A DECISION SUPPORT MODEL TO IMPROVE ROLLING STOCK MAINTENANCE SCHEDULING BASED ON RELIABILITY AND COST

by
Asekun Olabanji Olumuyiwa

Thesis presented in fulfilment of the requirements for the degree of Master of Engineering in Engineering Management in the Faculty of Engineering at Stellenbosch University

Supervisor: Prof. Cornelius J. Fourie
Co-supervisor: Prof. P. J. Vlok

December 2014

DECLARATION

By submitting this thesis electronically, I declare that the entirety of the work contained therein is my own, original work, that I am the sole author thereof (save to the extent explicitly otherwise stated), that reproduction and publication thereof by Stellenbosch University will not infringe any third party rights and that I have not previously in its entirety or in part submitted it for obtaining any qualification.

15 August 2014

ABSTRACT

The demand for rail travel has increased over the years. As a result, it is becoming mandatory for railway industries to maintain very high availability of their assets to ensure that service levels are high. Railway industries require both their infrastructure and rolling stock assets maintained efficiently to sustain reliability. There has been on-going research on how maintenance can be carried out in a cost effective manner. However, the majority of this research has been done for infrastructure and the rolling stock maintenance has not been properly covered.

The purpose of this research is to contribute to the maintenance sector of rolling stock for railway industries by developing a decision support model for rolling stock based on reliability and cost. The model is developed as an optimization problem of a system containing several components dependent on each other with different reliability characteristics. In this model, a mixed integer nonlinear problem is developed and solved using an exact method and metaheuristics methods. The Metrorail facility in Cape Town was chosen as a case study. Failure history and cost data were gathered from the facility and the information was applied to the model developed. The case study was investigated and different results were achieved using both exact and metaheuristics methods.

The final result from the study is an optimal maintenance schedule based on reliability and cost. The developed model serves as a practical tool railway companies can adopt to schedule rolling stock maintenance to achieve a high level of reliability and at the same time maintaining minimum cost expenditure.

OPSOMMING

Die vraag na spoorvervoer het oor die jare toegeneem. Dus het dit belangrik geword dat die spoorweg se bates hoogs toeganklik moet wees om te verseker dat die vlak van dienslewering hoog bly. Die spoorweg industrie besef dat hulle infrastruktuur, lokomotiewe, waens ens. effektief in stand gehou moet word sodat dit betroubaar kan wees. Navorsing word nog steeds gedoen oor hoe instandhouding op ’n koste-effektiewe wyse gedoen kan word. Die meeste van hierdie navorsing gaan egter oor infrastruktuur en instandhouding word nie ordentlik gedek nie.

Die doel met hierdie navorsing is om by te dra tot die instandhoudingsektor van die spoorweg deur om ’n besluit-ondersteunende model vir lokomotiewe, waens, ens wat op betroubaarheid en koste gegrond is, te ontwikkel. Die model is ontwikkel as ’n optimasie probleem van ’n sisteem wat verskillende komponente wat van mekaar afhanklik is maar oor verskillende betroubaarheidskenmerke beskik, inluit. In hierdie model word ’n gemengde, heeltal nie-lineêre probleem ontwikkel en met ’n eksakte metode en metaheuristiese metodes opgelos. Die Metrorail fasiliteit in Kaapstad is vir die gevalle studie gekies. Die geskiedenis van mislukkings en koste data is by die fasiliteit versamel en die inligting is op die model wat ontwikkel is, toegepas. Die gevalle studie is ondersoek, en verskillende resultate is met eksakte en metaheuristiese metodes bereik.

Die finale uitkomste van die studie is ’n optimale instandhoudingskedule wat op betroubaarheid en koste gegrond is. Die model wat ontwikkel is dien as ’n praktiese instrument wat spoormaatskappye kan gebruik om die instandhouding van lokomotiewe, waens ens. te reël sodat ’n hoë vlak van betroubaarheid bereik kan word en kostes terselfdertyd tot ’n minimum beperk kan word.

ACKNOWLEDGEMENTS

I would like to express my deepest appreciation to the following people for their support in making this thesis a success:

- To the Almighty God for making His grace available to me throughout this research.
- To Prof C. J. Fourie for his support, guidance and productive criticism throughout the period of this research.
- To Prof Vlok, for his guidance during this research
- To my parents Mr. & Prof. Asekun and my sisters for their love, support and prayers during my studies.
- To members of PRASA Engineering Research Chair Stellenbosch team for their support and willingness to assist me whenever I called on them.
- To the staff of Metrorail for availing the necessary information I needed to complete the research.
- To the Ishekwene's for their financial and moral support.
- To Uvile Kwatsha for her patience, understanding and words of encouragement during though times.
- To the ministers and members of The Redeemed Christian Church of God Desire of Nations Stellenbosch for providing spiritual support during difficult times.

"Every good and perfect gift is from above, coming down from the Father of the heavenly lights, who does not change like shifting shadows."
(James 1:17 NIV)

Table of Contents

LIST OF FIGURES

LIST OF TABLES

GLOSSARY

CM	Corrective Maintenance
RM	Reactive Maintenance
RTF	Run-To-Failure
PM	Preventive Maintenance
TDM	Time Directed Maintenance
PdM	Predictive Maintenance
CBM	Condition based Maintenance
RCM	Reliability Centred Maintenance
TPM	Total Productive Maintenance
PRASA	Passenger Rail Agency of South Africa
FMMS	Fleet Maintenance Management Software
MIP	Mixed Inter Programming
MINLP	Mixed integer Non-linear Programming
DP	Dynamic programming
GA	Genetic Algorithm
SA	Simulated Annealing
HPP	Homogeneous Poisson Process
NHPP	Non-homogeneous Poisson Process
GRG	Generalized Reduced Gradient

CHAPTER 1: INTRODUCTION

1.1 Background

Railway systems consist of both mechanical and electrical components combined into several systems containing a large number of moving parts. To achieve an acceptable railway service level, each system needs to kept operational and regular maintenance is the essential factor to achieving this. A railway system can be sub-divided into two sub-systems namely: rolling stock and Infrastructure. Rolling stock refers to all the vehicles that move on a railway. These vehicles can either be powered or unpowered vehicles or a combination of both. Examples of rolling stock include locomotives, railroad cars, coaches and wagons. Rolling stock is the most maintenance intensive part of the railway system and therefore, the most vulnerable if maintenance is neglected. According to Wyman (2009) "maintenance accounts for approx. 30% of the lifecycle costs of a high-speed train, making it the largest rolling stock operating cost factor besides energy". When a train breaks down during operation, it immediately blocks the railway track. This delay causes a disruption to the timetable schedule for that track untill the train either becomes operational or removed from the track. Reliability is therefore the key to a successful railway operation thus making maintenance the number one priority if ongoing reliability is to be ensured.

