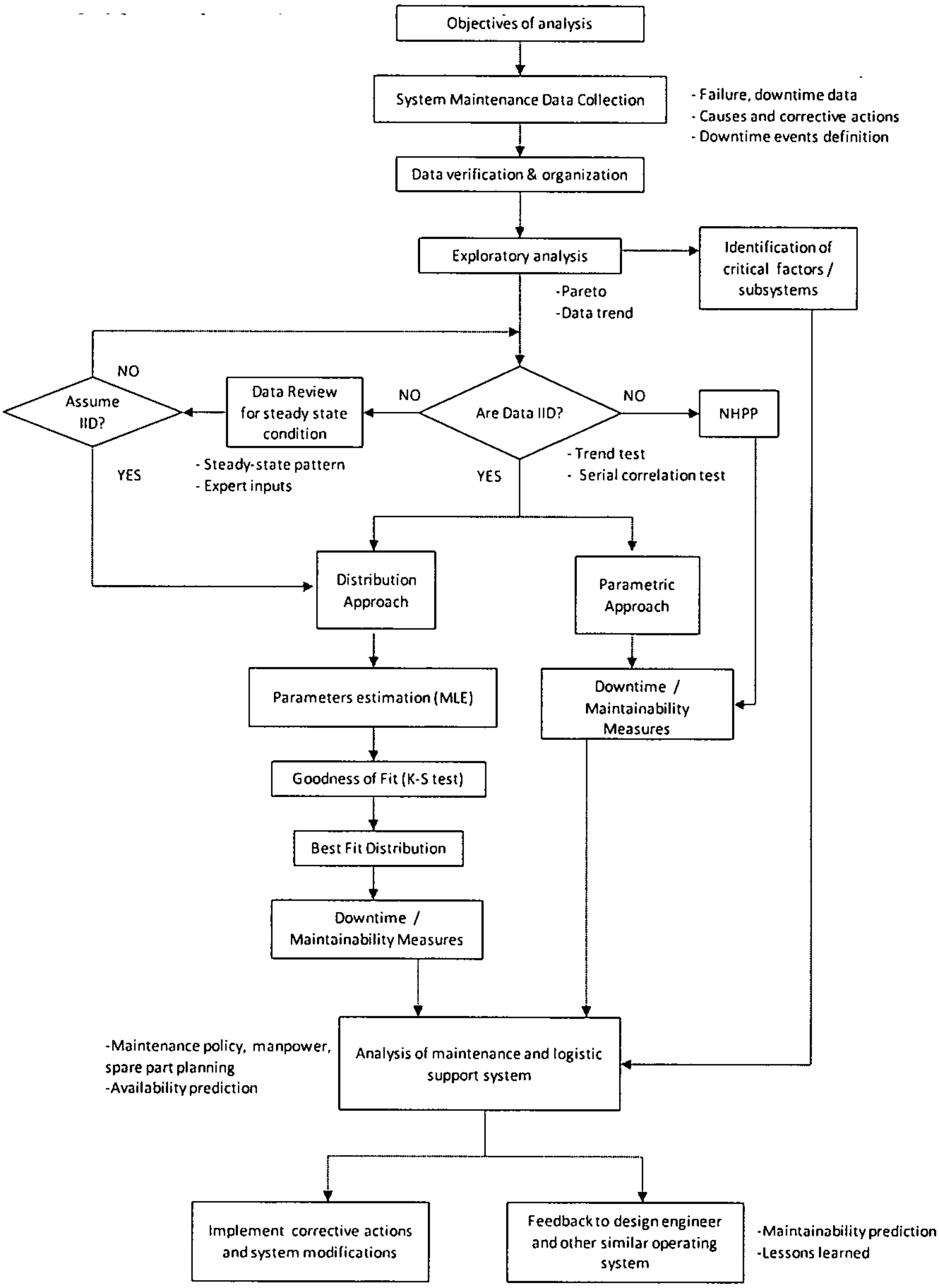


Figure 5.19: Proposed framework for CM maintainability analysis

5.5 Preventive Maintenance (PM) Maintainability Analysis

5.5.1 Exploratory Analysis

The trend over years of PSD downtime with breakdown for various PM types has been illustrated in Figures 5.6 and 5.10. The trend shows PSD downtime also has some effect on the system availability especially in the recent years, where it overweights the downtime caused by CM as a results of execution of more PM actions. For example, in 2008, train 1 experienced the highest PM downtime with 400 hours because of planned compressor bundle change-out. For train 2, the implementation of GT engine change out pushed up the overall PM downtime in 2009. In 2008, the increase was mainly due to relatively high 8K PPM downtime. The planned compressor bundle and GT engine change out, however, do not happen often, since they are normally planned once in every 3-4 years of operation. Nevertheless, based on their consequences on the system's availability, proper planning on timing and execution are crucial to avoid sudden drop in plant production output.

For 4K, 8K and EW PM they are regularly performed each year to maintain the performances of the trains. As such, they have more data compared to compressor and engine change out planned maintenance, hence will be the focus of maintainability measures analysis next. The breakdown of PM downtime from 2002 till 2009 for the overall GCT system is shown in Figure 5.20. Additionally, the Pareto of average downtime per PM event is described in Figure 5.21, which indicates CCO is the highest average downtime at 336 hours per event. However, it is important to note that the data gathered are rather limited as indicated by low PSD downtime events recorded in early years of operation. This low PM trend was due to tight production schedule which drove plant to extend or prolong time interval between PM and unrecorded data. Some of PMs had been performed concurrently with other maintenance repair during high CM downtime such as in 2003 and 2004 for train 2, hence there were no exact downtime data recorded on them.

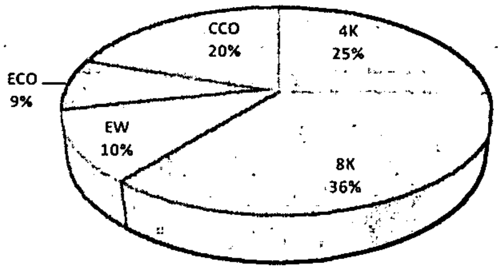


Figure 5.20: PM downtime breakdown (year 2002 - 2009)

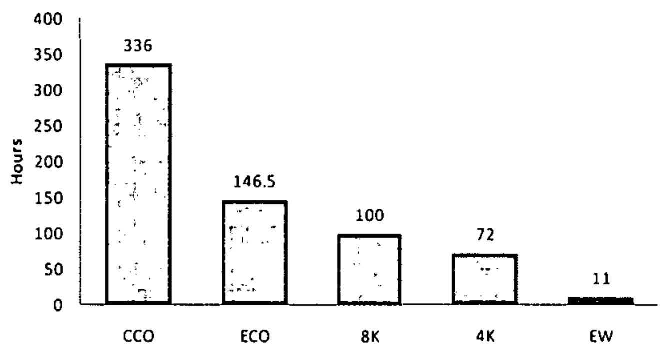


Figure 5.21: Average downtime on each PM event

5.5.2 Estimation of 4K, 8K and Engine Wash PM Downtime Measures

Based on the maintenance data from 2002 till 2008, the shutdown durations for each PM is acquired and described in Table 8. The available data are quite limited, thus preventing accurate modelling of PM downtime distribution. To overcome this issue, an approach based on expert opinion has been proposed.

Table 5.8: PM downtime data for year 2002-2008

PM types	Downtime data (hrs)	Average	Std	90% confidence interval
4K	44 55.5 67.5 72	59.75	12.6	30.02 – 80.48
8K	68.5 78 94 104 174	124.9	41.6	56.47 – 193.33
Engine wash	3 5 5.4 9 9.5 10 11 11 11 13 16	9.4	3.75	3.23 – 15.57

5.5.2.1 Motivation for Eliciting Expert Opinion

Even though there are no fixed rules concerning the number of samples required to develop statistical distribution of downtime, a large number of data are needed in order to distinguish the best fit among various possible models and get more accurate measures (Wadsworth, 1997). Since the data are limited and widely dispersed, standard statistical methods are generally inadequate to accurately estimate the downtime within the required statistical confidence levels. Field experts who are involved and familiar with maintenance and engineering aspects of the system can provide alternative source of estimation on PM actions duration. This estimation is stemmed from experts' observation and experience especially on issues, changes and improvement actions undertaken in the maintenance system, thus, can generally represent the existing maintainability performance. More importantly, the results of the evaluation will reflect more up-to-date information on maintenance capability as a result of all the improvement actions mentioned earlier, hence will produce better estimate of PM durations for future maintenance and operation planning. Involvement of experts in this analysis will also encourage more participation and ownership of plant personnel in the study, expose them to the techniques and most importantly tap their tacit knowledge. The proposed approach will provide a systematic and effective mean of utilization of experts' judgement for prediction which is generally not fully exploited in the industry.

5.5.2.2 Proposed Methodology

A general method in elicitation of expert opinion, which involves three major steps: preparation; elicitation and measurement; has been presented in Chapter 2. Figure 5.22 depicts a proposed flow in elicitation and measurement steps for estimating PM downtime.

Elicitation on PM downtime distribution was done by interviewing experts who were the mechanical and maintenance engineers of that particular offshore plant. They had vast experience on that gas compression system operation, failure data and maintenance system. The elicitation data derived were based on the consensus between them. Before the downtime distribution for each PM action was elicited, various factors that affect the distribution had to be identified and considered. Neil and Marquez (2010) in their modelling of corrective repair time distribution, refer these conditions as "repair lines" where each line has the probability of the occurrence and can be categorized by a repair time distribution. Examples of different types of repair lines include maintenance first line support, second line support and manufacturer support.

Following a similar approach, in this study we requested the expert to state various scenarios which will affect the downtime duration of PM actions. In contrast to Neil and Marquez (2010) approach, which use arbitrary probability numbers in the model, this study use expert opinion inputs to estimate the downtime distribution for each scenario. The question asked during the interview was rather straight forward "what is the probability of scenario A to occur presently?". However to make the expert more comfortable, an alternative question was also asked "in 100 events of the particular PM, how many times scenario X occurs?". Table 5.9 presents the result of this elicitation process in which four different scenarios were identified.

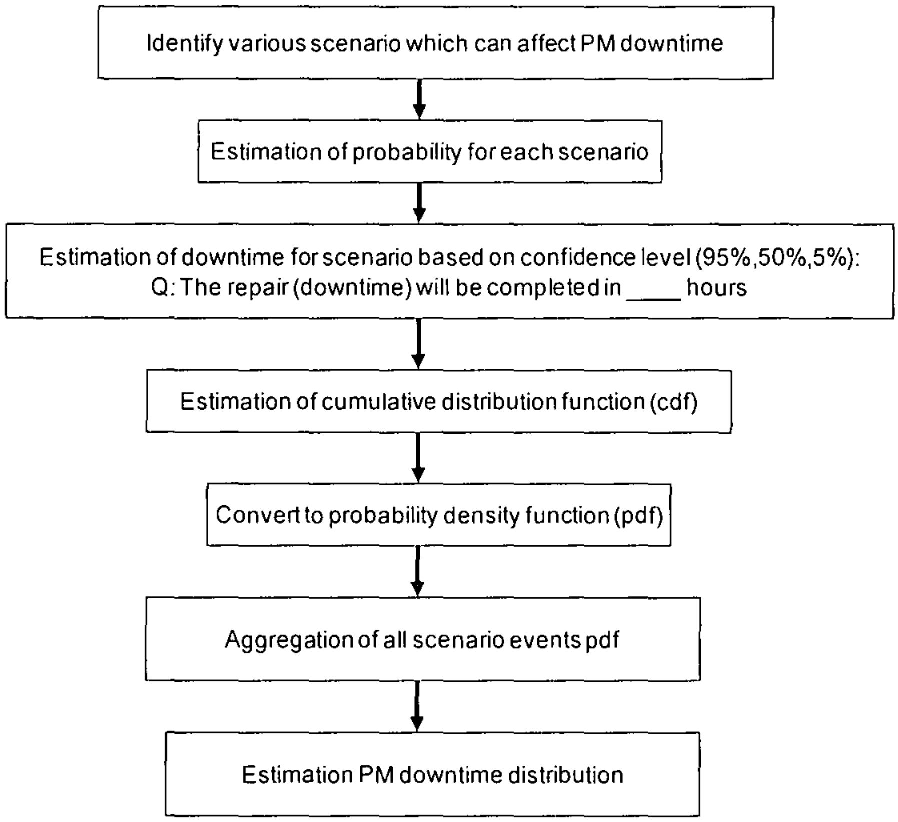


Figure 5.22: Proposed flow for elicitation and measurement processes

Table 5.9: Expert inputs on various scenarios affecting downtime distribution

Scenario	Description	Probability
1	No fault found during PM	0.9
2	Minor fault found during PM (eg. Valve)	0.05
3	Major fault found during PM (eg. Blade)	0.025
4	Delay due to external factor (eg. Logistics)	0.025

The next process involves the estimation of probability distribution of each PM type (4K, 8K and engine wash) for each scenario. To facilitate the process, the average value of each PM event based on historical data was shared with the experts for their reference. Due to expert's lack of knowledge on the probability distribution family, an indirect elicitation approach using a fractile technique similar to those used by Walls and Quigley (2001) was employed. Here, the expert was required to estimate the downtime duration based on specific confidence level in his belief. Instead of asking question, the statement approach was used where the expert was asked to complete the statement. An example of the statement is as follow: "I'm 95% confidence that the specific PM action will be completed in x hours", where the expert had to estimate that "x" downtime hours. The estimation of downtime hours were also sought for 50% and 5% confidence levels. The result of this process is shown in Table 5.10.

Table 5.10: Results of eliciting downtime distribution by percentile

	Scenario	1	2	3	4
PM types	Confidence level %	Downtime (hours)			
4K	5	48	60	144	72
	50	72	84	192	108
	95	96	108	216	144
8K	5	72	84	144	96
	50	96	108	192	132
	95	120	132	240	168
Engine Wash	5	4	16	124	28
	50	6	18	150	42
	95	12	24	180	60

5.5.2.3 Modelling of Downtime Distribution

The expert inputs in Table 5.10 represent indirectly the cumulative distribution function (cdf) for the downtime distribution. The 50% confidence level represents the median in which half of the downtime distribution is below that point. In this study, we first assume the downtime to follow a lognormal distribution since this is the most commonly used distribution for downtime found in the literature. This assumption, however, is subjected to change if the expert believes otherwise. The lognormal cdf can be expressed as

$$F(x;\theta,s) = \Phi\left(\frac{\ln x - \theta}{s}\right) \tag{5.1}$$

where θ and s are the mean and standard deviation of downtime's natural logarithm, Φ is a standard normal distribution cdf and x is the estimated downtime hours. The pdf equation is given by

$$f(x;\theta,s) = \frac{1}{xs\sqrt{2\pi}} e^{-\left(\frac{\ln x-\theta}{2s^2}\right)^2} \quad , x > 0 \tag{5.2}$$

The mean and standard deviation (std) of the actual downtime distribution is given by

$$mean = e^{\theta + \frac{1}{2}s^2} \tag{5.3}$$

$$std = e^{\theta + \frac{1}{2}s^2}\sqrt{e^{s^2} - 1} \tag{5.4}$$

For the case of 4K scenario 1, Equation (5.1) can be expressed as

$$\Phi\left(\frac{\ln 48 - \theta}{s}\right) = 0.05 \tag{5.5}$$

$$\Phi\left(\frac{\ln 72 - \theta}{s}\right) = 0.50 \tag{5.6}$$

$$\Phi\left(\frac{\ln 96-\theta}{s}\right)=0.95 \tag{5.7}$$

Referring to the normal distribution table, the corresponding equations are as follows

$$\left(\frac{\ln 48-\theta}{s}\right)=-1.64 \tag{5.8}$$

$$\left(\frac{\ln 72-\theta}{s}\right)=0 \tag{5.9}$$

$$\left(\frac{\ln 96-\theta}{s}\right)=1.64 \tag{5.10}$$

Solving for θ and s based on these three equations resulted in no single value for each parameter. Thus approximation technique using Solver function in Excel worksheet was employed. The estimated values of $\theta = 4.27$ and $s = 0.194$ were obtained and later being used to create a smoothed cdf plot as shown in Figure 5.23. This histogram plot was later shown to the experts for further verification and agreement.

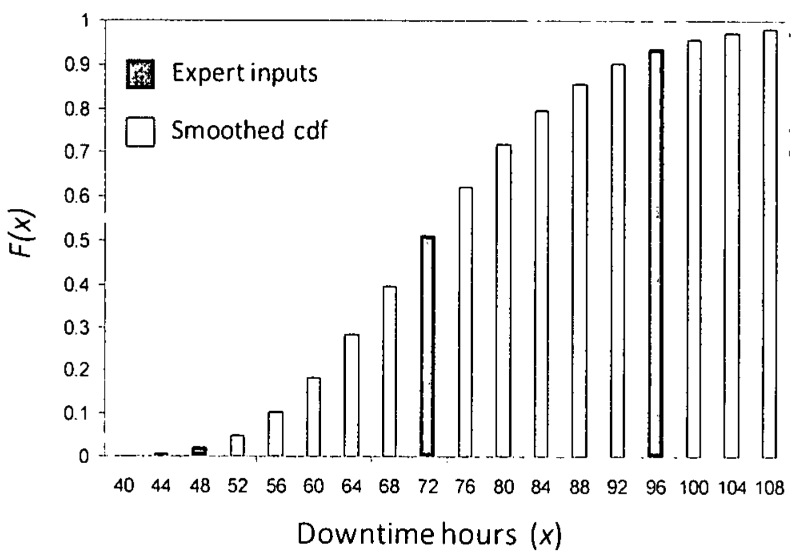


Figure 5.23: Lognormal cdf for 4K scenario 1

The corresponding pdf plot is shown in Figure 5.24. The downtime mean and standard deviation were calculated to be 72.9 and 14.2 hours respectively.