The importance of the maintenance functions and maintenance management has greatly grown in all sectors of manufacturing and service organizations. The principal reason for this growth is the continuous expansion in the capital inventory, the requirements for the functioning of systems and the outsourcing of maintenance. Thus, as maintenance management gains importance, support from science is needed to improve it. Maintenance being a key to maintaining reliability in a system needs to be performed properly to ensure effective use of resources. There are several strategies for carrying out maintenance but irrespective of the strategy adopted by an organisation, proper planning and scheduling is necessary to ensure the objectives of maintenance are met. For this reason, it is important to have a decision support system in place which would aid in efficient planning and scheduling of the maintenance strategy adopted. According to Dekker and Scarf (1998), maintenance management could have benefited from the advent of a large area in operations research, called maintenance optimization.

The failure of a critical component in a rolling stock system during operation can cause multiple ripple effects. Firstly, the system is delayed and then fails to adhere to time schedules. Secondly, other planned operations using the same infrastructure would be delayed and ultimately, this would cause a loss and a decrease in service levels for the rail service provider. Therefore, it is important to have a tool in place to ensure that maintenance is efficiently carried out to reduce the probability of a failure occurring during system operation. This tool can be referred to as maintenance optimization. Maintenance optimization is a useful tool to aid in decision support for maintenance. The results achieved from the process can be used by a maintenance manager for efficient maintenance planning and scheduling support.

The optimization process can be developed using various methods. It can involve a process of improving maintenance policies by making changes to the features and conditions to make it more practically applicable. For example by taking into account working conditions, the service schedule of the corporation, safety issues, perfect and imperfect actions. In general, maintenance optimization models are categorized by the way they represent fuzziness in parameters, models and set-ups as well as how they represent expected variability. The model can either use deterministic or probabilistic methods for representation. Probabilistic models make use of probability distributions to add fuzziness in parameters, the model and scenarios as well as the expected variability for the scenarios. On the other hand, deterministic methods do not provide information about potential risk which results in non-optimal maintenance planning for systems (Ghosh & Roy 2009).

The overall efficiency of any rail company is a function of its operations and maintenance planning, scheduling and quality of service. It can be assumed that like many organizations, there are opportunities to improve the overall efficiency of the maintenance department of a rail company even when the opportunities are not very obvious. This research is focused on how the maintenance function of rail companies, corporations and establishments can be improved, by developing a decision support model for maintenance scheduling of rolling stock based on reliability and cost. The study includes a practical application of the model in a maintenance facility of a suitable case, the Metrorail Maintenance Facility Cape Town. Recommendations from this study could be used by the case study and other companies, corporations and establishments to improve the maintenance scheduling of their rolling stock or systems.

1.2 Problem Statement

The railway industry is an asset intensive industry that depends heavily on the performance of their assets, in particular rolling stock. A railway industry cannot survive if their trains are allowed to deteriorate because of lack of or poor maintenance. This implies that a high level of reliability is required. Maintenance of rolling stock components can become very expensive; it becomes even more expensive to replace the equipment that has deteriorated as a result of poorly planned maintenance or neglect of maintenance. Little research has been carried out to improve rolling stock maintenance in the railway industry. The majority of the research carried out in this area has focused on how to solve maintenance problems in railway infrastructure. There is no standard decision model based on cost and reliability that maximizes the efficiency in rolling stock maintenance scheduling has been developed.

1.3 Research Purpose and Objectives

The purpose of this research is to develop a decision support model based on reliability of components and cost associated with maintenance of rolling stock to produce an efficient maintenance schedule for rolling stock components. The study aims to apply the developed model to a suitable case study as well as use efficient maintenance planning and scheduling to assist rail companies that could improve reliability at lower maintenance costs.

1.4 Research Design and Methodology

For the purpose of achieving the stated research objectives, an extensive literature study will be conducted to understand experts' opinions on decision models in maintenance planning and scheduling. Various models and methods for maintenance planning and scheduling from other rail companies and industries will be investigated. An appropriate decision support model will be identified and used to develop a decision support model for rolling stock maintenance. This will be achieved using relevant sources of information.

The research will be of empirical form, i.e. it will involve the collection of rolling stock components failure and cost data from a suitable rolling stock maintenance facility's database. The data gathered would be analysed to identify critical failing components. The failure data of these components as well as their cost will be used to develop the decision support model. The information gathered will also be used as input data to the proposed decision support model and the results could be tested at the company's maintenance facility. From the model, recommendations on how to improve the current process in rolling stock maintenance will be made.

1.5 Research Hypothesis

The use of reliability and cost as objective criteria for maintenance decision support modelling in rolling stock will result in a more efficient maintenance schedule that could improve the maintenance function of a railway company

1.6 Thesis Outline

This thesis is organized as follows:

- Chapter 1 gives an introduction to the research and outlines the objectives and method of the research that would be carried out.
- Chapter 2 presents a comprehensive literature survey on maintenance; maintenance strategies; maintenance planning and scheduling; and rolling stock maintenance.
- Chapter 3 presents a review of literature on maintenance decision models.
- Chapter 4 discusses the decision support model developed and presents methods of solution for the developed model.
- Chapter 5 gives an overview of the case study selected for this research and discusses how maintenance planning and scheduling is carried out in the specific case. The proposed model is applied to the case study.
- In chapter 6 results and the implications of the results of the decision support model is discussed.
- Chapter 7 concludes the research and presents recommendations and potential future research.

In keeping with the outlined layout, the next chapter presents a comprehensive review of literature on the topic of study.

CHAPTER 2: MAINTENANCE, MAINTENANCE PLANNING AND SCHEDULING

2.1 Introduction

Chapter one presented the research problem, stated aims and hypothesis of the study. In this chapter, an overview of maintenance and its objectives are presented. A literature study on the different maintenance strategies as well as the importance of planning and scheduling maintenance is discussed to provide a background to the research problem. Also given in the chapter is an overview of maintenance planning and scheduling highlighting their key elements. The chapter closes with a discussion of literature on maintenance in the rolling stock environment.

2.2 Maintenance

The role of maintenance has become very important in all kinds of industries. As such, the need for maintenance has increased over the years and companies have come to adopt maintenance as an activity that adds value rather than view it as a necessary evil for expenses which contributes to the business profit (Sharma, Yadava & Deshmukh 2011). Maintenance actions involve implementing every decision made at all levels of an organisation in order to achieve and sustain a high level of reliability and availability of its asset. It deals with specific methods, resources and personnel utilized in order to keep a piece of equipment or system running efficiently during its designed life (Anderson & Neri 1990).