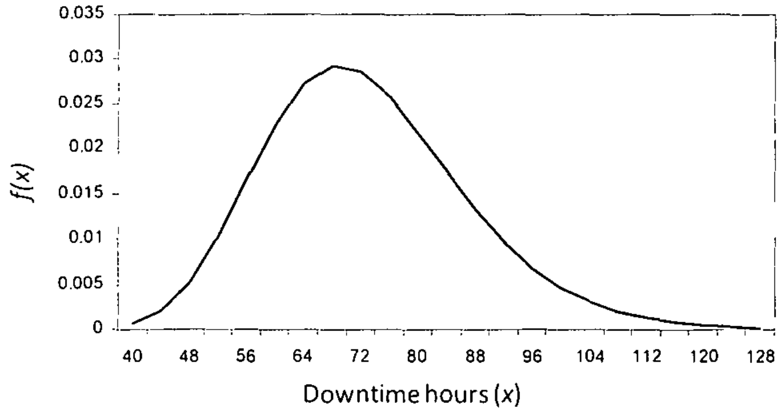


Figure 5.24: Corresponding lognormal pdf for 4K scenario 1

5.5.2.4 Downtime Distribution Model

The complete analysis results on each scenario for each PM type are presented in Table 5.11 which shows the proposed distribution and estimated parameters for each scenario. Lognormal distribution was accepted to be best model for all types of PM.

Table 5.11: Summary of pdf distributions and parameters

PM types	Scenario	lognormal		Downtime pdf	
		θ	s	*mean*	*std*
4K	1	4.27	0.194	72.9	14.2
	2	4.43	0.169	84.3	14.3
	3	5.26	0.072	193	13.9
	4	4.68	0.194	109.8	21.5
8K	1	4.56	0.149	96.7	14.5
	2	4.68	0.133	108.7	14.5
	3	5.25	0.149	192.7	28.9
	4	4.88	0.162	133.4	21.7
Engine Wash	1	1.79	0.259	6.2	1.6
	2	2.89	0.072	18	1.3
	3	5.0	0.113	150.9	17.1
	4	3.73	0.229	42.8	9.9

To get a single distribution for every PM type, all distributions from each scenario need to be combined taking into consideration the weighting factor of probability of occurrence. This distribution is called a marginal distribution and can be calculated using a linear opinion pooling technique (Clemen and Winkler, 1999) :

$$f(D) = \sum_{i=1}^{4} f(d \mid scenario = i) * P(scenario = i) \tag{5.11}$$

where

$f(D)$ = marginal downtime probability distribution for a particular PM type

$f(d \mid scenario = i)$ = the probability distribution for scenario i (i = 1,2,3,4)

$P(scenario = i)$ = probability of scenario i as given in Table 5.9.

The resulted marginal distribution for 4K PM is illustrated in Figure 5.25. The best estimation of lognormal distribution (Figure 24) based on that marginal distribution was determined also using Solver function in Excel. The summary of estimated lognormal distribution parameters and calculated sum of squared errors (SSE) for all PM types is shown in Table 5.12.

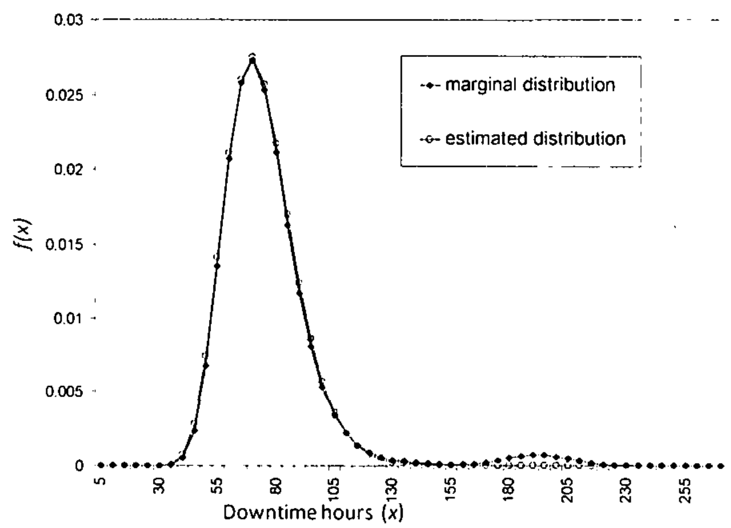


Figure 5.25: Marginal distribution and estimated lognormal distribution for 4K PM

Table 5.12: Estimated lognormal distribution parameters and errors

PM	θ	s	SSE
4K	4.28	0.204	5.80E-06
8K	4.57	0.157	2.60E-06
Engine wash	1.8	0.278	1.70E-03

5.5.2.5 Plant Maintenance Data vs. Expert Opinion

The conventional method to determine the downtime distribution is by using historical plant data. The PM downtime distributions from plant maintenance data in Table 5.8 are analyzed using Reliasoft Weibull software and the estimated parameters are presented in Table 5.13.

Table 5.13: Downtime distribution based on plant maintenance data

PM	Distribution	θ	s	mean	std
4K	Lognormal	4.07	0.254	60.5	15.6
8K	Lognormal	4.59	0.395	106.5	43.8
Engine wash	Lognormal	2.15	0.496	9.7	5.1

Based on these parameters, the pdf plots of downtime for each PM type are plotted and then compared against the one derived from expert opinion. Figures 5.26, 5.27 and 5.28 show the comparison plot for each PM type. The summary of downtime distribution mean and std is shown in Table 5.14.

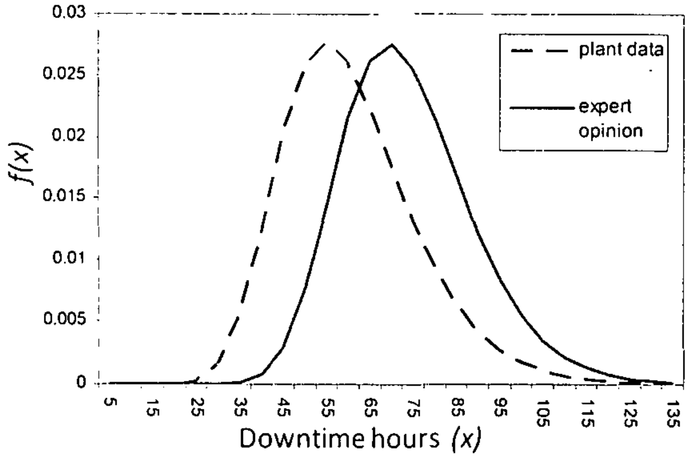


Figure 5.26: Expert opinion vs. plant data for 4K

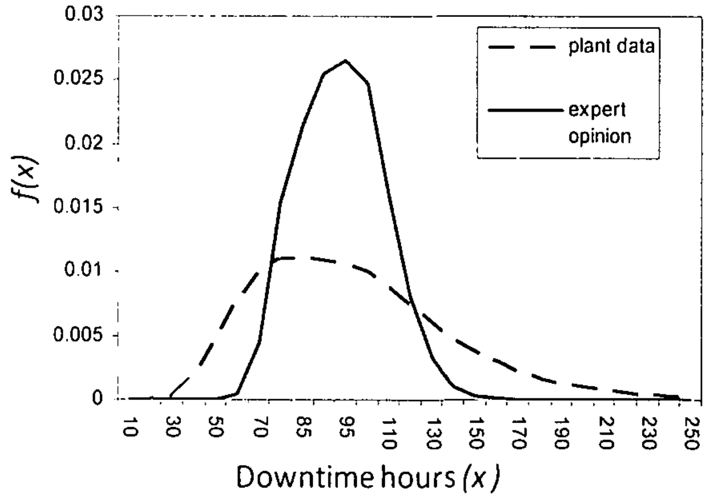


Figure 5.27: Expert opinion vs. plant data for 8K

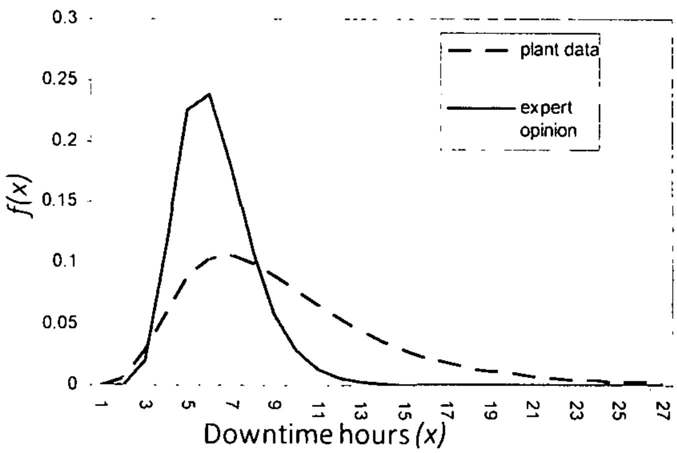


Figure 5.28: Expert opinion vs. plant data for Engine wash

Table 5.14: Comparison between plant data and elicited expert opinion downtime distribution

		Plant data	Expert opinion
4K	mean	60.5	73.8
	std	15.6	15.2
8K	mean	106.5	97.7
	std	43.8	15.4
Engine Wash	mean	9.7	6.3
	std	5.1	1.8

From the plots it can be clearly seen that expert opinion produces better prediction for downtime distributions of 8K and Engine wash. The spread of the distribution is much tighter thus resulted in more accurate estimation. In the case of 4K, the distribution variation is comparable; however, the experts' prediction on downtime mean is higher than the prediction based on plant data. Based on the latest data for 2009 and 2010, the average PM recorded downtime for 8K and 4K PM were 85 and 95 hours respectively. These data are relatively closer to the value predicted by expert, thus also signifies that the expert opinion prediction method produce better estimate. There was no Engine wash downtime data recorded in 2009 and 2010.

5.6 Chapter Summary

The practical approach and applications of maintainability analysis have been clearly demonstrated in this chapter. Furthermore, the study highlights the importance of maintainability analysis as part of strategic tool for system improvement at operation phase. As such, this analysis is worthy of being considered and performed by plant management in more complete and extensive way on regular basis alongside reliability analysis. The case study presented has indicated that the GCT system's availability performance is predominantly influenced by trend in maintainability rather than trend in reliability, thus further highlights the significance of performing maintainability analysis for the system. The proposed framework for maintainability analysis of plant maintenance data, presented in Figure 5.19, is found practical to measure maintainability of system with improvement trend. The role of field experts beyond a traditional method of merely providing and validating maintenance data in the analysis process has also been explored in this chapter. Here, their experience and judgement are directly used to estimate the duration to complete certain maintenance activity. The proposed method as described in Figure 5.22 provides a fresh approach of acquiring and employing such tacit knowledge for more effective decision making and can also be applied in other types of analysis such as reliability, safety and hazards when there is limited data availability.

CHAPTER 6

AVAILABILITY ANALYSIS

6.1 Introduction

An in-depth discussion on availability analysis with regards to definition and related techniques has been presented in Chapter 2. Moreover, in Chapter 3, detailed step of the proposed methodology framework for conducting practical analysis at operation phase has been discussed. This chapter presents the applications of the proposed availability analysis approach and discusses its role as a strategic tool for assessing plant system performance and evaluate various plausible options or solutions to increase system availability leading to overall improvement in operation profitability. To demonstrate the importance of this technique, two case studies are presented; first, an acid gas removal unit (AGRU), a system in a gas processing plant; second, a gas compression train (GCT) system at an offshore platform, a similar system which has been used as a case study in previous reliability and maintainability studies.

The following two case studies are presented to demonstrate the practical applications and importance of availability analysis for enhancing plant availability. In both cases, the methodology used for analysis follows the proposed steps in the framework for availability analysis described in Chapter 3.

6.2 Case Study I: Availability Analysis on Acid Gas Removal Unit (AGRU)

6.2.1 Objectives and Scope of the Study

The plant management has raised the need to study the availability performance of AGRU as part of their efforts to improve the overall GPP operational profitability. Besides, the management sees the initiative as important for understanding and exploring availability modelling simulation technique as a strategic plant improvement tool. Upon further discussion with them, the specific objectives for the study are set as follows:

- To model the existing AGRU system
- To assess the availability of AGRU based on that model and its availability performance
- To identify critical factors / equipment affecting the reliability, maintainability and availability performances
- To assess various options for enhancement of AGRU availability

The scope of the study is on analysis of AGRU system of GPP3, one of the gas processing plants.

6.2.2 Data Collection and Analysis

Generally three types of data are needed when performing availability study: Process flow diagram (PFD) supported with piping and instrumentation diagram (P&ID); Reliability and Maintainability (R&M) data; and maintenance system data. PFD and P&ID are needed for the construction of reliability block diagram (RBD) and for specification of the boundary for the studied system. R & M data used in this study are mainly in-house and collected from various sources such as maintenance records, SAP database (a computerised maintenance management system) and engineering report. In the absence of any particular information, other sources of data such as

OREDA database and pump flow reading are utilized. The process for R&M analysis is similar to those presented in Chapter 3. Due to many uncertainties related to data, constant verification exercise with field personnel is carried out throughout data gathering and analysis to ensure the outcomes are valid and relevant. The data used in the study are those from April 2008 till June 2010..

Gathering relevant data is the most time consuming and difficult task, due to the nature of the data availability in the plant. Most of failure data can be tracked in maintenance tripping record, which states when the trip started and ended. However, not all data in there, for example, P202 pump data are captured in another record which is totally in different format and not as complete as the maintenance tripping record. Besides issue with non-centralised failure data storage location, some of the existing records also suffer from error, missing and incomplete data. Hence, to minimise uncertainties, further verification are performed by cross-checking the data with SAP and consulting field experts.

Extraction and segregation of relevant data on SAP is found rather complicated since the SAP is overcrowded with too many information (e.g. it contains records of all actions on the equipment including those planned for the future), has unclear status whether a repair action has completed and is prone to human error during recording. Furthermore, failure data need to be transformed into operating time-based format, as discussed in previous chapters, before they can be analyzed for IID conditions and assigned appropriate reliability and maintainability model. This is quite a challenging task since maintenance tripping records only capture failure and downtime duration, but do not keep track various operating conditions such as operation, standby / idle modes and maintenance time. One particular example is when performing R&M analysis for P201 and P202 pumps, which are subjected to different types of operating modes. Since there is incomplete and vague record on operating modes, alternative method based on the real time flow rate reading recorded by sensors had been proposed by engineers to establish the operating time profile for pumps. In this approach, a graph of flow rates against time is plotted for each pump and compared with the specific operating conditions represented by the flow readings proposed by engineer. Table 6.1 shows the corresponding conditions set for different flow levels of each pump type. The flow profile is also checked against maintenance activities such as turn-around (TA), mini TA and plant shutdown. An example of a flow reading plot for pump P201C of GPP3 is illustrated in Figure 6.1. To differentiate various operation modes, the flow is plotted with different codes: 1 = operating, 0.5 = standby, 0.25 = turn-around / AGRU shut down, and 0 = down due to failure. From this plot, the time to failure (TTF) of each failure event is determined by accumulating all operating time (Coded 1) since the previous failure event. Prior to that, all events with zero flow rates are verified by comparing them with maintenance failure record and consulting respective plant personnel for consistency.

Table 6.1: Pump operation mode conditions based on flow rate

Pump / Operation mode	P201	P202
Operating	Flow rate ≥ 400 m^3/hr	Flow rate ≥ 200 m^3/hr
Standby	Flow rate < 400 m^3/hr	Flow rate < 200 m^3/hr
Down (failure)	Zero flow rate and not in standby	Zero flow rate and not in standby

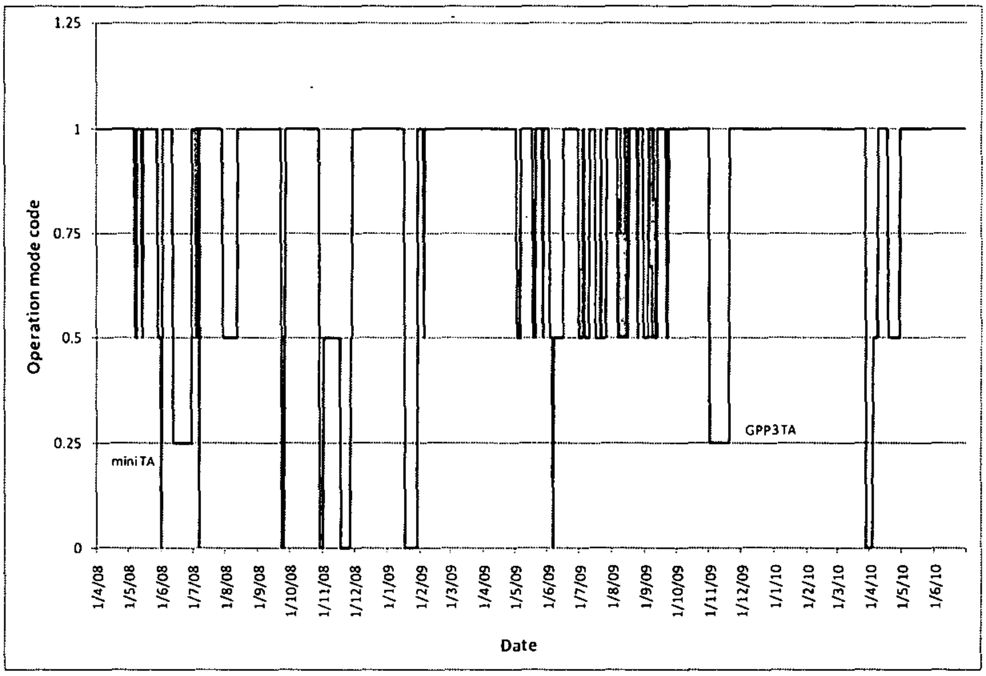


Figure 6.1: GPP3 P201C coded flow rate profile

Flow rate data also provide insight on the existing configuration of pump operation. Previously it was assumed that P201 pumps are operating based on two out three arrangements. However, the operation breakdown based on flow rates data indicates that most of the time only one pump or slightly more is on operation out of three, as illustrated in Figure 6.2.

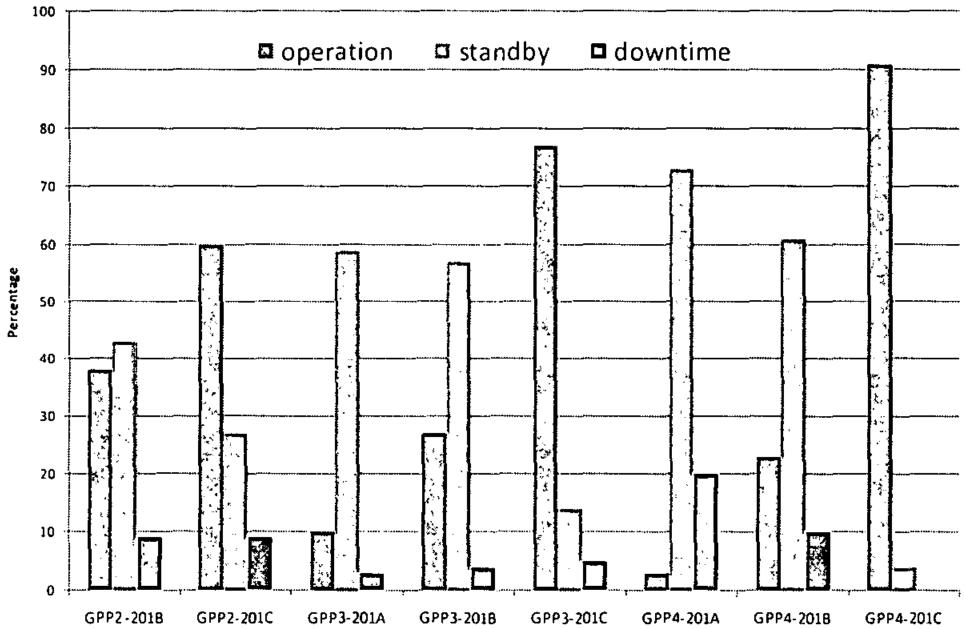


Figure 6.2: Operation mode breakdown of P201 pumps for GPP2, GPP3 and GPP4
(Notes: P201A pump of GPP3 was put out-of service)

6.2.3 Assumptions on Model

Based on the collected data and discussions with plant engineers the following assumptions are made in the study:

i. Constant failure rate is used for equipment with limited or no failure data
ii. Perfect switching from standby mode to operational mode
iii. Downtime measurement is based on days (per the available flow rate data taken at 6 am daily)
iv. Preventive Maintenance (PM) action is done concurrently with planned plant shutdown activities such as TA, mini TA etc. (opportunistic maintenance). For that, the simulation model does not include PM downtime distribution
v. The downtime is assumed to include mean logistic delay and mean administrative delay in addition to the actual repair time (operational downtime)
vi. Failures during standby / PM / turnaround are not considered as unplanned downtime
vii. P201 and P202 are on 1 out of 3 configuration (only one is needed for the system to run)
viii. All static equipment is assumed in perfect condition since there is no failure recorded. For equipment with failure data less than 4, the average value is used to measure both failure rate and downtime

6.2.4 RBD Model Construction

The equivalent RBD model of the AGRU system constructed based on PFD, P&ID and plant engineers' inputs is depicted in Figure 6.3. The developed RBD is based on reliability wise arrangement which consists mainly of equipment that can potentially cause AGRU to down. Hence, the blocks arrangement is not the same as the process flow diagram. After the model is verified by the engineers, it is then reconstructed in Blocksim software, a specialised software used for availability simulation analysis. The equivalent diagrams of RBD in Blocksim are shown in Figures 6.4. In Blocksim, sub-diagram can be used to facilitate model construction and keep the RBD in simple and neat arrangement as illustrated in Figure 6.4. Based on the finding of existing operational pump configuration, the model uses 1-out-of-3 configuration for p201 and p202, instead of the designed configuration of 2-out-of-3, to produce realistic estimation of availability which is comparable with the recorded plant data. P202 and p201 pumps basically have to run in pair with the same configurations for smooth operation.

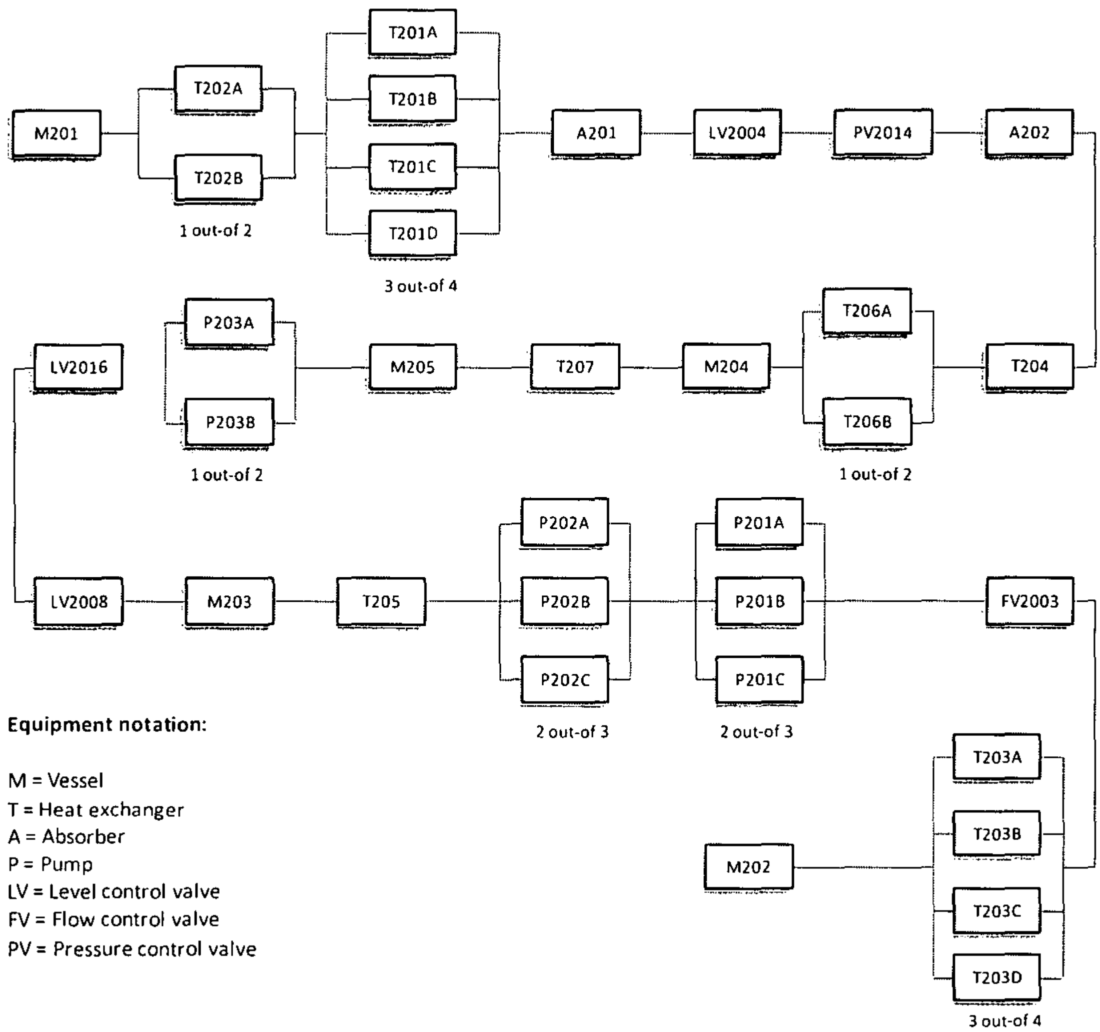


Figure 6.3: A conceptual RBD model for AGRU system

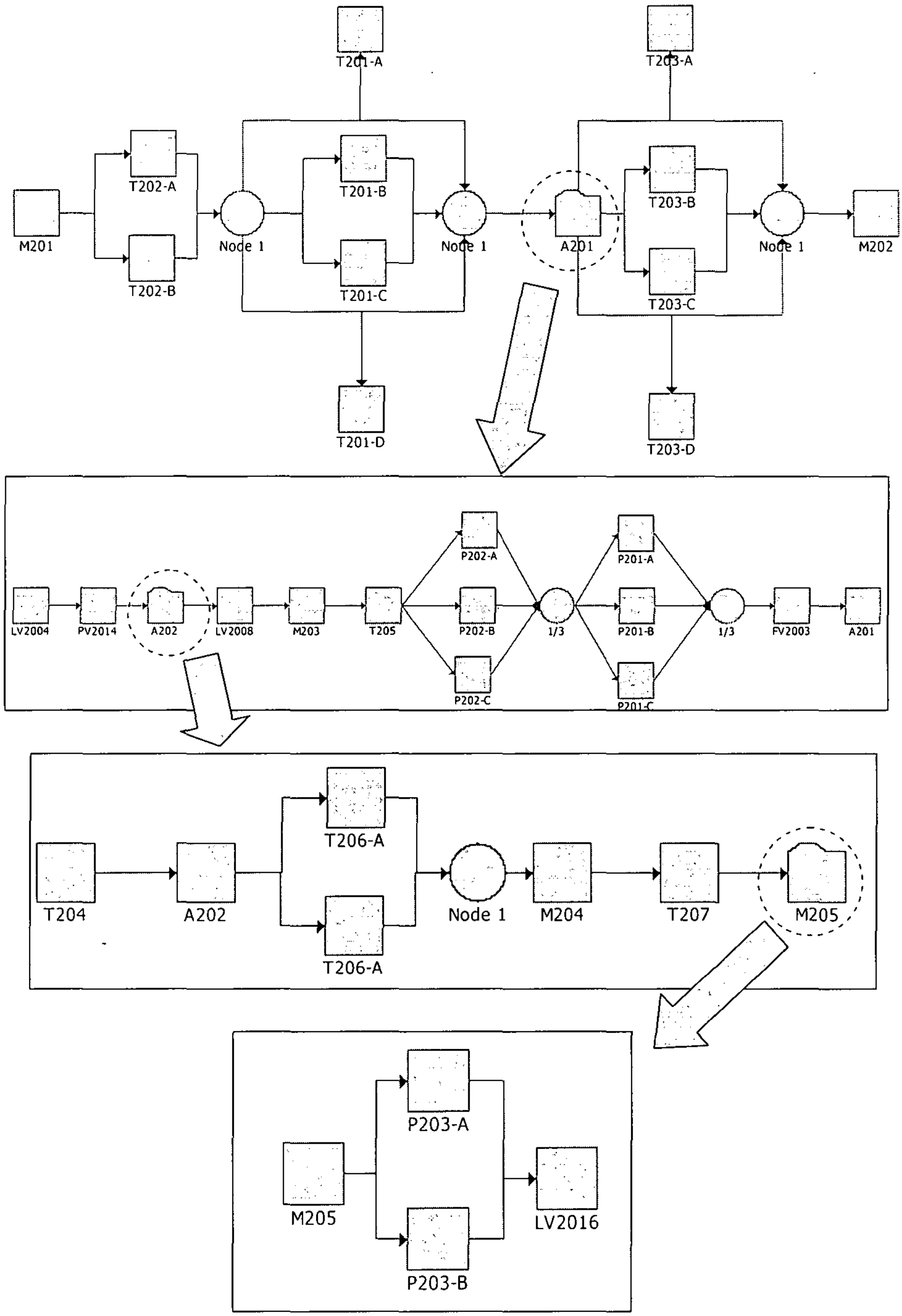


Figure 6.4: AGRU RBD constructed in Blocksim which contains sub-diagrams A201, A202 and M205

Before simulation is performed, all relevant information related to reliability, maintainability and maintenance scheme need to be input into each block of RBD. Reliability inputs include type of distribution model and its parameters. In maintainability, the required information is the distribution types and parameters (or downtime average for assumed constant repair rate) for CM actions. Since all PM activities are carried out during major shutdown, no PM input is required in the model. Based on the maintenance data for the period of study, only a small number of equipment in the system experiences many failures. Many of equipment have zero failures and some have less than three failures. In the latter case, an average value is used for estimation of R&M values. In reliability, the estimated value is assumed to follow exponential (constant failure rate) and for maintainability it is considered a fixed downtime duration. Statistical modelling is not appropriate here due to small sample, otherwise it will produce inaccurate model with high uncertainties. The list of equipment with R&M data are shown in Table 6.2. These data are then used to populate respective block in the RBD.

Table 6.2: R&M data inputs for GPP3

	Reliability		Maintainability	
Equipment	Distribution	Parameters	Distribution	Parameters / downtime
P3-201A	Exponential	λ=0.000514	Fixed duration	347.5 hrs
P3-201B	Exponential	λ=0.0005	Lognormal	$\mu = 4.785$, $\sigma = 1.29$
P3-201C	Exponential	λ=0.0005	Lognormal	$\mu = 4.063$, $\sigma = 1.47$
P3-202A	Exponential	$\lambda=4.6 \times 10^{-4}$	Fixed duration	1344 hrs
P3-202B	Exponential	$\lambda=1.986 \times 10^{-4}$	Fixed duration	72 hrs
P3-202C	Exponential	$\lambda=5.6 \times 10^{-5}$	Fixed duration	372 hrs
LV-2004	Exponential	λ=0.0001075	Exponential	λ=0.286
PV-2014	Exponential	λ=0.0001613	Fixed duration	1.95 hrs

Once the RBD is populated with required data and verified by plant experts, the next process is to set a proper design for simulation process. In this study, the following variables are set: number of iteration = 1000; time duration = 1 year (8760 hours); and seed number = 1. The simulation outputs are recorded after running 1000 iterations, where each iteration corresponds to a model run over one year period. An example of simulated operating state for the last iteration is illustrated in Figure 6.5. The plot shows the simulated up and downtime state for all affected components in one operation year. The availability of the system can be calculated based on the average uptime and downtime of all iteration results. The corresponding instantaneous system availability plot during the simulation run is depicted in Figure 6.6. In early part of the plot, the point availability indicates high variation as the number of iteration is still small; however it reaches asymptotic level towards the end of simulation period as the average value becomes more stable.