Any piece of equipment is designed to function for a period of time after which its performance is expected to degrade. When this happens, maintenance is needed to rectify the equipment after failure or when a failure is foreseen. In a (normal case) maintenance is performed to keep a piece of equipment functional during its designed life considering that the practical operation of the components of a piece of equipment is a time-based function. It can therefore, be said that poor maintenance will degrade the condition of the equipment.

A brief understanding of the fundamental principles of failure is required to fully grasp the concept of maintenance. A piece of equipment is said to have failed when it no longer operates within its stipulated design specifications. Smith (1993) explains that failure can also occur within a complex system which consists of other subsystems that have failed even when these may not be visible and the equipment still stays in operation. This is called a “hidden failure”. It is necessary to check for such failures, as they could result to operational failures and/or accidents.

A component’s statistical lifespan can be illustrated with the use of a graphical representation called the bathtub curve (see Figure 2.1). The curve shows that a component has a high probability of failure during its first few weeks of operation, which could be as a result of errors during its installation or manufacturer. This period is referred to as the infant mortality period. Following the infant mortality period is the normal life period. In this period, the equipment exhibits a relatively low probability of failure for a long period although the component may experiences random failures. After the normal life period, the probability of failure becomes relatively high as a result of the equipment reaching its wear-out period (Klutke, Kiessler & Wortman 2003).

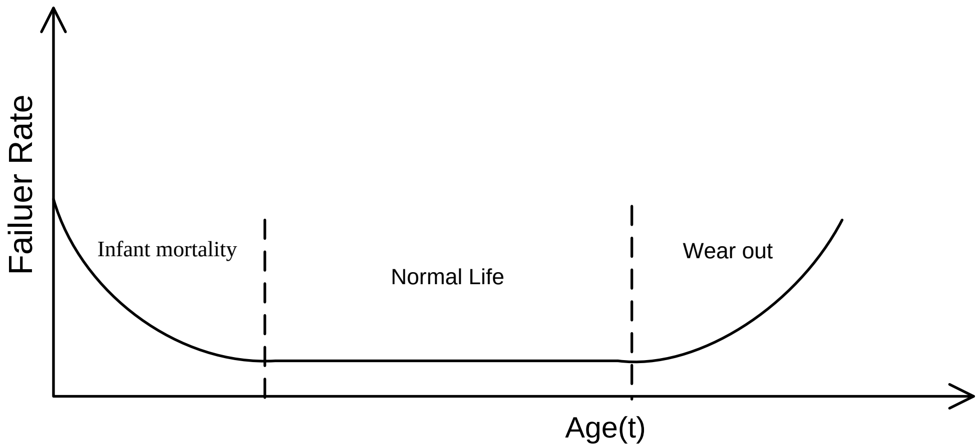


Figure 2.1: Components failure rate over time (Bathtub Curve)(Klutke, Kiessler & Wortman 2003)

It has however, been shown by the commercial avaition industry, that this is not the case for every component. An investigation conducted by Smith (1993) found that a component can experience five other failure forms besides the bathtub curve. These forms are based on the age-reliability relationship of the components and are illustrated in Figure 2.2

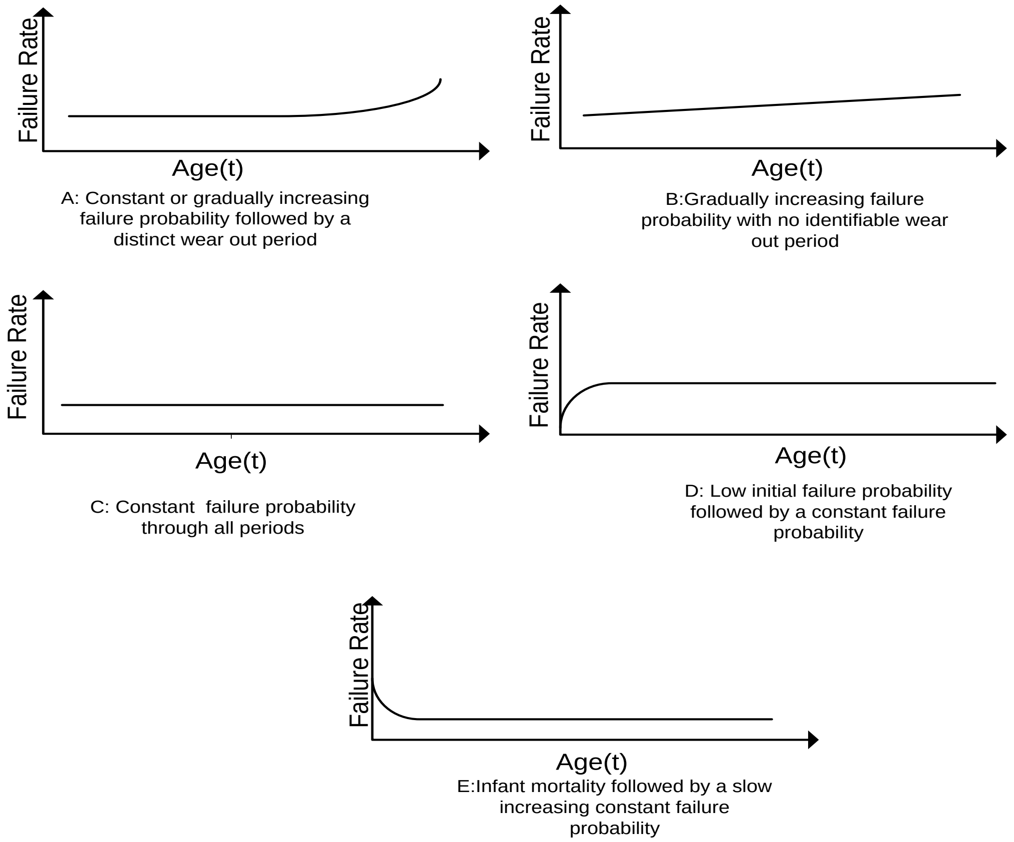


Figure 2.2: Failure forms of a component of a piece of equipment (Smith 1993)

Although these failure forms represent the combinations of failure probabilities in the aviation industry, it can also be assumed that the probability of failures of components in other industries can take these forms. However, one must consider that the ratio of these probabilities could differ slightly with respect to the type of component. Smith's study established that the most common age-reliability failure form (in Figure 2.2 above) shows a high initial probability of failure rate and decreases to a lower and constant probability of random failure with time. According to Smith (1993), an understanding of these different failure forms has an effect on choosing an appropriate maintenance strategy.

2.3 Maintenance Objectives

Maintenance has been practised as far back as the 1930s before the Second World War, when the engineers believed maintenance was not needed as it increased cost of production and had no impact on the value of the production. Emphasis was to minimize the system cost rate but the importance of reliability performance was not taken into consideration (Sharma, Yadava & Deshmukh 2011). As a result, maintenance was only carried out after a system breaks down. However, during the World War II in the 1940s, there were advances in engineering and scientific technology which brought about new kinds of maintenance that were cost effective and maintenance was categorized as a function of the production system.