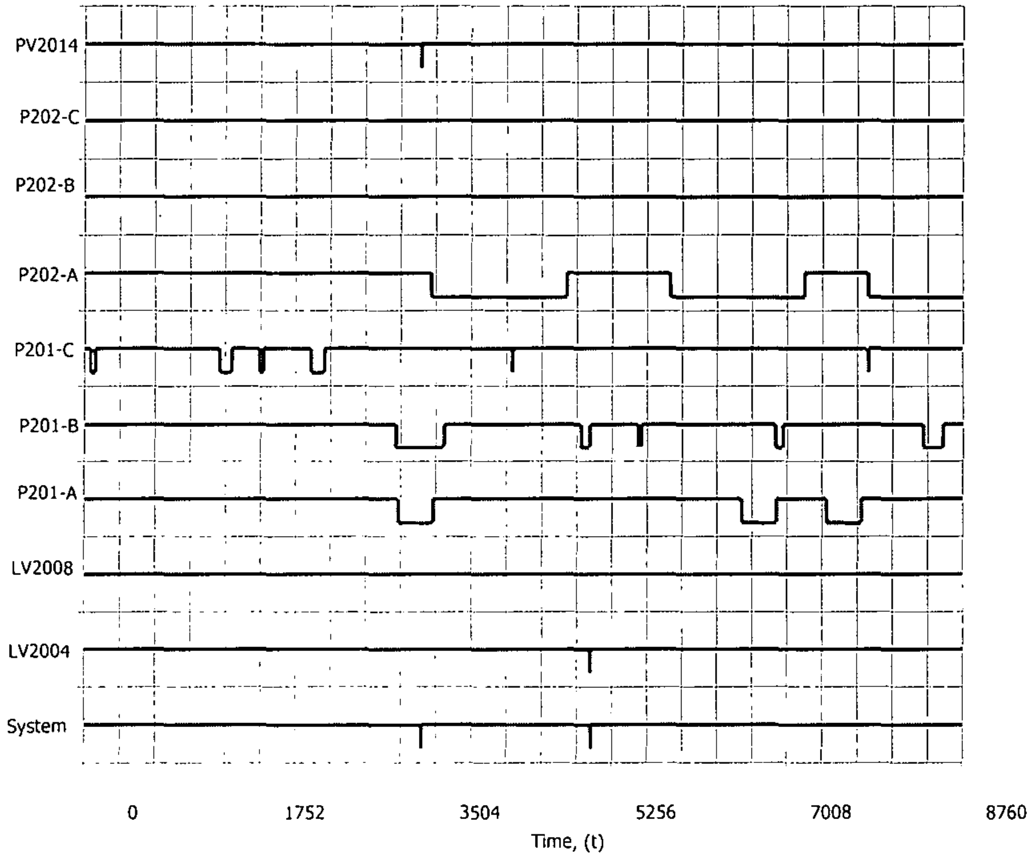


Figure 6.5: Snapshot of simulated block up / down (operating states) in the last iteration

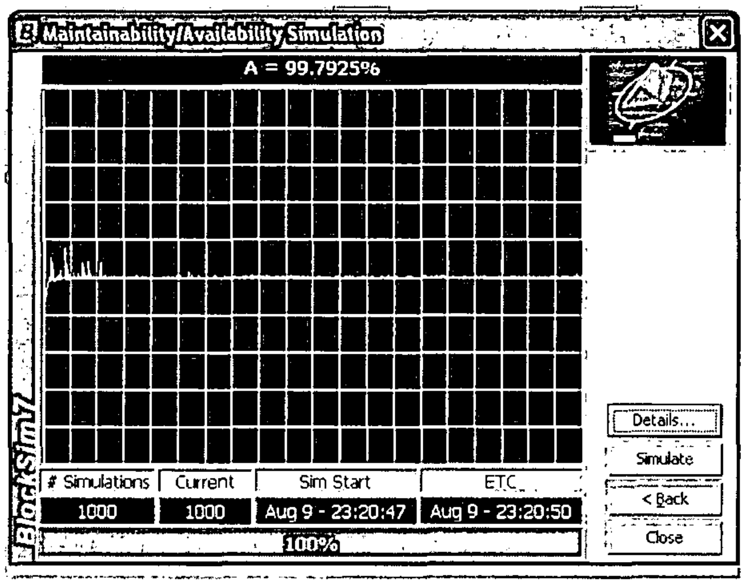


Figure 6.6: The instantaneous system's availability value during simulation

6.2.5 Model Simulation and Validation

The results of the simulation and the equivalent availability from plant report are tabulated in Table 6.3 for comparison and validation. The difference in result is highly expected due to different method of calculation and uncertainties related to data, RBD and various assumption used. Hence, generally in many studies, the simulation result is often used as an indicator of the existing system performance (Al-Thani *et al.*, 2001). This indicator is used as a base value for assessing relative performance of the system when the system parameters and operation conditions are changed.

The estimated availability from simulation is slightly higher than that of plant report but still within the acceptable range of accuracy (< 1%). Hence, it can be concluded that the model is valid to represent the real AGRU in term of availability performance estimation. This model can be referred to as a base case for the existing system configuration and performance, and can be used for strategic decision making to improve the system. Using this model, engineers can perform various studies on the system such as evaluations on the impact of modification in plant design (i.e. adding new section or expanding the existing facilities), utilization of new equipment, adding standby equipment, changing in spare parts allocation and maintenance system, policy, crew and effectiveness, to system's availability. Understanding influential factors to system performance will assist plant management and engineers produce right and effective decision making when planning for improvement actions.

Simulation based on OREDA data is also conducted for comparison (Table 6.3). Here, the failure rate of critical failure based on operational time and active repair time of centrifugal pump, general pump and control and safety valves are inputted into the model. The estimated availability based on 1-out-of-3 pump configuration is 99.87%, relatively better than the simulation result based on plant data indicating that the system real performance is slightly lower than the industrial average.

Table 6.3: Comparison of actual system availability and simulated results

Scenario	Availability (%)	std	95% confidence	delta	% difference
AGRU field report (2008-2010)	99.4	-	-	-	-
Simulation (1 year)	99.79	0.0057	99.76-99.83	0.39	0.39
OREDA (simulation)	99.87	0.0012	99.86-99.88	0.47	0.47

The simulated availability of the system can also be verified based on analytical calculation (static availability) of equipment under steady state condition (constant failure and repair rate). The obtained result is 99.77%, which is comparable to the simulation result. Detailed calculation of the analytical approach is presented in Appendix C.

6.2.6 Applications of Availability Simulation as a Decision Support Tool

6.2.6.1 Analysis of factors affecting system performance

The above simulation results are based on the assumption that only one out of three pumps is needed for operation instead of the specified operation design of 2-out-of-3. The existing configuration is set because current gas stream received from offshore fields contain relatively low CO_2 level thus does not require many pumps in operation. In the case of failure, the operation can quickly switch to any of two standby pumps resulting in minimum duration of system downtime. Depending on gas well compositions of incoming gas stream and possibly the inception of newly found fields, there is possibility in the future that the plant may receive gas with high CO_2 concentration. At this moment P201 and P202 pumps operation has to be reverted to 2 out of 3 configurations. It is imperative to understand what would be the resultant impact to AGRU and overall plant performances so that appropriate counter measure actions can be planned ahead. The simulation result of the system with 2-out-of 3 against 1-out-of-3 pumps configurations, set as a base case, is shown in Table 6.4. The impact of running 2-out-of-3 configuration in the model is a 4.16% reduction in availability. This is considerably significant value since the equivalent loss is estimated to be US$998K per month (based on daily production of 800 tonnes/day and Ethane price at US$1000/tonne). Running of simulation using OREDA data (2-out-of-3 configurations) resulted in availability of 99.44%, a mere 0.35% reduction from the base case. When compared to OREDA simulation with 1-out-of-3 configuration, the difference is 0.43%. These findings indicate that the existing system's availability is highly dependent on P201 and P202 performances. The availability assessment based on analytical method (Appendix C) for 2-out-of-3 case resulted in 94.96%, which is relatively close to the simulated result (less than 2% discrepancy).

Table 6.4: 2-out-of-3 configuration vs. base case

Simulation scenario	Availability	delta	% difference
1-out-of-3 (base)	99.79	-	-
2-out-of-3	95.64	-4.15	4.16

From the simulation results, further analysis on equipment performance and their contribution to system downtime can also be conducted. The criticality of equipment to system's availability can be assessed based on the percentage of time a downing event of that equipment caused the system to go down. This percentage is also called downing event criticality index and is used to rank equipment criticality with regards to system's unavailability (Reliasoft, 2007). Table 6.5 lists the performances of critical equipment based on simulation results. As expected P201 pumps top the list, followed by pressure control valve PV2014, level control valve LV2008 and p202 pumps. PV2014 and LV2008 have high criticality index since any failure of these equipment will definitely bring the system down due to their reliability-wise arrangement in series. Nevertheless, their downtime durations for each failure event are extremely lower than those of P201 and P202 pumps. Despite running on 2-out-of-3 configurations, P201 and P202 pumps criticality are high mainly due to their long downtime.

Table 6.5: Performances of critical equipment

Equipment	system down event	criticality index	no of failures	equipment downtime(hrs)
P201	2.31	41.87%	11.47	2839.7854
PV2014	1.424	25.81%	1.424	2.7768
LV2004	0.903	16.36%	0.903	3.1128
P202	0.881	15.96%	4.665	3374.6639

6.2.6.2 Evaluate availability improvement options for 2-out-of 3 pump configuration

To mitigate possible loss in production as a result of increased requirement in pumps utilization, appropriate counter-measured plans need to be considered by management. Generally, increase in system's availability can be achieved either by adding redundancy or reducing repair time (downtime) or improving reliability. The question is how much improvement is needed? Hence, to assess various possible scenarios to achieve at least 99% availability target (close to current performance), the following improvement actions are evaluated:

i. Redundant unit for P201 and P202 pumps
ii. Reduction in P201 and P202 maintenance downtime
iii. Increase in PV2014 reliability

In the first case, each unit of P201 and P201 pumps is put into the system and the system is run with 2 out of 4 configurations. There are two possible options in choosing the pump type; turbine driven pump (P201/P202 A/B) and electric motor driven pump (P201/202 C). For a redundant pump based on turbine driven, reliability and maintainability performances similar to P201B and P202B are opted since the values, particularly downtime, are better than those of P201A and P202A.

Improvement in pump reliability (decrease in failure rate) and maintainability (decrease in downtime) also can improve system's availability. When compared with OREDA data, both failure rate and downtime values of all pumps are higher than those of OREDA (OREDA failure rate = 70.52 per 10^6 hrs; repair time = 39.7 hrs), however, the difference is more significant for the downtime than for the failure rate. Therefore, in this study, the analysis will focus on downtime improvement since it has greater impact to increase availability. Two options based on reduction of downtime are analysed. In the first option, the average of downtime for all pumps is set to 5 days (120 hrs), while in the second option the downtime average is set to 3 days (72 hrs).

Based on the ranking of criticality index, PV2014 is a critical equipment next to P201, hence it is worth to investigate its impact on overall system's availability. Compared to OREDA, the performance of PV2014 reliability is much worst (6.79 per

10^6 hours vs. 1.613 per 10^4 hours), whereas its maintainability is better (9.1 hrs vs. 1.95 hrs). Hence, in this simulation, PV2014 will use OREDA data as a reliability input while maintaining the operational data for downtime.

From the simulation results of all possible scenarios, sensitivity analysis can be done to understand the impact of each improvement option. The results of the sensitivity analysis for all five simulated scenarios (two with redundancy, two with downtime improvement, and one with reliability improvement) are shown in Table 6.6.

Table 6.6: Sensitivity analysis for various improvement options

No	Sensitivity title	Estimated Availability (%)	Absolute impact (%)	% impact	Remarks
1	Base case	95.64	-	-	2-out-of-3 configuration
2	Redundancy A*	99.43	3.79	3.97	Add P201B and P202B
3	Redundancy B*	99.55	3.91	4.09	Add P201C and P202C
4	Downtime set at 120 hrs	98.82	3.18	3.33	For all P201 and P202
5	Downtime set at 72 hrs	99.49	3.85	4.03	For all P201 and P202
6	PV2014 with OREDA data	95.57	-0.07	0.07	Use OREDA failure rate

Note*: 2 out of 4 configurations

The results show that adding redundancy into the system basically will generate an average of 4% improvement in the system's availability performance. This action, however, will incur some costs due to new equipment installation. Improvement in PV2014's reliability, on the other hand, has no apparent impact to overall system's availability, thus it is not a good consideration. The impact of having improvement (reduction) in equipment maintenance downtime for comparison is an estimated increase of 3 to 4% to system's availability. This seems to be a better option since it involves investigation on reasons why the downtime is high and taking appropriate corrective actions to rectify the problems. It is expected that high equipment downtime is mainly due by current maintenance practise of putting low priority on getting back the equipment into operational mode since only one operated pump is sufficiently required to support production at any time. Another reason is the ineffectiveness of repair actions, which based on the data analysis shows some failures with long downtime are multi-causes hence require more time to fix. Sending faulty equipment to overseas for repair/overhaul also increases downtime since it normally takes longer time for equipment to return. In order to improve equipment maintainability hence system's availability, it is necessary for plant to revise its maintenance priority of attending pump failure and carry out other improvement actions which can cut down maintenance downtime. These actions may include improvement in logistics (spare parts allocation and location; repair strategies: in-house or external; etc.), manpower planning and skills, and more effective root cause failure analysis, trouble shooting and repair actions.

6.3 Case Study II: Availability Analysis on Gas Compression Train (GCT)

6.3.1 Objectives of the Study

To further demonstrate the strategic roles of availability modelling for effective decision making, a case study on GCT is presented. The analysis on reliability and maintainability of the system has been discussed in detailed in the previous chapters. In this chapter, the availability modelling and simulation are carried out on each of the train and on the overall system when both trains are arranged in parallel system. The objectives of the study are to develop an appropriate availability model for the GCT system and to assess the impact of removing 4K ppm activity from the operation. The latter objective stems from the result of discussion with plant maintenance management about possible improvement actions to further reduce maintenance and operational costs.

6.3.2 Development of Availability Model

Similar to the AGRU system, the GCT system can be modelled using RBD approach in Blocksim. In this model, however, RBD blocks are specially created for various maintenance activities conducted on the system unlike the normal practice of assigning each block to represent individual component in the system. This approach is necessary since Blocksim has limitation in capturing more than one PM activity in one equipment block. The proposed model for each train consists of 4 blocks as illustrated in Figure 6.7, where each block represents each maintenance action. These blocks are arranged in series since any occurrence of maintenance event in any block will bring down the GCT operation. The schedule and frequency of each PM actions are set following the existing system arrangement, where 4K and 8K ppm are done once per year, and engine wash (EW) is conducted twice a year. The reliability data (time to failure distribution) is input into a CM (corrective maintenance) block. These data are taken from the results of reliability analysis which are presented in Chapter 4 (Table 4.6). For maintainability input, the type and parameters of CM downtime distribution of each train is estimated based on 2006 till 2009 data. The data for PM downtime distributions (4K, 8K ppm and engine wash) on the other hand, are derived from the outcome of expert opinion presented in Chapter 5 (Table 5.12). Other important data that need to be input into the PM blocks are the scheduled time for performing each of the PM action. The summary of reliability and maintainability inputs for train 1 and 2 are described in Table 6.7 and 6.8 respectively.

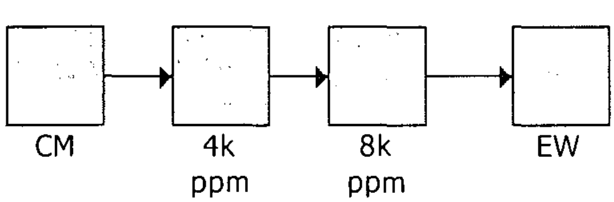


Figure 6.7: RBD configuration for a single GCT which consists of one CM block and three PM blocks

Table 6.7: R&M input data for GCT 1

Block	Data*	Distribution	Parameters
CM	TTF	Exponential	λ: 0.000513 / hr
CM	DT	Lognormal	μ:1.713, σ:1.6852
4K ppm	DT	Lognormal	μ:4.28, σ:0.204
8K ppm	DT	Lognormal	μ:4.57, σ:0.157
EW	DT	Lognormal	μ:1.8, σ:0.278

Table 6.8: R&M input data for GCT 2

Block	Data*	Distribution	Parameters
CM	TTF	Exponential	λ: 0.000596 / hr
CM	DT	Lognormal	μ:1.702, σ:1.2215
4K ppm	DT	Lognormal	μ:4.28, σ:0.204
8K ppm	DT	Lognormal	μ:4.57, σ:0.157
EW	DT	Lognormal	μ:1.8, σ:0.278

Note: TTF – time to failure, DT - Downtime*

6.3.3 Availability Simulation and Validation

Simulation runs are carried out for each train based on 1000 iterations for one year period. Apart from that, the overall availability of CGT system is assessed by having both trains arranged in parallel. Figure 6.8 shows the RBD that describes this arrangement. In this model, even though both blocks have been assigned with the same PM schedule, a slight change in PM schedule inputs is required in one of the train (in this case train 2) by adding 200 hours lagging factor. Otherwise, the PM events for both trains will occur concurrently (both trains are down for PM actions on the same time), which is not realistic as per current maintenance practise where schedule PM are carried out in staggered between both trains to avoid total system shutdown. The resulted simulation output is shown in Figure 6.9, which confirms that none of similar PM actions happen at the same time.

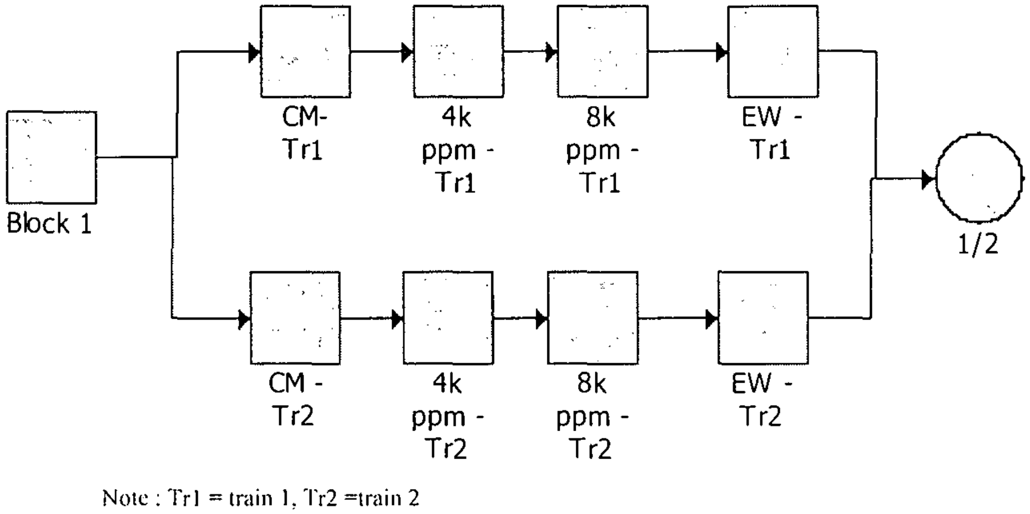


Figure 6.8: CGT system with both trains run in parallel

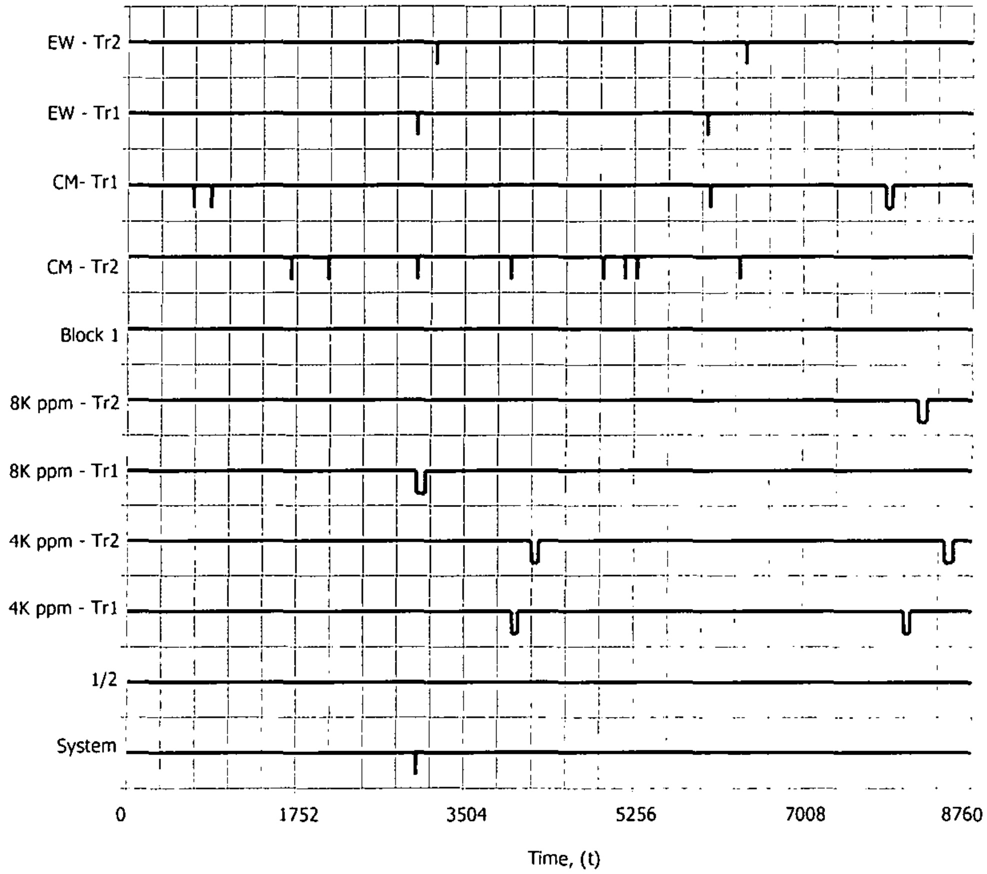


Figure 6.9: Simulated up and down states in the last iteration of simulation for each block

The simulated values of the availability then can be compared with the availability figures recorded in engineering report for year 2009 for validation. The results of simulation and recorded plant data are shown in Table 6.9. Comparatively, for both trains, there is not much different between the simulated results and the plant data, thus indicating the model is valid and can reasonably be used to assess the system further. There is however, a significant different for the overall GCT system results. This discrepancy is anticipated due to the differences in the calculation of both techniques. The plant record determines its overall availability by taking average value of both trains; whereas in the simulation, based on the parallel configuration, the overall GCT system is down only when both CGTs down in the same time interval.

Table 6.9: Results comparison between simulation and plant data

	Simulation	Plant data	Delta
GCT 1	95.99	96.8	-0.81
GCT 2	96.66	96.9	-0.24
Overall GCT system	99.71	96.85	2.86

6.3.4 Availability Analysis as a Strategic Improvement Tool

Based on the discussions with maintenance management, they are contemplating on running with one PM action; 8K ppm, per year to further improve plant's availability and reduce overall plant maintenance cost. Previous analysis using proportional hazard model and Kaplan Meier in Chapter 4 indicate that there is no clear evidence that PM actions (4K and 8K ppm) have significant influence on system's time-to-failure distribution (except when perform together with Engine wash). Thus, it can be safely assumed that the removal of 4K ppm alone most likely will not deteriorate the system performance.

To illustrate the practical use of availability simulation, a scenario in which 4K ppm is removed from the maintenance scheme is evaluated. The corresponding simulation results are shown in Table 6.10.

Table 6.10: Estimated impact on availability from removing 4K ppm based on simulation

	Existing configuration		Without 4K ppm		
	Availability (%)	Downtime* (hrs)	Availability (%)	Downtime* (hrs)	Availability Gains (%)
Overall GCT system	99.71	25.27	99.95	4.26	0.24
GCT 1	95.99	351.3	97.63	207.6	1.64
GCT 2	96.66	292.7	98.35	144.5	1.69

Note*: Estimation of overall downtime (CM plus PM) in one operation year

Based on the results, by removing 4K ppm maintenance operation, the system availability can be increased by only 0.24% when both trains are running in 1-out-of 2 configurations (50% shared loading). However, if the trains are expected to run in full capacity (both are running), the estimated gain is higher at an average of 1.66% per train. Based on the estimated current price of gas at US$ 4 per mcf (thousand cubic feet) and output of 140 MMSCFD per train, the estimated value of output per train per day is around US$560K (1 MMSCFD = 1000 mcf). Hence, the equivalent saving per train when it is run with this configuration is estimated at US$9.3K per day or US$3.42 million/year. In comparison, the estimated amount of saving when the system operates in 50% shared loading is only US$1.33K per day (US$487K/year). Looking at the current trend where most of the time both trains are running full capacity to meet demand, the proposal to eliminate 4K ppm seems very attractive due to its significant potential saving hence it is worth consideration.

6.4 Chapter Summary

This chapter demonstrates the applications of availability modelling and simulation using the proposed methodology framework in Chapter 3 to evaluate the existing operational system performances. As demonstrated in the two case studies, the availability analysis can be used effectively as a strategic management tool in decision making process for improving plant bottom line. Using "what if" approach, various possible scenarios can be simulated and their impact to system's availability can be determined. Based on the case studies, the results of availability modelling technique using RBD and simulation is found practical to appropriately represent real performance of existing systems within the acceptable accuracy range. The application of blocks in RBD is not just limited to description of equipment and their reliability-wise arrangement in the system, but as in the GCT case study, it can be used to represent various maintenance schemes and conditions for appropriate availability modelling. The validity of availability analysis, however, is highly dependent on the accuracy of reliability and maintainability data. Hence, the use of good quality and sufficient field data are critical in the analysis. Involvement of plant personnel throughout the study is necessary to furnish, correct and verify all relevant data. In the case of lack of relevant data, as in AGRU case study, alternative source of information such as flow rate is proposed to describe operating states of equipment (in this case pump) more accurately.

CHAPTER 7

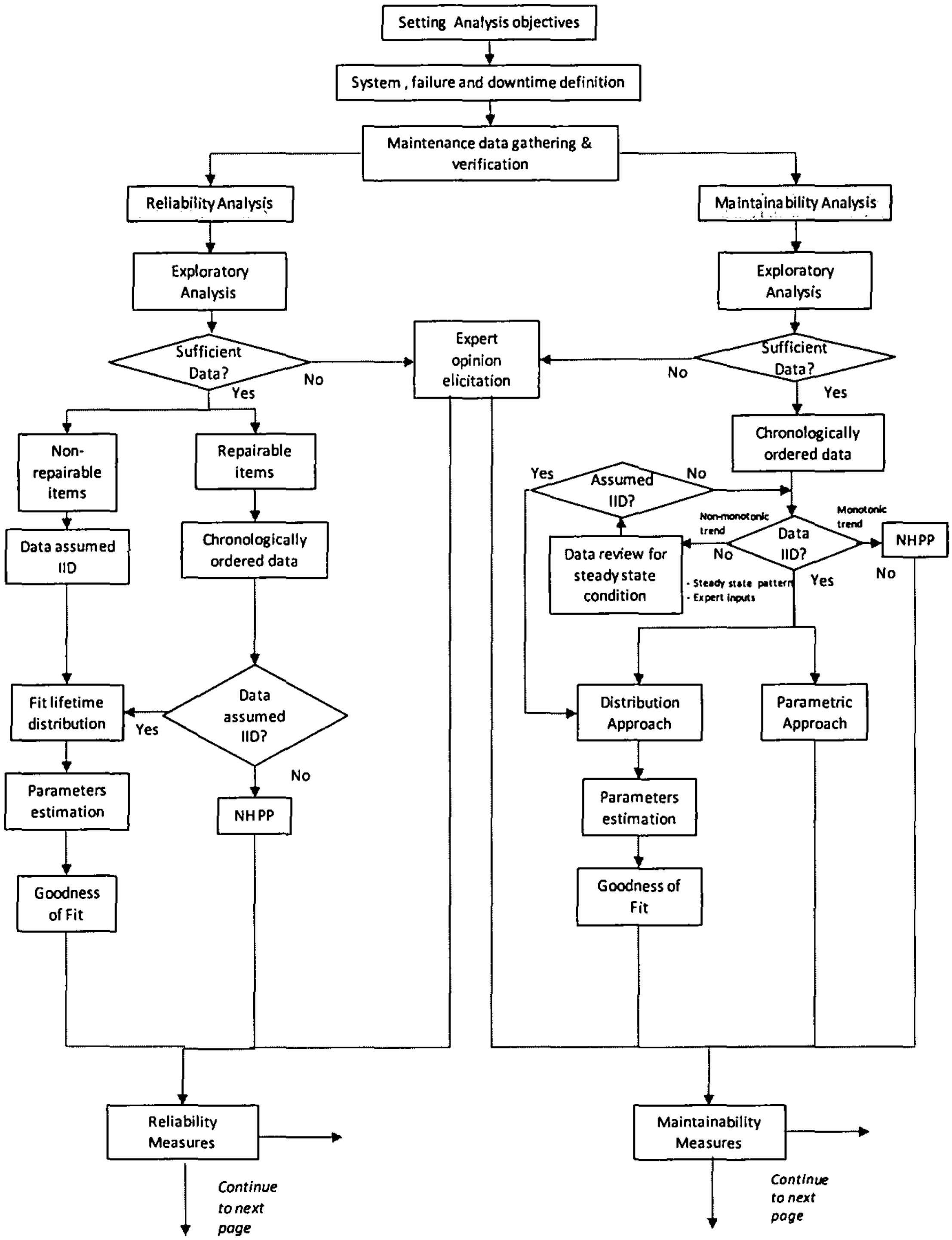
CONCLUSIONS AND RECOMMENDATIONS

7.1 Introduction

This chapter summarizes the findings and highlights the contributions of the research. The findings include several important points relating to the case studies and current industrial practice based on observation and field feedback. Research contributions to the knowledge, in particular the frameworks for applying reliability, maintainability and availability analysis as a strategic tool for improving system performance are also presented. Further, this chapter discusses on research limitations and recommends potential areas for future research.

7.2 Conclusions

The proposed framework presented in this thesis is found effective in analysing gas processing systems at operation phase for improving their operational and maintenance performances. Three proposed frameworks for applying reliability; maintainability; and availability analysis, as demonstrated through real industrial case studies, can be potentially applied by management as a strategic tool for assessing current operation and maintenance conditions, identifying weaknesses in the system and deciding on the best improvement option. Each one of the analysis can be performed separately or can be integrated into a comprehensive RAM study for overall improvement of system performances.


Setting Analysis objectives
System , failure and downtime definition
Maintenance data gathering & verification
Reliability Analysis
Maintainability Analysis
Exploratory Analysis
Exploratory Analysis
Sufficient Data?
No
Yes
Expert opinion elicitation
Sufficient Data?
No
Yes
Non-repairable items
Repairable items
Chronologically ordered data
Data assumed IID
Chronologically ordered data
Assumed IID?
Yes
No
Non-monotonic trend
Data IID?
Monotonic trend
NHPP
Data review for steady state condition
No
- Steady state pattern
- Expert inputs
Yes
No
Fit lifetime distribution
Yes
Data assumed IID?
No
Distribution Approach
Parametric Approach
Parameters estimation
NHPP
Parameters estimation
Goodness of Fit
Goodness of Fit
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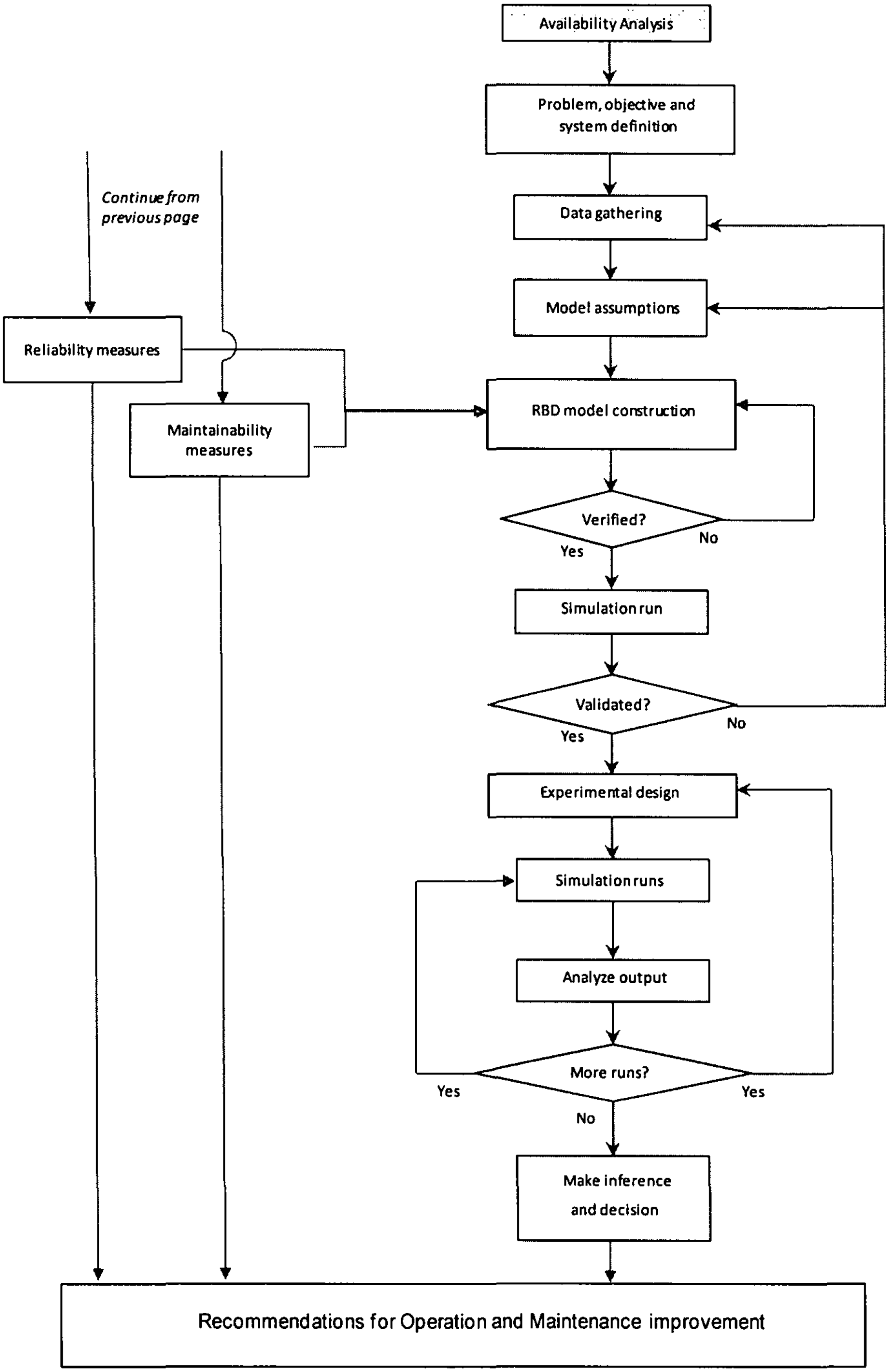

Figure 7.1: Proposed integrated framework for reliability, maintainability and availability analysis ofgas processing system at operation phase

The overview of an integrated framework of reliability, maintainability and availability analysis was presented in Chapter 3 (Figure 3.1). A more comprehensive description of the proposed integrated framework is shown in Figures 7.1. The study should start with clear objectives before proceeding to further detailed analysis. Both reliability and maintainability (R&M) analysis follow a general flow described in Figure 3.2, which include exploratory and inferential analysis to produce estimation of R&M measures. In case of insufficient data, expert opinion elicitation method based on Figure 5.22 can be employed. The results of R&M measures estimation are then input into the availability modelling during the RBD construction step. In availability analysis, simulation technique is used to estimate system's availability and perform "what-if" scenario improvement options. The results of R&M and availability analysis can be used to assess the system and recommend appropriate actions to improve its performances.

The case study approach used in this research managed to expose actual and new problems faced by industries and in the analysis processes. Issues such as insufficient data and data with non-monotonic improvement trend have been highlighted and addressed in the study. Although the frameworks were formulated and demonstrated on the two gas processing systems, they are equally applicable to other systems in oil and gas industries.

Plant personnel involvement in the analysis processes, particularly experts was found crucial in the implementation of the proposed frameworks. The level of engagement varied across the analysis depending on the field data conditions and system complexity. Besides general tasks of providing inputs on data collection, verification and classification processes and validating model, the roles of field experts was extended to provide valuable assessment on effectiveness of maintenance improvement actions and estimation on data distribution. This level of participation has provided a good platform for engineers to incorporate their tacit knowledge on plant operation into reliability analysis systematically. Direct involvement of field personnel during the study also assisted in promoting the applications of reliability analysis and techniques in the organization under studied, which is currently still relatively low.