In recent times, organizations have been made aware of the importance of environmental safety, quality of products and services thereby making maintenance an important aspect of their asset to contribute to the growth and success of the company. These have led to the need for defining the purpose of maintenance and creating maintenance objectives in order to measure performance in meeting these objectives. According to Dekker (1996:230), the purpose and objectives of maintenance are defined as follows:

- Reducing breakdowns and emergency shutdowns.
- Maximizing production at lower cost, highest quality and within optimum safety standards.
- Optimizing the use of maintenance resources.
- Optimizing the utilization of resources to reduce downtime.
- Increasing reliability of the operating systems.
- Improving spares parts stock control.
- Optimizing capital equipment life.
- Improving equipment efficiency which reduces scrap rate.
- Identifying and implementing cost reductions.
- Optimizing the useful life period of the equipment.
- Minimising energy usage.

Maintenance contributes towards organizational profit, hence the need to include it in corporate objective (Sharma, Yadava & Deshmukh 2011). It is therefore important that maintenance objectives are consistent with the goals of production and that they are comprehensive enough to include specific responsibilities (Kelly 2006).

Dekker (1996:230) summarized maintenance objectives into four distinctive heading namely;

- Ensuring system function
- Ensuring system life
- Ensuring safety
- Ensuring human well-being

Dekker suggests that providing the correct reliability, availability, capability and efficiency should be the main maintenance objectives for a system to be maintained.

2.4 Maintenance Strategies

Mobley (2011) identifies run to failure and preventive maintenance as the two most common maintenance management strategies used by organizations to achieve their maintenance objectives. These strategies can be managed using the different types of maintenance, that is, corrective, reactive, preventive, proactive and improvement. These are explained in the sections that follow and summarized in Figure 2.3 below. It is important to note that each of these strategies has different age reduction impacts on system, as will be discussed in detail in Chapter 3:

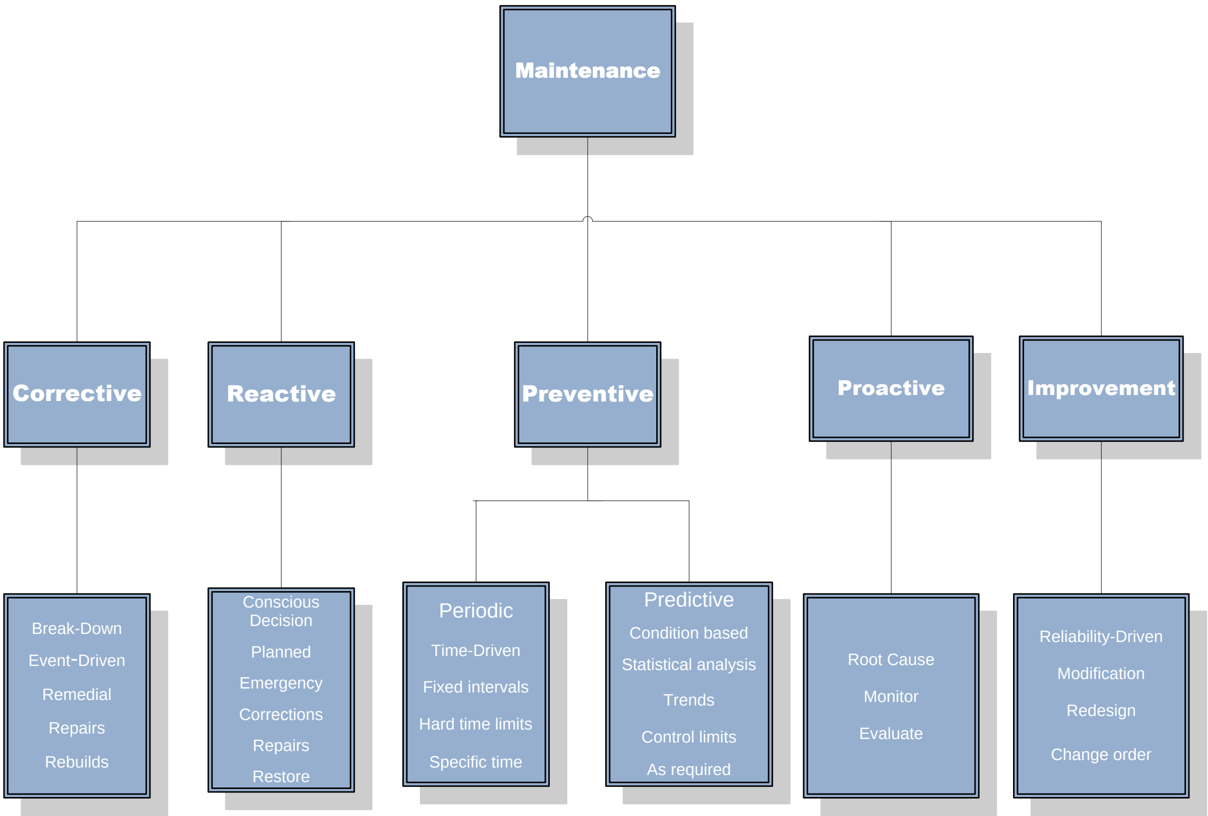


Figure 2.3: Structure of maintenance adapted from (Mobley 2011:9)

2.4.1 Corrective Maintenance

Corrective Maintenance (CM) aims to maximise the effectiveness of all critical systems, minimise breakdowns, minimise unnecessary repairs, and reduce the deviations from optimum operating conditions. CM is event-driven and involves tasks performed to identify, isolate, and amend faults of a failed piece of equipment so that its operational conditions can be restored within the tolerances or limits established for in-service. CM is associated with break downs, emergencies, remedial and repairs and often times require rebuilding the equipment. Depending on the impact of the fault, CM can either be performed instantly or delayed if the system requires to be shut down in order to make repairs. It is by far the simplest type of maintenance strategy. Equipment service levels are generally below acceptable levels and the quality of product is usually affected (Wireman 2005).

2.4.2 Reactive Maintenance

Reactive maintenance (RM) is similar to corrective maintenance (CM) but defers in that RM involves a conscious decision to allow a piece of equipment operate until it breaks down before CM actions are carried out. It is used for run-to-failure maintenance management approach therefore sometimes referred to as Run-To-Failure maintenance (RTF). RM is carried out in order to repair, replace and restore actions performed on a system after a failure has occurred for the purpose of restoring the system to an acceptable working condition (Mobley 2011). This is the oldest and most expensive type of maintenance practiced. This type of maintenance is known to be associated with high expenses in spare parts inventory, machine down time, overtime labour costs and low production availability. RM can be subdivided into two different categories, namely:

Emergency maintenance (EM): refers to maintenance which is done immediately or at the earliest possible time in order to reinstate a failed equipment to achieve maximum productivity with minimum wasted effort or expense.

Breakdown maintenance (BM): refers to maintenance performed after a failure which is considered to be advanced has occurred. In this case, provision would have been made in the form of repair method, spares, materials, labour and equipment to tackle the breakdown.

2.4.3 Preventive Maintenance

Preventive maintenance (PM) aims to minimize the probability of failure occurring during the operation of a piece of equipment. PM involves maintenance tasks carried out to avoid premature equipment damage as well as reducing unscheduled interruption that could lead to corrective activities. The maintenance tasks are based on completed time or hours of operation and scheduled on the basis of the mean time to failure (MTTF) statistic (Mobley 2011). According to Vasili, Hong & Ismail (2011), PM involves a set of management, administrative and technical actions which are aimed at reducing the age of the equipment for the purpose of improving the availability and reliability of the system.

PM can become very expensive if not done effectively and efficiently. It is generally understood that it involves regular inspection of equipment to check for failures or faults. This is not always the case as PM activities can be used to satisfy most of the maintenance objectives set out by an organisation. PM can either be performed as Periodic (Time-based) maintenance or as Predictive (Condition-based) maintenance.

PM tolerates planned downtime’s addition into the production schedule and decreases the occurrence of breakdowns. It also reduces maintenance cost because cost is used for part replacement only while also reducing the risks of injury and environmental degradation.

2.4.4 Periodic Maintenance (Time directed maintenance TDM)

Time directed maintenance are activities that take place based on a measure of interval. This could be in the form clock time, calendar days, number of cycles or number of kilometres travelled. The activities consist of occasionally inspecting, overhauling and cleaning a piece of equipment, replacing affected parts to prevent unexpected failure and process complications (Levitt 2003).

TDM is broken down into two tasks: Time-Based (TB) which is an Inspection task and Time-Based Instructive task (TBI) which refers to tasks that involve opening up a piece of equipment. TB has been the major application of PM, but lately, there has been an increase in computer simulations and automation which necessitating a shift from TB maintenance to Predictive maintenance.

2.4.5 Predictive Maintenance

Predictive maintenance (PdM) is done by forecasting possible failures based on regular monitoring of a piece of equipment for the purpose of preserving its components from failure and sustain it against hazards. PdM a data oriented type of maintenance and doesn't necessarily require the purchase of new equipment (Levitt 2003). PdM is sometimes also referred to as Condition based maintenance (CBM) or Condition Monitoring.

PdM/CBM is a systematic or scheduled maintenance where specific components are replaced at regular intervals as they become worn. It is a process in which the decision to replace or not is based on the outcome of a diagnosis study (Lyonnet 1991). PdM is made popular by the use of control systems in a piece of equipment for the purpose of gathering data and feeding the data to a condition-based maintenance decision system.

PdM is a tool used to generate corrective activities. CM activities generated from PdM can be planned and scheduled because of the time interval between the diagnosis and the required corrective action. It is a very accurate PM strategy when used to manage serious equipment wear. PdM can be expensive to implement at first, but this effect is cushioned by its ability to bring maintenance closer to production and supporting quality programs (Levitt 2003).

PdM improves system reliability while reducing maintenance costs in that, the reduced number of maintenance activities causes a decrease of human fault impacts. As mentioned earlier, PdM implementation has high installation cost, the costs involved are divided unequally as a result of unpredictable maintenance periods. The value of minor part of a piece of equipment is usually higher than the actual equipment; hence, PdM is used rarely for less important parts of a piece of equipment (Liu, Wang & Golnaraghi 2010).

2.4.6 Proactive Maintenance

Proactive Maintenance is the opposite of RM; its focus is on determining the root causes of machine wear and failure and resolving those causes before they manifest. Proactive maintenance is seen as money saving maintenance practice because of its ability to reduce machine wear and failure thereby reducing the need for maintenance. It uses a technique of monitoring and correcting failure root causes in a piece of equipment for example contamination (Swanson 2001).

Proactive maintenance differs from PM and PdM in that it makes use of corrective activities to eradicate the sources of failure. This strategy extends equipment life as opposed to relying on conventional conditions for impending machine breakdown. It also uses systematic scheduled maintenance to avoid e breakdowns. Proactive maintenance does not accept failure as a routine or anticipate crisis failure maintenance, all of which are characteristics of PM and PdM. When used correctly, proactive maintenance prevents loss of productivity due to broken or inoperable piece of equipment and this saves costs (Swanson 2001).

2.4.7 Reliability-Centered Maintenance (RCM)

This type of maintenance is reliability-driven. It is aimed at reducing the need for maintenance of equipment by improving the reliability of the machine. This is achieved by focusing on ways to preserve the function of a piece of equipment in its totality and not part specific. It involves modification of the equipment by adding accessories that could support a part thereby reducing its need for regular maintenance. It also involves redesigning or changing the order of operation if applicable (Mobley 2011). Reliability-centered maintenance (RCM) is based on the principle that analysing the costs of failure and the definite preventive maintenance with the use of a well-disciplined decision logic analysis process can give room for more efficient life time maintenance and logistic support programs (Duarte *et al.*, 2010).

RCM has been identified as a very efficient and well used strategy for the preservation of operational efficiency of a piece of equipment. RCM functions by finding an equilibrium point between high maintenance costs and cost of preventive maintenance policies while, taking into consideration the potential shortening of useful life of the piece of equipment (Afefy 2010). RCM is defined by four characteristic features which include preserving system functionality, identifying specific failure modes that result to functional failures, prioritizing the failure node by order of importance, and selecting an applicable and effective PM activities to eliminate the failure modes (Rommelspacher 2012).

2.4.8 *Total Productive Maintenance*

Total Productive Maintenance (TPM) is a newly defined concept of maintenance program. TPM is a strategy that gives emphases on operator's involvement in the basic aspects of maintenance. In TPM, operators are expected to take possession of any piece of equipment they operate by performing routine maintenance activities during the normal operation of the piece of equipment (Rommelspacher 2012). The goal of the TPM program is to increase production significantly while simultaneously increasing employee self-esteem and job satisfaction. It is directed primarily to the commercial manufacturing environment (Kalbande, Sawlekar & Thampi 2010).

TPM shows the importance of accepting maintenance as a vital part of a business and not to be viewed as a non-profit activity. Activities of maintenance such as down town, repairs, are to be scheduled as part of the production process. The reason for doing this is to reduce unscheduled maintenance, breakdown and emergency during system operation. This aligns with the objective of TPM which is to eliminate equipment breakdowns, speed losses and inconsequential stoppages. According to Kalbande, Sawlekar & Thampi (2010), TPM promotes defect-free production, just-in-time (JIT) production, and automation.