7.2.1 Observations from this Research

This research reveals several important points and real issues related to managing and performing reliability analysis in the industry. These points should be considered in any reliability related study, to ensure the analysis is effective and the organization gains the most benefits. The following are highlights of key findings of this research.

i) The collection, organization and verification of field data are the most critical components of reliability analysis processes since they determine the quality and usefulness of the results. These, however, are the most difficult and time consuming tasks. It is evidence from the case studies that some of the pertinent issues with field data include incomplete, missing, non-centralized and non-standardized data, even for an old operating plant. All of these make the analysis process tedious and more challenging. To overcome these problems, inputs from field personnel are fundamentally crucial and the use of unconventional form of data can be a good option. For example, as demonstrated in the study of AGRU, the flow rate value is used to establish the operating conditions of pumps in the absent of relevant data.

ii) Exploratory analysis plays critical roles in reliability and maintainability study of field data and should be performed in the early stage of study before more in depth statistical analyses. This analysis can provide insights on the performance of the system under studied. The plots of cumulative number of failures over cumulative operating time, and cumulative downtime numbers over cumulative downtime duration, for example, are found very useful in gauging current system operational patterns, providing clues on outlook of system performance and identifying suitable mathematical model for predicting future trends.

iii) Maintainability analysis is found to be as critical as reliability analysis for system at operation phase since it can be a dominant factor influencing the availability performance, as demonstrated in the gas compression train system case study. The findings from maintainability analysis will reveal the overall effectiveness of maintenance system and improvement actions. Important attributes from the findings such as lesson learned, best practices and effective mitigation actions should be well shared not only with others at operation but also be feedback to the design team responsible for the development of similar systems in future. Proven improvement program addressing logistics issues such as vendor support and spare parts availability should be well established before the system commences operation.

iv) The assumption of constant failure and repair rate (random event) has to be tested first by means of statistical analysis, before it can be applied, even though it is generally acceptable for failure rate at system level due to the effects of various subsystems and components. Similarly an IID test should be performed on the field data before they can be analyzed using life data analysis (LDA) approach.

v) Reliability data analysis is not a well-known technique among engineers and management even though they are aware of the importance of having reliable operation. The analysis is usually done on ad-hoc basis and generally suffers from unstructured and unsystematic approach. Issues such as inadequacy, poor reliability and traceability of the existing database usually cause the studies to take longer time to complete and the results to be subjected to greater uncertainty. Other concerns include lack of skills and competency in the techniques and prevailing scepticism towards statistical-based analysis results amongst management. Nevertheless, the tendency in considering reliability analysis as an important improvement tool is rapidly apparent in the organization under studied based on their good support and participation in the case studies.

7.2.2 Contributions of the Research

This research aims to fill in the gap found in the literature on the applications of RAM analysis in the industries, particularly in oil and gas sector. Main contribution of the research is the proposed framework for implementing reliability, maintainability and availability analysis effectively to improve gas processingsystem performances.

This research further enhances the knowledge thus far in the RAM analysis of plant system at operation phase in actual industrial applications in the following areas:

1. It provides generic frameworks on how to perform and apply reliability, maintainability and availability analysis individually (Figures 3.1, 3.2 and 3.4) and collectively (Figure 7.1) as a strategic tool for plant management to evaluate existing performances, identify critical factors and overcome operational challenges.

2. It presents practical approach on how to tap, engage and exploit plant personnel and field expert's knowledge in the analysis processes (Figure 5.22). The proposed expert elicitation method to quantitatively estimate probable distribution of maintenance data can also be applied to other situations where the data are scarce and limited.

3. It addresses the issue of predicting system performance having non-monotonic trend as a result of maintenance and operation improvement, as in the case of corrective maintenance downtime of gas compression train system. Approaches based on linear regression and expert censoring techniques have been proposed in that situation (Figure 5.19).

4. It presents a framework (Figure 5.19) for conducting maintainability analysis at operation phase thatenhances the maintainability requirement model described by Blanchard *et al.* (1995) in Figure 2.5, by looking at ways of sharing lessons learned and providing more effective feedback on operation performance to both the design team and other plant personnel working on similar system.

5. It outlines a framework for integrating availability modelling and simulation techniques to assess various operational situations and estimate availability gained, upon which can be used to assist management in the strategic decision making process (Figure 3.4).

7.3 Limitations of the Research

The main limiting factor in this research is the unavailability of relevant and quality field data which is a crucial element in the analysis processes for producing more accurate, complete and meaningful results. The lack of failure data within the system hierarchy impede more exhaustive analysis to be conducted. For example, a lifetime analysis on components could not be adequately performed because the data are not generally well established at the component level compared to those at the equipment and system levels. Besides that, there is an issue with limited number of failure data due to fewer failure events during the observation period which prevents more in-depth reliability analysis such as data analysis by failure modes. Such analysis is important for assessing the impact of certain failure modes and providing some physical justification to system lifetime distribution (Doganaksoy *et al.*, 2002). Some data are also not readily broken down into more specific categories. For example, in the current recording system of downtime data, main elements of downtime breakdown i.e. active repair time, logistics and administrative delay, are not clearly distinguished. Consequently, it is not possible to proceed with higher level of analysis beyond downtime and single out the main cause of high downtime incident.

Another issue is the unavailability of costing data, which is an important element for analyzing the best economic option. Maintenance and operation optimization generally involves trade off of different factors for achieving the most cost effective solution. This approach however is not being explored in-depth in the research. The main obstacle is on the unwillingness of plant personnel to release information on the matter, most possibly due to difficulty to quantify and generalize the impact of failure in terms of different cost elements such as labour and spare parts. Despite that, an attempt to consider this factor has been presented in Chapter 6 for justifying the proposed preventive maintenance strategy for gas compression train system on the basis of gas production rate and its equivalent price.

7.4 Recommendations for Future Research

This research indicates maintainability as a significant factor influencing system availability at operation phase, hence an in-depth study should be carried out to identify the real causes of high downtime. Poor maintainability could be due to various factors such as maintenance support policy, operators' allocation and skill, process workflow and documentation, spare parts provision and supplier contract policy (IEC 60300, 2001). The study should start with breakdown analysis of downtime data for each of downtime elements i.e. repair time, logistics and administrative delay time, and then further investigate what are the contributing factors for each downtime element. Improvement and optimization actions in maintenance and support system (e.g. optimization of spare part and manpower allocations) can be proposed accordingly after real issues to downtime are identified.

It is also evident from the case studies that most existing plant field data suffer from various issues related to quality and documentation of data. Common problems include incomplete, outdated, unorganized, non-centralized and non-standardized data. Consequently, many reliability studies usually take longer time to complete as significant portion of time have to be spent on finding relevant data and verification process. The main cause of the problem can be traced back to the failure data management system in the plant, which was established primarily for reporting and not for conducting in-depth reliability related analysis. Hence, there is a pressing need to study and improve the existing data collection procedures and database system. A comprehensive study should be done on how to effectively and systematically gather, record, classify, format, verify, centralize and report all related data in a highly reliable database to facilitate relevant reliability, maintainability and availability analyses. Downtime report, for example, should be structured in such a way that it is possible to indicate how much downtime is contributed by each of the downtime elements. Having highly systematic and reliable database for plant failure data will definitely reduce the analysis time, provide foundation for further comprehensive analysis to be performed and more importantly enable more accurate analysis results.

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Book Chapter

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APPENDIX A

GAS COMPRESSION TRAIN FIELD MAINTENANCE DATA

Original data from the availability tracking record (field data) need to be rearranged and reformatted in order to capture essential information and ease the analysis process. The formatted table being used is described in Figure A.1. Different colour coding is used to distinguish events related to different types of maintenance, operation mode (single loading, standby) and failures. From the reorganized data, the following investigation can be performed

- Tracking of cumulative operating time for each train
- Determining the time between failures (TBF) more accurately based on operating time rather than calendar time. This information is crucial for in-depth analysis on reliability trend analysis (IID test) and reliability measures.
- Analysis on possible key variables (covariates) having influence on GCT reliability performances using Kaplan Meier and Proportional Hazards Model. From the table, the TBF related to the covariates can be traced and hence further analysis can be performed. These covariates include:

    a. Loading configuration (single loading vs shared loading)
    b. Train (train 1 vs train 2)
    c. Equipment (gas turbine and gas centrifugal compressor)
    d. PM types (8K, 4K ppm, engine wash)
    e. Failure type (start up failure)

legends:

	Standby > 4 hours
	Failure
S	Failure occurs after this start up
	single loading
	pm
	wash
	plant shutdown
S	start-up process event after: USD STDBY > 4 hours PSD

TRAIN 1

count	calendar time	failure	start up	PM 8/4K	wash	Loading single	oper days
1	2002 April - 1						
2	2						
3	3						
4	4						
5	5						
6	6						
7	7						
8	8						
9	9						
10	10						
11	11						
12	12						
13	13						
14	14						
15	15						
16	16						
17	17						
18	18						
19	19						
20	20						
21	21						
22	22						
23	23						
24	24		S				
25	25						
26	26						
27	27						
28	28						
29	29		S				1
30	30						2
31	31						3
32	May 1						4
33	2						5
34	3					1	6
35	4						7
36	5						
37	6						
38	7						
39	8						
40	9		S				8
41	10						9
42	11						10
43	12		S				11
44	13						12
45	14						13
46	15						14
47	16		S				
48	17						
49	18						
50	19						
51	20		S				15
52	21						16
53	22						17
54	23						18
55	24						19
56	25						
57	26						
58	27						
59	28						
60	29						
61	30						
62	31		S				
63	June 1						20

TRAIN 2

count	calendar time	failure	start up	PM 8/4K	wash	Loading single	oper days
1	2002 April - 1						
2	2						
3	3						
4	4		S				1
5	5						2
6	6						3
7	7						4
8	8						5
9	9						6
10	10						7
11	11						8
12	12						9
13	13						10
14	14						11
15	15						12
16	16						13
17	17						14
18	18						15
19	19						16
20	20						17
21	21						18
22	22						19
23	23						20
24	24						21
25	25		S				
26	26						
27	27		S				22
28	28						
29	29						
30	30		S				
31	31						
32	May 1						
33	2						
34	3						
35	4						
36	5						
37	6						
38	7						
39	8						
40	9						
41	10						
42	11						
43	12						
44	13						
45	14						
46	15		S				
47	16						23
48	17						24
49	18						25
50	19						26
51	20						27
52	21						
53	22		S				
54	23						28
55	24		S				29
56	25						30
57	26						31
58	27						32
59	28						33
60	29						34
61	30						35
62	31						36
63	June 1						37

Figure A.1: Sample of table for reformatted field data

APPENDIX B

KAPLAN MEIER AND PROPORTIONAL HAZARDS MODEL ANALYSIS

Data Inputs

For Kaplan Meier and proportional hazards model studies, the data need to be keyed-in the appropriate format for the analysis to be conducted. The data are extracted from the reformatted field data described in Appendix 1. Table B-1 depicts the variables, covariates and their coding used in the analysis format. The complete formatted data is shown in Table B-2.

Table B-1: Variable and categorical covariate codings

Variables	Description	Coding
Failtime	Time between failures	-
status	Status of failtime data	0= failure occurs 1= failure does not occur (censored data)
Covariates	**Description**	**Coding**
startup	Start up failures	0=other failures 1=fail after start up
operationmode	Operation mode	0=on sharing load 1=on single load
Train	Train types	0=Train 1 1=Train 2
subsystem	Subsystems	0=other subsystems 1=Gas Turbine + Gas compressor
PM	4K and 8K ppm	0=other failures 1=failures after PM
PMplusEW	4K, 8K ppm and Engine wash	0=other failures 1=failures after PM+wash

Table B-2: Covariates and their coding

failtime	startup	operationmode	status	Train	subsystem	PM	PMplusEW
15	0	0	0	0	1	0	0
6	0	0	0	0	1	0	0
195	0	0	0	0	0	1	1
295	0	0	0	0	1	0	1
107	1	0	0	0	0	0	0
129	0	1	0	0	0	0	0
65	0	1	0	0	0	0	0
20	0	0	0	0	0	0	0
22	1	0	0	0	1	0	0
118	0	0	0	0	0	0	1
32	0	0	0	0	1	1	1
263	1	0	0	0	1	0	1
113	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0
84	0	0	0	0	1	1	1
31	0	0	0	0	1	0	0
23	0	0	0	0	0	0	0
43	0	0	0	0	0	0	1
217	0	0	0	0	1	1	1
6	0	0	0	0	0	0	0
52	0	0	0	0	1	1	1
126	1	0	0	0	1	0	0
30	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0
3	0	0	0	0	1	0	0
68	0	0	0	0	1	1	1
3	0	0	0	0	0	0	0
22	0	0	0	1	0	0	0
31	1	1	0	1	0	0	0
327	0	0	0	1	1	0	0
132	0	0	0	1	1	1	1
77	0	0	0	1	0	1	1
6	0	0	0	1	0	0	1
104	1	0	0	1	1	0	1
17	0	0	0	1	0	0	0
42	0	0	0	1	1	0	0
45	0	0	0	1	1	0	1
208	0	0	0	1	1	0	1
22	1	0	0	1	1	0	0
28	0	0	0	1	0	0	0
8	0	0	0	1	0	0	0
56	0	0	0	1	1	0	0
22	0	0	0	1	1	0	1
7	1	0	0	1	1	0	0
30	1	1	0	1	1	0	0
151	0	0	0	1	0	1	1
17	0	0	0	1	0	0	0
64	0	0	0	1	1	1	1
89	0	0	0	1	0	0	0
100	0	0	0	1	0	1	1
80	0	0	0	1	0	0	0
4	0	0	0	1	0	0	0
91	0	0	0	1	0	0	0
124	0	0	0	1	1	1	1

Kaplan Meier Analysis

1. Train types

Table B-3 (a,b,c) : Summary of analysis results

Case Processing Summary

Train	Total N	N of Events	Censored	
			N	Percent
Train 1	27	27	0	.0%
Train 2	27	27	0	.0%
Overall	54	54	0	.0%

(a)

Means and Medians for Survival Time

Train	Mean[a]				Median			
			95% Confidence Interval				95% Confidence Interval	
	Estimate	Std. Error	Lower Bound	Upper Bound	Estimate	Std. Error	Lower Bound	Upper Bound
Train 1	77.148	15.857	46.069	108.227	43.000	18.174	7.379	78.621
Train 2	70.519	13.956	43.164	97.873	45.000	21.636	2.594	87.406
Overall	73.833	10.472	53.309	94.358	43.000	15.309	12.994	73.006

a. Estimation is limited to the largest survival time if it is censored.

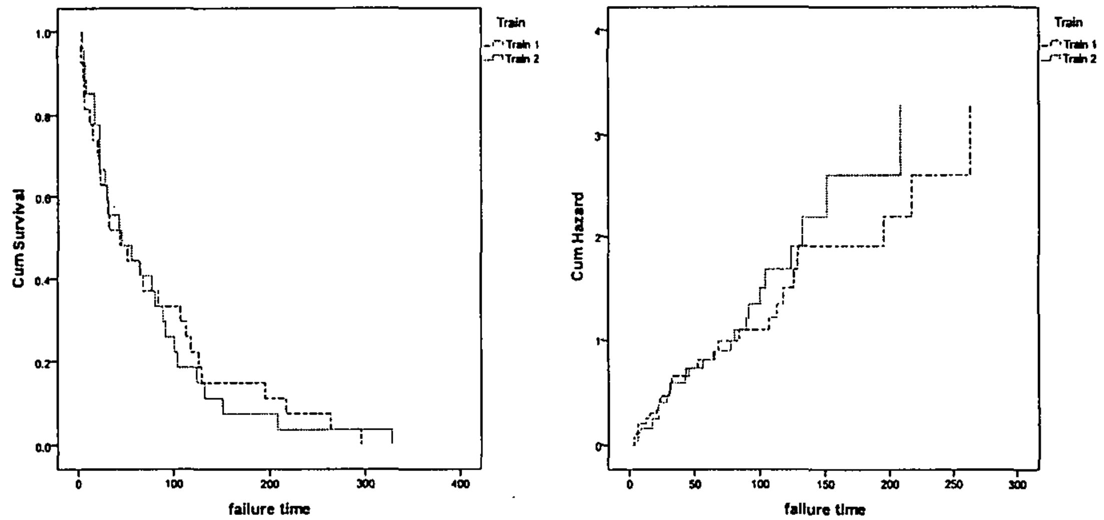
(b)

Overall Comparisons

	Chi-Square	df	Sig.
Log Rank (Mantel-Cox)	.027	1	.870

Test of equality of survival distributions for the different levels of Train.

(c)



(a) (b)

Figure B.1 (a,b): Survival and hazard plots for covariate train

2. Operation modes

Table B-4 (a,b,c) : Summary of analysis results

Case Processing Summary

operation mode	Total N	N of Events	Censored	
			N	Percent
on sharing load	50	50	0	.0%
on single load	4	4	0	.0%
Overall	54	54	0	.0%

(a)

Means and Medians for Survival Time

operation mode	Mean[a]				Median			
			95% Confidence Interval				95% Confidence Interval	
	Estimate	Std. Error	Lower Bound	Upper Bound	Estimate	Std. Error	Lower Bound	Upper Bound
on sharing load	74.640	11.193	52.702	96.578	43.000	14.731	14.126	71.874
on single load	63.750	23.221	18.236	109.264	31.000	17.500	.000	65.300
Overall	73.833	10.472	53.309	94.358	43.000	15.309	12.994	73.006

a. Estimation is limited to the largest survival time if it is censored.