2.4.9 *Lean Maintenance*

Lean maintenance was introduced as a prerequisite for successfully implementing lean in maintenance. It is a planned and scheduled maintenance approach which is achieved by the combination of TPM practices and RCM strategies. Lean maintenance has a foundation of TPM; this means in order to successfully implement lean in maintenance, TPM should have been established and operating efficiently (Smith & Hawkins 2004). The objective of lean maintenance is eliminating every type of waste in the maintenance process without taking serious reliability problems into account. However Ghayebloo and Shahanaghi (2010) state that this is not necessarily the case and developed a multi-objective decision making model to apply lean maintenance to decrease waste and increase system reliability. Lean maintenance is shown in Figure 2.4.

.

LEAN MAINTENANCE PRACTICES					
PLANNING AND SCHEDULING	DOCUMENTATION	WORK ORDER SYSTEM	CMMS	PREDICTIVE MAINTENANCE	ROOT CAUSE FAILURE ANALYSIS
TOTAL PRODUCTIVE MAINTENANCE (TPM)					

Figure 2.4: Lean maintenance practices (Smith, Hawkins 2004)

2.5 Importance of Maintenance planning and scheduling

Organizations are making efforts to increase profitability by increasing labor productivity, while at the same time maintaining a high level of quality, service and timelines. For this to be achieved, the importance of maintenance management has grown in all organizations. Maintenance is an important aspect in the life cycle of assets and needs to be planned and scheduled efficiently to minimize the costs involved. As maintenance operations increase in complexity, so does the complexity of the maintenance functions. These operations involve complex mechanical faults which require a level of skilled human resources to tackle. Assigning the right repair skills to carry out the maintenance operations would reduce the downtime of production. It is therefore important to ensure that maintenance activities meet the organizational objectives whereby total operating and maintenance costs are reduced (Paz & Leigh 1994).

Manpower, equipment and material are the three major resources required for executing maintenance. These resources differ in their impacts on production and are managed differently. Manpower has been shown to be the most vulnerable of the resources, which makes it very difficult to control. Maintenance management is not involved with manpower's direct labor cost, rather it can be used to schedule i.e. how, when and where maintenance work is to be carried out which eventually has an effect on the total maintenance cost. An effective distribution of manpower through scheduling would increase the productivity of the workforce (Paz & Leigh 1994). Duffuaa *et al.*, (2001) also state the importance of planning and scheduling by regarding it as the most critical aspect of the maintenance process.

The objective of maintenance planning and scheduling is to reduce the idle time of equipment and maintenance personnel, minimize total scheduling time, reduce delay time of certain job, increase work time efficiency, maximize equipment availability and minimize shut-down cost and time (Duffuaa & Al-Sultan 1997). When this objective is carried out successfully, maintenance cost is reduced considerably, maintenance workforce is utilized efficiently thereby reducing disruptions in the system. The quality of maintenance work is improved with efficient planning and scheduling as it undertakes the best methods and actions and assigns the most experienced workers for the job (Al-Turki 2009). A module for maintenance planning and scheduling is presented in Figure 2.5.

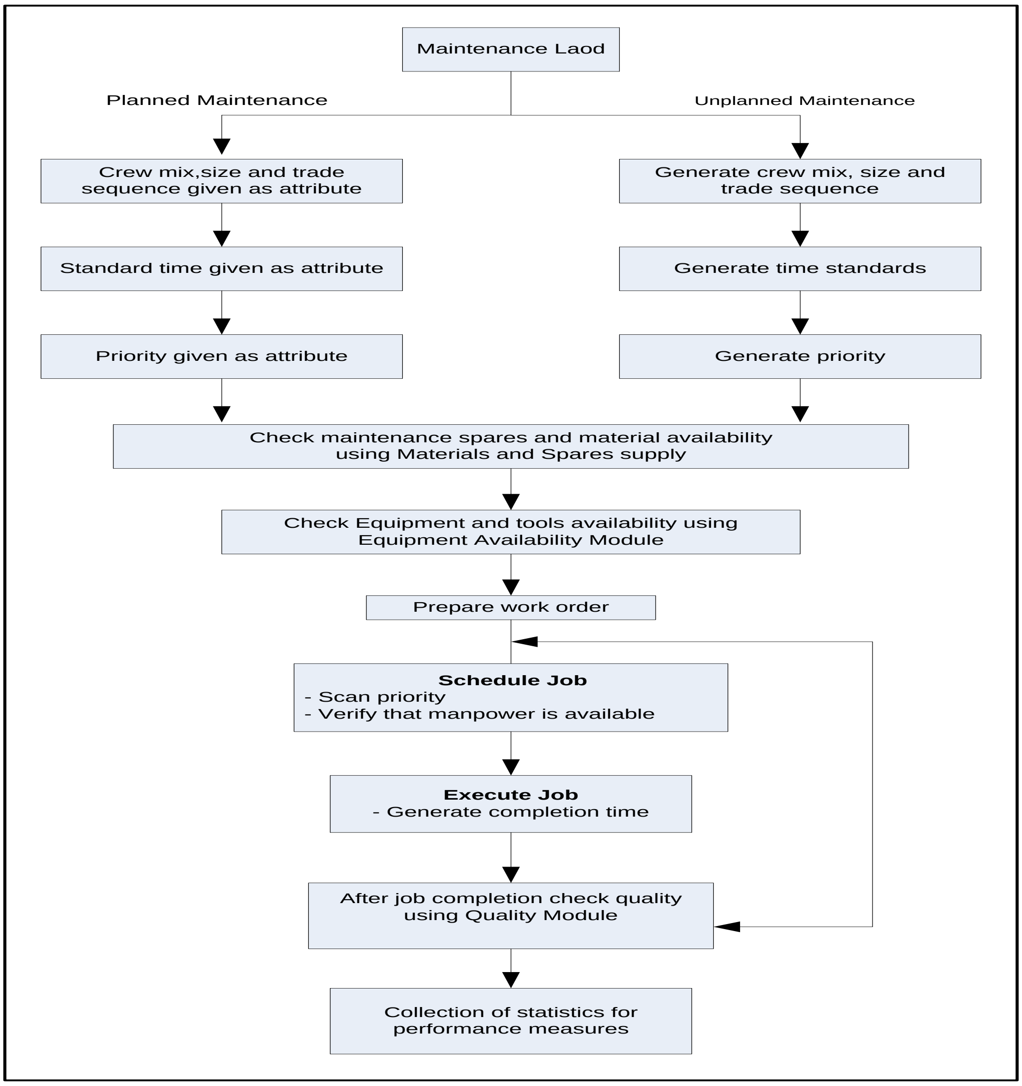


Figure 2.5: Maintenance planning and scheduling module (Duffuaa *et al.*, 2001)

2.6 Maintenance Planning

An understanding of the process of successfully carrying out maintenance is required for all the different strategies of maintenance discussed above. Irrespective of the kind of maintenance, some kind of preparation or plan is needed to carry out the necessary maintenance activities. This preparation is known as maintenance planning, which helps to increase overall efficiency and effectiveness in maintenance (Al-Turki 2009).