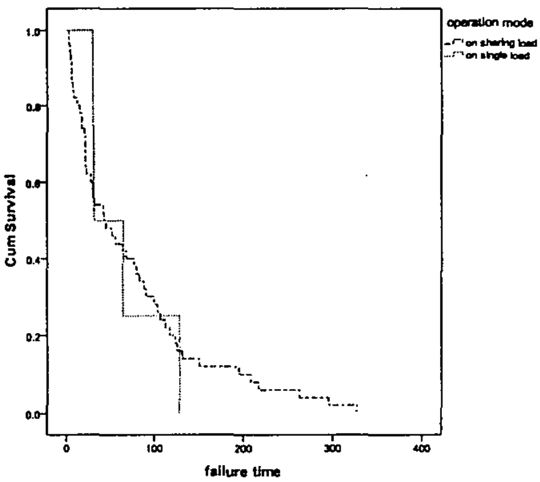
(b)

Overall Comparisons

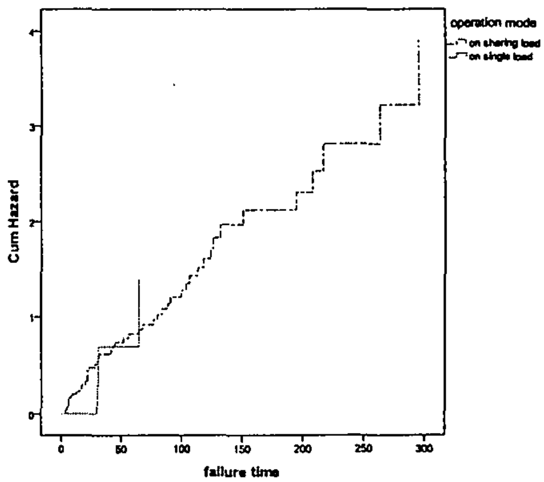
	Chi-Square	df	Sig.
Log Rank (Mantel-Cox)	.011	1	.918

Test of equality of survival distributions for the different levels of operation mode.

(c)



(a)



(b)

Figure B.2 (a,b): Survival and hazard plots for covariate operation mode

3. Subsystems

Table B-5 (a,b,c) : Summary of analysis results

Case Processing Summary

subsystem	Total N	N of Events	Censored N	Censored Percent
other subsystems	28	28	0	.0%
Gas Turbine + Gas compressor	26	26	0	.0%
Overall	54	54	0	.0%

(a)

Means and Medians for Survival Time

subsystem	Mean[a]				Median			
	Estimate	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound	Estimate	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
other subsystems	56.786	9.953	37.278	76.294	30.000	13.229	4.072	55.928
Gas Turbine + Gas compressor	92.192	18.483	55.966	128.418	52.000	14.022	24.516	79.484
Overall	73.833	10.472	53.309	94.358	43.000	15.309	12.994	73.006

a. Estimation is limited to the largest survival time if it is censored.

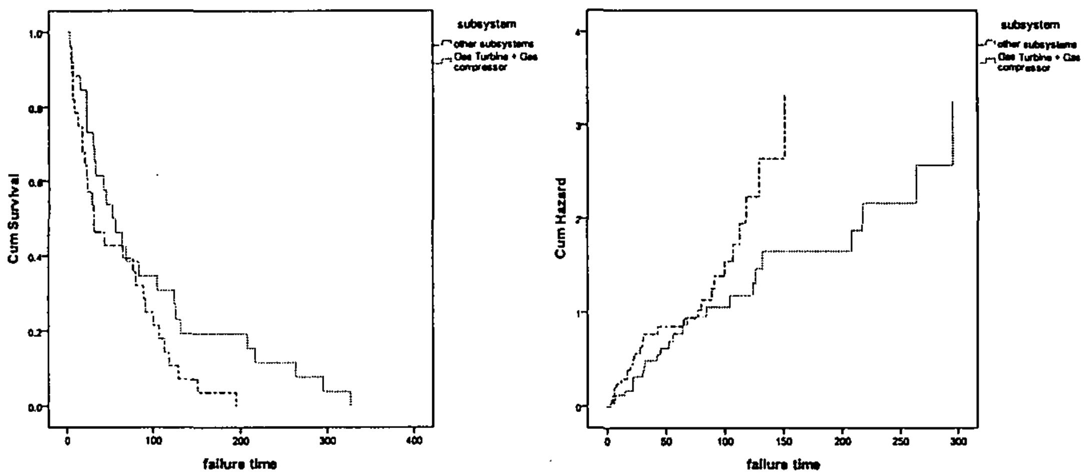
(b)

Overall Comparisons

	Chi-Square	df	Sig.
Log Rank (Mantel-Cox)	3.341	1	.068

Test of equality of survival distributions for the different levels of subsystem.

(c)



(a) (b)

Figure B.3 (a,b): Survival and hazard plots for covariate subsystem

4. Start-up failures

Table B-6 (a,b,c) : Summary of analysis results

Case Processing Summary

failure after start up	Total N	N of Events	Censored	
			N	Percent
other failures	45	45	0	.0%
fail after start up	9	9	0	.0%
Overall	54	54	0	.0%

(a)

Means and Medians for Survival Time

failure after start up	Mean[a]				Median			
			95% Confidence Interval				95% Confidence Interval	
	Estimate	Std. Error	Lower Bound	Upper Bound	Estimate	Std. Error	Lower Bound	Upper Bound
other failures	72.778	11.452	50.332	95.224	45.000	16.096	13.452	76.548
fail after start up	79.111	27.351	25.503	132.719	31.000	1.491	28.078	33.922
Overall	73.833	10.472	53.309	94.358	43.000	15.309	12.994	73.006

a. Estimation is limited to the largest survival time if it is censored.

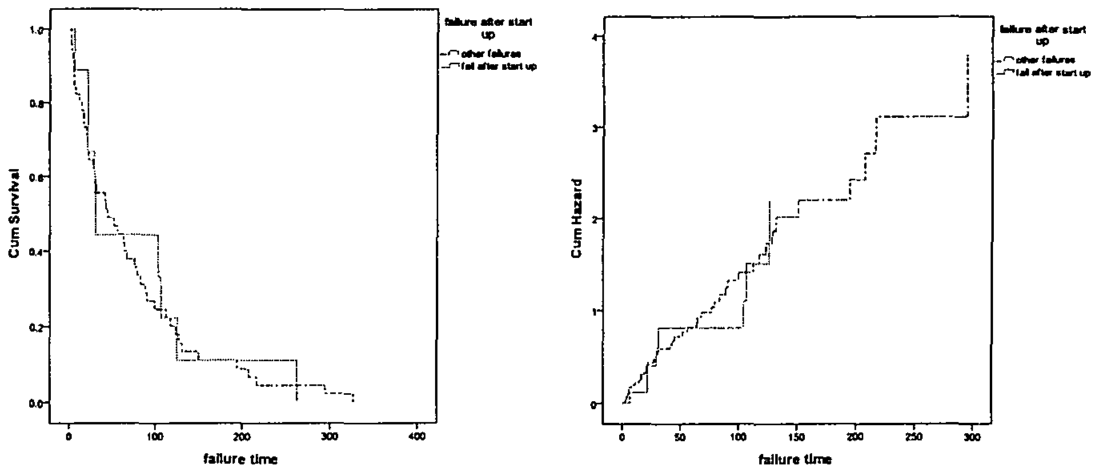
(b)

Overall Comparisons

	Chi-Square	df	Sig.
Log Rank (Mantel-Cox)	.038	1	.846

Test of equality of survival distributions for the different levels of failure after start up.

(c)



(a) (b)

Figure B.4: Survival and hazard plots for covariate start up failure

5. PM (4K and 8K ppm)

Table B-7 (a,b,c) : Summary of analysis results

Case Processing Summary

PM	Total N	N of Events	Censored	
			N	Percent
other failures	42	42	0	.0%
failures after PM	12	12	0	.0%
Overall	54	54	0	.0%

(a)

Means and Medians for Survival Time

PM	Mean[a]				Median			
			95% Confidence Interval				95% Confidence Interval	
	Estimate	Std. Error	Lower Bound	Upper Bound	Estimate	Std. Error	Lower Bound	Upper Bound
other failures	64.071	12.279	40.004	88.139	30.000	4.855	20.484	39.516
failures after PM	108.000	16.556	75.551	140.449	84.000	19.919	44.960	123.040
Overall	73.833	10.472	53.309	94.358	43.000	15.309	12.994	73.006

a. Estimation is limited to the largest survival time if it is censored.

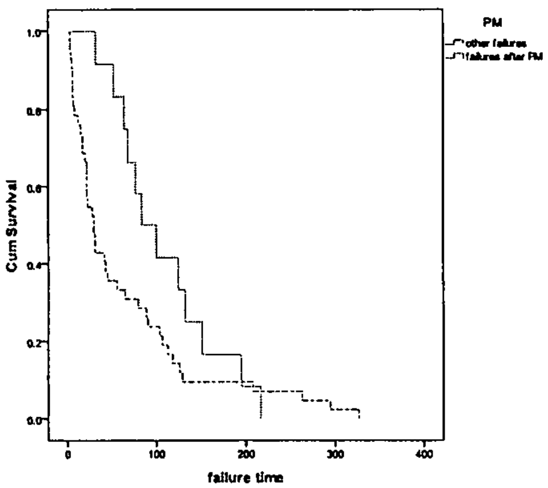
(b)

Overall Comparisons

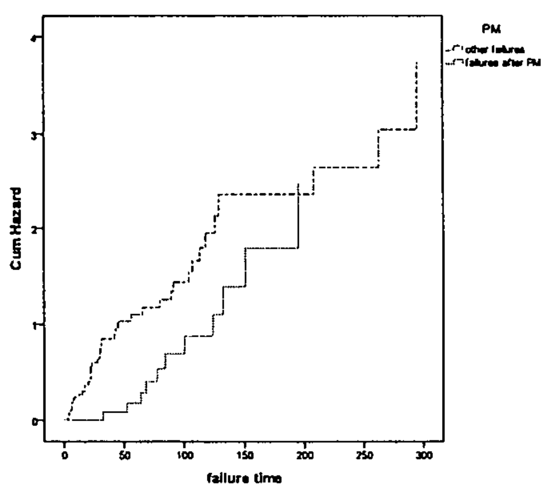
	Chi-Square	df	Sig.
Log Rank (Mantel-Cox)	2.415	1	.120

Test of equality of survival distributions for the different levels of PM.

(c)



(a)



(b)

Figure B.5: Survival and hazard plots for covariate PM

6. PM (4K and 8K ppm + Engine wash)

Table B-8 (a,b,c) : Summary of analysis results

Case Processing Summary

PM + Engine wash	Total N	N of Events	Censored	
			N	Percent
other failures	33	33	0	.0%
failures after PM+wash	21	21	0	.0%
Overall	54	54	0	.0%

(a)

Means and Medians for Survival Time

PM + Engine wash	Mean[a]				Median			
			95% Confidence Interval				95% Confidence Interval	
	Estimate	Std. Error	Lower Bound	Upper Bound	Estimate	Std. Error	Lower Bound	Upper Bound
other failures	48.091	10.973	26.584	69.598	23.000	4.101	14.961	31.039
failures after PM+wash	114.286	17.624	79.743	148.829	100.000	20.598	59.628	140.372
Overall	73.833	10.472	53.309	94.358	43.000	15.309	12.994	73.006

a. Estimation is limited to the largest survival time if it is censored.

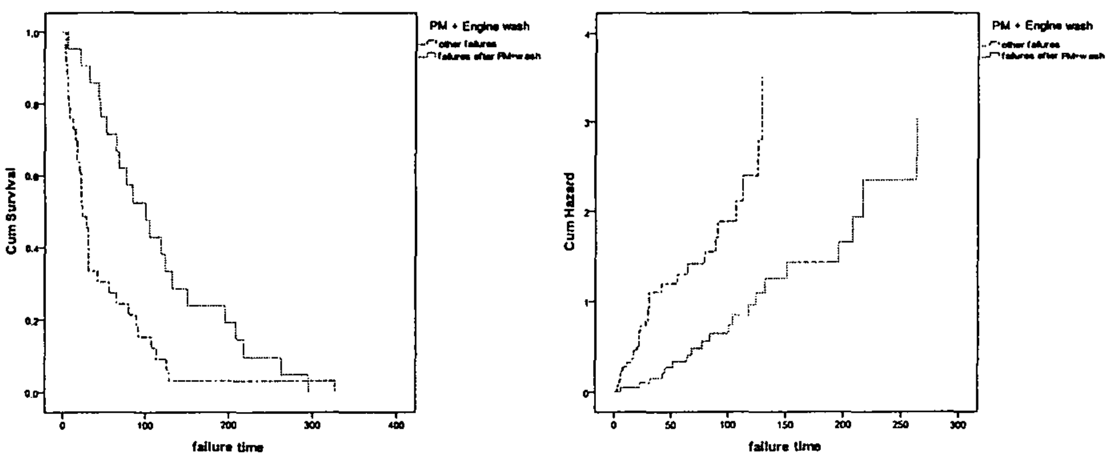
(b)

Overall Comparisons

	Chi-Square	df	Sig.
Log Rank (Mantel-Cox)	8.522	1	.004

Test of equality of survival distributions for the different levels of PM + Engine wash.

(c)



(a) (b)

Figure B.6: Survival and hazard plots for covariate PM + engine wash

Proportional hazards model

Table B-9 (a-f) : Summary of analysis results

Case Processing Summary

		N	Percent
Cases available in analysis	Event[a]	54	100.0%
	Censored	0	.0%
	Total	54	100.0%
Cases dropped	Cases with missing values	0	.0%
	Cases with negative time	0	.0%
	Censored cases before the earliest event in a stratum	0	.0%
	Total	0	.0%
Total		54	100.0%

a. Dependent Variable: failure time

(a)

Categorical Variable Codings[b,c,d,e,f,g]

		Frequency	(1)
startup[a]	0=other failures	45	0
	1=fail after start up	9	1
operationmode[a]	0=on sharing load	50	0
	1=on single load	4	1
Train[a]	0=Train 1	27	0
	1=Train 2	27	1
subsystem[a]	0=other subsystems	28	0
	1=Gas Turbine + Gas compressor	26	1
PM[a]	0=other failures	42	0
	1=failures after PM	12	1
PMplusEW[a]	0=other failures	33	0
	1=failures after PM+wash	21	1

a. Indicator Parameter Coding

b. Category variable: startup (failure after start up)

c. Category variable: operationmode (operation mode)

d. Category variable: Train (Train)

e. Category variable: subsystem (subsystem)

f. Category variable: PM (PM)

g. Category variable: PMplusEW (PM + Engine wash)

(b)

Block 0: Beginning Block

Omnibus Tests of Model Coefficients

-2 Log Likelihood
329.279

(c)

Block 1: Method = Enter

Omnibus Tests of Model Coefficients[a]

-2 Log Likelihood	Overall (score)			Change From Previous Step			Change From Previous Block		
	Chi-square	df	Sig.	Chi-square	df	Sig.	Chi-square	df	Sig.
318.711	10.815	6	.094	10.568	6	.103	10.568	6	.103

a. Beginning Block Number 1. Method = Enter

(d)

Variables in the Equation

	B	SE	Wald	df	Sig.	Exp(B)
Train	-.045	.296	.024	1	.878	.956
operationmode	-.533	.557	.917	1	.338	.587
subsystem	-.368	.323	1.302	1	.254	.692
startup	-.090	.405	.049	1	.824	.914
PM	.006	.466	.000	1	.989	1.006
PMplusEW	-.837	.416	4.050	1	.044	.433

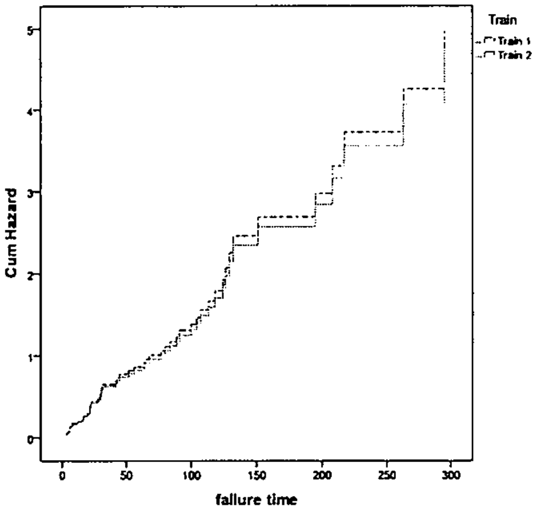
(e)