Planning involves the process of determining future decisions and actions required to achieve a set of objectives. It involves the identification of parts and tools required and suitable to carry out a job. Planning helps to achieve set out objectives efficiently by minimizing costs, reducing risks and missing possibilities (Umar M & Al-Turki 2009). A maintenance plan is important in that it helps to determine the most cost-effective way to maintain the value of an asset. The three basic levels of planning processes are:

1. Long Range planning (covers a period of 2 years and above)
2. Medium range planning (between a month and a year)
3. Short range planning (includes daily and weekly plans)

Maintenance planning relates to the job capacity and workforce planning. It gives a detailed process of how a maintenance force should operate and a comprehensive outline for major overhauling, construction jobs, preventive maintenance plans, plant shutdowns and vacation planning. Duffuaa *et al.*, (1999) summarises the process of a proper planning after a job request has been made as follows:

- Define job content.
- Plan job work order by specifying job scope.
- Specify craft and establish skill level for the job.
- Estimate required time to execute the job.
- Specify anticipated parts and tools.
- Order parts and tools.
- Specify special tools required and obtain them.
- Review safety process.
- Create a priority work sheet for the job.
- Estimate cost required to complete the job
- Complete the work order.
- Review and control backlog.
- Use an effective forecasting system to predict maintenance load.

Maintenance planning strategies

The state of a piece of equipment is affected by the operating capacity and the maintenance actions carried out on it. Commercial consumption and market considerations determine the production plans for a system. This in turn determines the operational load the system is scheduled to undergo. Therefore maintenance planning has to take into consideration the production planning, maintenance decisions, equipment inherited reliability as well as market and commercial requirements (Al-Turki 2009).

Tsang (2002) identified four dimensions of maintenance strategies as service delivery strategies (in-house vs. outsourcing maintenance), organization and work structure, maintenance methodology, and support system (information system, training performance management and reward system). The first dimension deals with service delivery, which involves the decision to either assign maintenance internally within the organisation or outsource it. Outsourcing maintenance activities has some potential benefits some of which include reduction of total System costs, work is done faster, use of specialists, new technologies are implemented and more attention given by the organisation to strategic asset management issues. However, there are some risks involved with outsourcing maintenance tasks such as loss of critical skills, loss of cross functional communications and loss of control over a supplier (Al-Turki 2009). In order to balance this, suggestions are made for organization to not outsource maintenance management and planning but rather outsource the implementation on the maintenance plan once the risk and costs involved have been carefully considered (Murthy, Atrens & Eccleston 2002).

The second dimension is the organization and work structure which is classified as a highly functionalized process within which maintenance is organized into specific jobs. Decisions to be made here include: plant flexibility or plant specialized tradesman, unified or isolated workshops, and trade specialized or multi-skilled trade-force. The third dimension, maintenance methodology, deals with the strategic decision to choose between the different maintenance strategies discussed earlier. In order to make this decision, the organization's global objectives are considered and the maintenance strategy selected based on it. (de Moura Xavier *et al.*, 2013)

The fourth dimension of selecting the support system involves choosing the appropriate tools for information system, training, performance measurement and reward system. Also the organizational objectives are to be considered when selecting the tools. One of the tools being adopted lately is the Enterprise Resource Planning (ERP) which has the ability to integrate different functional areas within the organization for efficient maintenance planning and scheduling.

Ambika (2009) investigated the use of Reliability, Availability, Maintainability and Safety (RAMS) and Life Cycle Cost (LCC) in maintenance planning strategy. The investigation showed that the combination of RAMS and LCC will provide a solution that will optimise maintenance strategy. The decision support models will be discussed in later sections of this research report.

Maintenance planning strategy is developed focusing on the corporate objectives in line with its strategies. Strategic decisions are made in relation to the service delivery, organization and work structure, maintenance strategies and supporting systems which result to the need to plan the capacity and workforce requirements. The weekly and daily plans are developed and scheduled for implementation. This is then followed performance measurement for continuous improvement (Al-Turki 2009). Figure 2.6 shows a summary of the maintenance planning process.

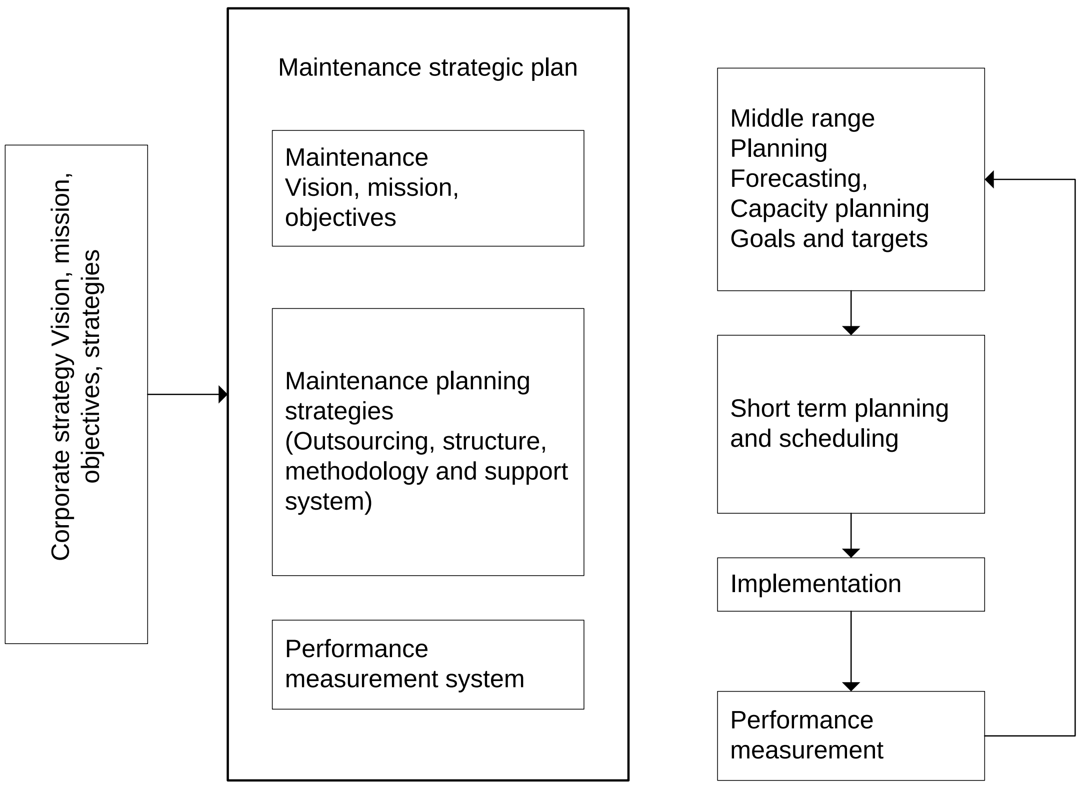


Figure 2.6: Maintenance planning process (Al-Turki 2009)