Covariate Means and Pattern Values

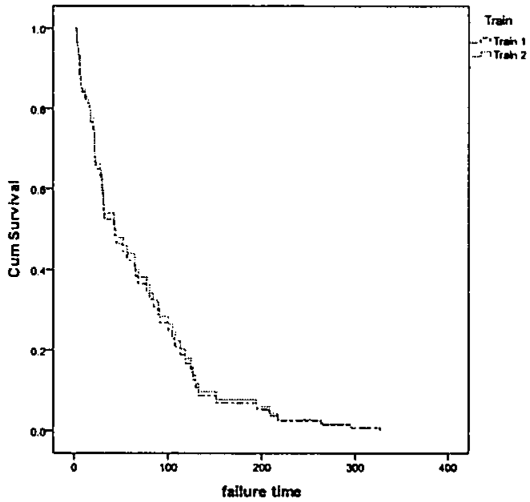
	Mean	Pattern 1	Pattern 2
Train	.500	.500	.500
operationmode	.074	.074	.074
subsystem	.481	.481	.481
startup	.167	.167	.167
PM	.222	.222	.222
PMplusEW	.389	.000	1.000

(f)

Train

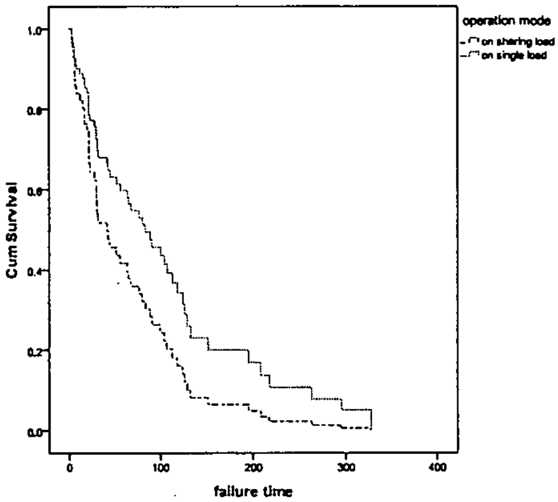


(a)

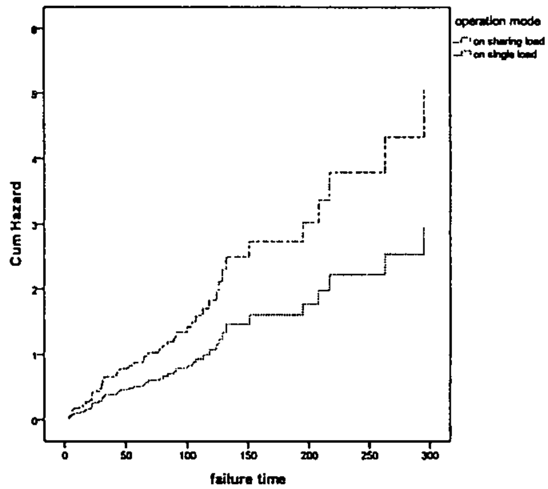


(b)

Operation Modes

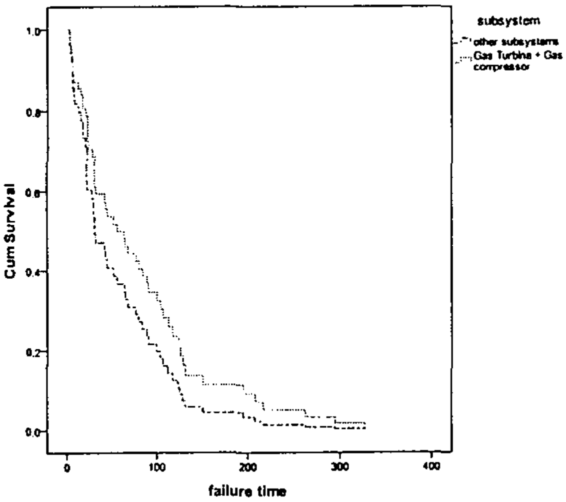


(c)

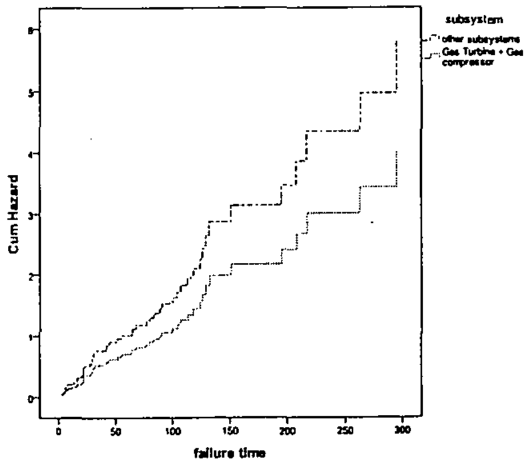


(d)

Subsystems

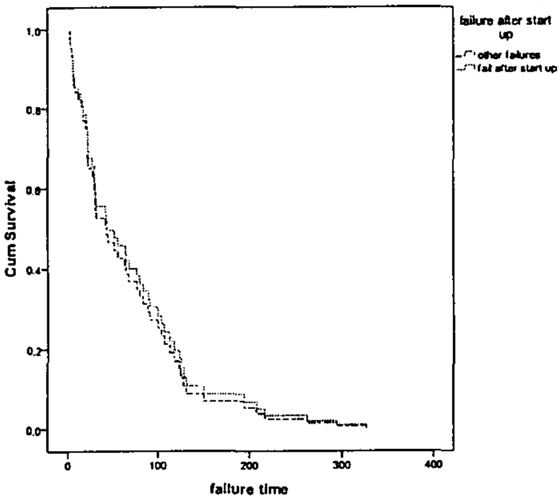


(e)

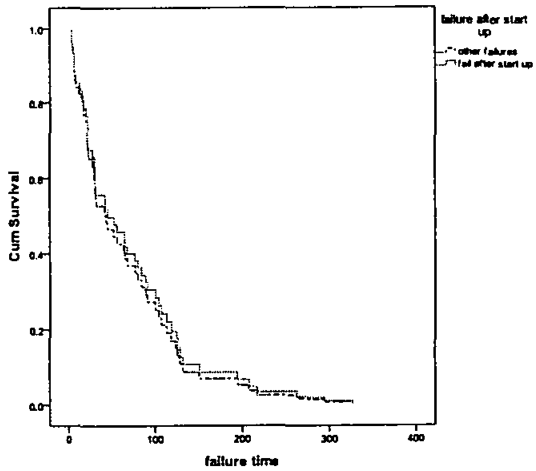


(f)

Start-up failures

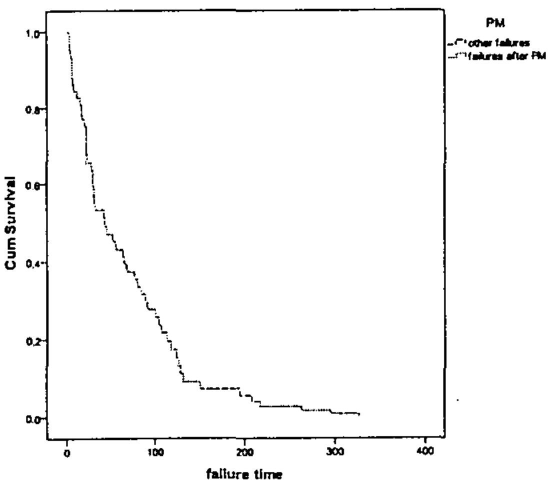


(g)

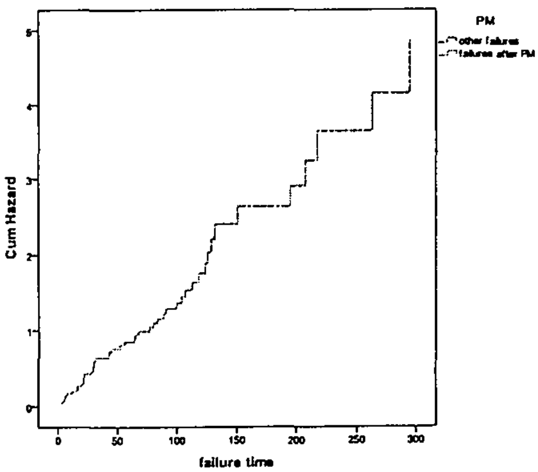


(h)

PM

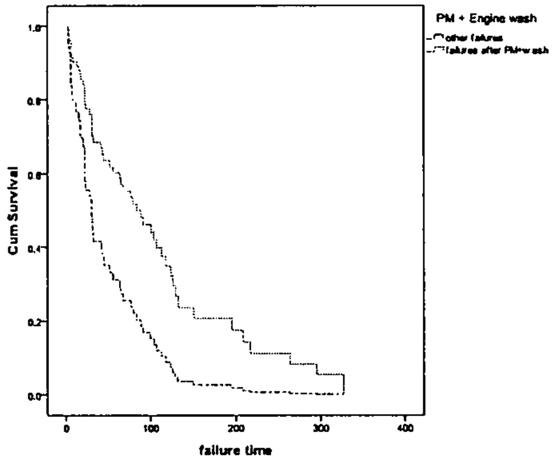


(i)

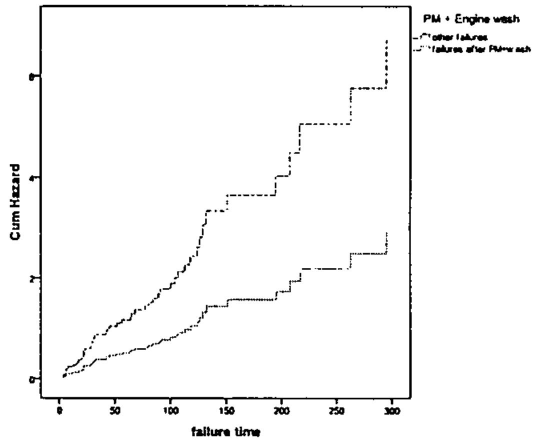


(j)

PM + Engine wash



(k)



(l)

Figure B.7 (a-l): Survival and hazards plots for each covariate

APPENDIX C

ANALYTICAL AVAILABILITY COMPUTATION

The structure of components in system can be either in series or parallel. In a series structure, the system is available if and only if all of its n components are available. An example of a series structure of order n is depicted in Figure C.1.

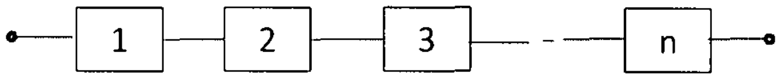


Figure C.1: Series structure

The availability of the system, A_s, can be calculated based on this function

$$A_s = A_1 \,.\, A_2 \,....\, A_n = \prod_{i=1}^{n} A_i \tag{1}$$

where A_1 is the availability for component 1 and so on.

In a parallel structure as illustrated in Figure C.2, the system is available if at least one of its n components are available.

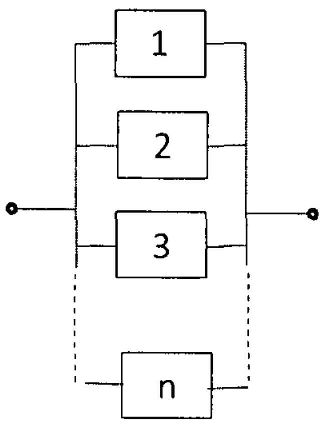


Figure C.2: Parallel structure

The respective availability function can be described as

$$A_s = 1 - \ (1 - A_1)\ (\ 1 - A_2)\ \ldots\ (1 - A_n) = \prod_{i=1}^{n}(1 - A_i) \tag{2}$$

A system that is available if and only if at least k out of n components are available, is also known as a k-oo-n structure. An example of RBD for 2-oo-3 system is illustrated in Figure C.3.

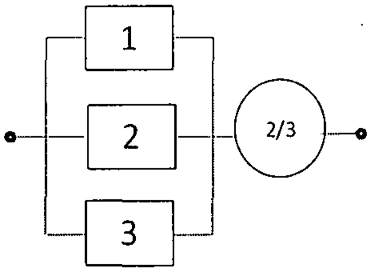


Figure C.3 : 2-oo-3 system

Alternatively, this structure can be represented by the following equivalent RBD (Figure C.4).

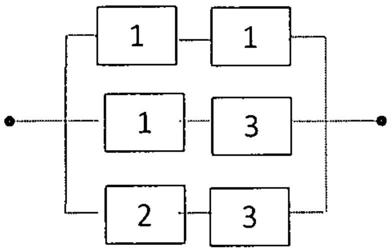


Figure C.4: Equivalent RBD for 2-oo-3 configuration

Hence, the system availability can be written as

$$A_s = 1 - (1 - A_1 A_2)(1 - A_1 A_3)(1 - A_2 A_3) \quad (3)$$

$$A_s = A_1 . A_2 + A_1 . A_3 + A_2 . A_3 - 2A_1 . A_2 . A_3 \quad (4)$$

If each component in the system has the same availability value, A, the system availability can be computed by the following binomial expression

$$A_s = \sum_{r=k}^{n} \binom{n}{r} A^r (1 - A)^{n-r} \quad (5)$$

where

n = total components in parallel

k = minimum number of components required for system success

Analytical computation of AGRU system's availability

First, the MTBF and MTTR for related equipment have to be calculated based on the steady state condition. For exponential, the MTBF is just a reciprocal of the failure rate, λ.

$$\text{MTBF} = \frac{1}{\lambda} \tag{6}$$

The value of MTTR is determined based the mean value. The availability of the equipment can be computed as follows

$$\text{Availability} = \frac{MTBF}{MTBF+MTTR} \tag{7}$$

The summary of the computed results is shown in Table C-1 below.

Table C-1: Reliability, maintainability and availability data for each equipment

Equip.	Reliability			Maintainability			Availability
	Distrib.	Parameters	MTBF (hrs)	Distrib.	Parameters / downtime	MTTR (hrs)	
P201A	Expon.	λ=0.000514	1945.5	Fixed duration	347.5 hrs	347.5	0.8485
P201B	Expon.	λ=0.0005	2000	Lognorm.	μ = 4.785, σ = 1.29	275	0.8791
P201C	Expon.	λ=0.0005	2000	Lognorm.	μ = 4.063, σ = 1.47	171	0.9211
P202A	Expon.	$\lambda=4.6 \times 10^{-4}$	2174	Fixed duration	1344 hrs	1344	0.6179
P202B	Expon.	$\lambda=1.986 \times 10^{-4}$	5035	Fixed duration	72 hrs	72	0.9859
P202C	Expon.	$\lambda=5.6 \times 10^{-5}$	17857	Fixed duration	372 hrs	372	0.9796
LV2004	Expon.	λ=0.0001075	9302	Expon.	λ=0.286	3.5	0.9996
PV2014	Expon.	λ=0.0001613	6199	Fixed duration	1.95 hrs	1.95	0.9997

Based on the available equipment data, the AGRU system can be simply represented by the following RBD (Figure C.5).

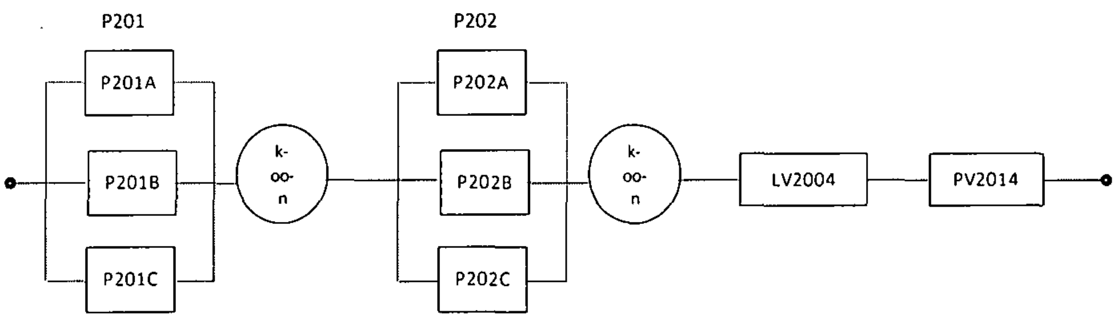


Figure C.5: Simplified RBD for AGRU system

For 1-out of-3 configuration, using Equation 2 and data from Table A-1, the availability of P201 can be calculated as follows

$A_{P201} = 1 - (1 - A_{P201A})(1 - A_{P201B})(1 - A_{P201C})$

$A_{P201} = 1 - (1 - 0.8485)(1 - 0.8791)(1 - 0.9211)$

$A_{P201} = 0.9985$

Similarly, the availability P202 is calculated and the result is 0.9999.

For 2-out of-3 configuration, the availability of P201 can be computed using Equation 4,

$A_{P201} = A_{P201A} .A_{P201B} + A_{P201A} .A_{3P201C} + A_{P201B} .A_{P201C} - 2A_{P201A} .A_{P201B} .A_{P201C}$

$A_{P201} = (0.8485)(0.8791) + (0.8485)(0.9211) + (0.845)(0.9211) - 2(0.8485)(0.8791)(0.9211)$

$A_{P201} = 0.9631$

Using the same approach, P202 availability is calculated as 0.9868.

The availability of the system can be computed as follows;

$A_S = A_{P201} \cdot A_{P202} \cdot A_{LV2004} \cdot A_{PV2014}$

For 1-out of-3 configuration:

$A_S = (0.9985)(0.9999)(0.9996)(.9997) = 0.9976$

For 2-out of-3 configuration:

$A_S = (0.9631)(0.9868)(0.9996)(0.9997) = 0.9496$

The summary of the results is shown in Table C-2.

Table C-2: Computed availability for both configurations

k-oo-n	P201	P202	LV2004	PV2014	System
1-out of-3	0.9985	0.9999	0.9996	0.9997	0.9976
2-out of-3	0.9631	0.9868	0.9996	0.9997	0.9496