2.7 Maintenance Scheduling

After a strategic maintenance plan has been developed, the next requirement for implementation is to allocate resources and workforce to the planned activities. This process is referred to as scheduling. Scheduling deals with assigning jobs with the necessary required resources (material and work force) which are arranged in the order of execution. The tasks are allocated durations, predecessors, successors and resource availability. Maintenance scheduling is therefore, the scheduling of planned maintenance activities (Al-Turki 2009). It is a process of executing the six elements of a successful maintenance job namely, the mechanic(s), tools, materials and spare parts, availability of scheduled machine, required information for job execution and approved permissions in an outlined efficient manner.

Scheduling can be categorized into three main levels

1. Master Schedule (Medium range schedule: 3 months to 1 year)
2. Weekly Schedule
3. Daily Schedule

The master schedule relies on existing maintenance work orders. It is used to create a balance between medium range planning activities and available resources. This level of scheduling gives an overview of resource requirements and necessary plans are put in place to have them available when needed. The master schedule is revised often and updated to reflect changes to plan and completed maintenance work. The weekly schedule is created from the master schedule; it gives the description of the current operations schedules and economic considerations. The daily schedule is prepared from the weekly schedule, it gives description of the activities to be executed for the day. In some cases the weekly schedule is interrupted for emergency maintenance activities.

Al-Turki (2009) presents the following as necessary requirements to carry out scheduling effectively:

1. Written work orders that are derived from a well-conceived planning process. This includes work to be done, methods to be followed, crafts needed, spare parts needed, and priority.
2. Time standards.

3. Information about craft availability for each shift.
4. Stocks of spare parts and information on restocking.
5. Information on the availability of special equipment and tools necessary for maintenance work.
6. Access to the plant production schedule and knowledge about when the facilities will be available for service without interrupting the production schedule.
7. Well-define priorities for maintenance work.
8. Information about jobs already scheduled that are behind the schedule (backlog).

Al-Turki (2009)) further outline the scheduling procedure as follows:

1. Sort backlog work orders by skills needed.
2. Arrange orders by their priority.
3. Compile a list of completed and carry over jobs.
4. Consider job duration, location, travel distance, and the possibility of combining jobs in the same area.
5. Schedule multi-skill jobs to start at the beginning of every shift.
6. Issue a daily schedule.
7. Authorize a manager to compose work assignments.

2.8 Rolling Stock Maintenance

Railway industries have been considered as an environmental friendly transportation mode and its demand has been increasing over the years. There is a need to maintain a high level of reliability, safety, availability and maintainability within a rail system. This however, is a challenging task to accomplish considering the two main sub-systems that make up the railway system, namely the Rolling stock and Infrastructure. Infrastructure includes signal, power supply and rail tracks while Rolling stock refers to all vehicles that move on a rail track which could be coaches, wagons and locomotives. Of these two, Rolling stock can be classified as the most important and most vulnerable (Park *et al.*, 2011).

Rolling stock has a huge effect on the service level of the system because the service level of the rail system is directly proportional to the safety and comfort of the passengers. In order to achieve the required service level, the quality of the rolling stock performance needs to be improved continually and this can be achieved with proper maintenance. A train is also classified as rolling stock and it comprises of several rail vehicles connected in series. The combination of these vehicles are complex, but can be redistributed and reconfigured to include embedded systems, which are combined together to provide a high quality transportation service (Umiliacchi *et al.,* 2011).

Rolling stock maintenance has been categorized generally into corrective maintenance and preventive maintenance (Cheng & Tsao 2010). Nevertheless, these maintenance strategies have been found to be ineffective. Majority of maintenance activities in rolling stock companies are directed towards preventive maintenance, which often leads to incorrect maintenance work, frequent down time, unnecessary maintenance tasks and often reverts to CM/BM (Rezvanizaniani *et al.*, 2008). Given this scenario, rolling stock industries need to select a maintenance schedule for the adopted strategy that will increase system reliability and reduce the need for regular maintenance.

Selecting an effective maintenance strategy is an essential concern for a rolling stock industry. Various studies have been done to try to achieve a more efficient maintenance strategy to maintain high system reliability and reduce maintenance cost. In rolling stock, safety is the most significant factor in achieving reliability and the wheel sets are the most critical part of the subsystem (Rezvanizaniani *et al.*, 2008).

2.9 Chapter Conclusion

The importance of maintenance as a value adding activity was highlighted in this chapter. The major objective of maintenance is to contribute to an organizations profit either by minimizing, identifying, or improving an element of the organization's objective. The reliability and availability of components increase when a proper maintenance strategy is adopted. These strategies have been described briefly and it can be summarised into two major categories which are corrective and preventive maintenance for rolling stock. To properly execute maintenance, it needs to be planned and scheduled efficiently to reduce the production loss time and cost. Off all the resources required for maintenance, manpower is the most challenging resource to control in maintenance management and should therefore be scheduled in the most efficient way possible.

CHAPTER 3: MAINTENANCE DECISION MODELS

3.1 Introduction

Chapter two discussed maintenance, maintenance planning and scheduling. This chapter covers the decision models for maintenance improvement. The chapter begins with a brief description of maintenance optimization as a tool for decision making. Maintenance optimization and its application are also discussed in detail in this chapter. Also discussed in the chapter are rolling stock systems and models used to achieve optimization in multi-component system and the methods used for optimization problems. The analyses and reliability of repairable systems are also covered by presenting the Homogeneous and Non-homogeneous Poisson processes.

3.2 Maintenance Optimization

Since maintenance became a frequent practice of industries, researchers have worked on various ways to efficiently schedule maintenance. The maintenance scheduling problem can also be formulated as a maintenance optimization problem (Paz & Leigh 1994). The aim would be to find an optimum balance between maintenance cost and maintenance objectives while considering all possible constraints. For example, the aim can be to derive a solution to either minimize or maximize system maintenance cost and a maintenance objective such as system reliability measures or some sort of other performance indicator. It could also be a combination of the two criteria to minimize maintenance cost and maximize reliability simultaneously (Sharma, Yadava & Deshmukh 2011).

Maintenance optimization models in this paper are defined as those models or processes by which maintenance strategies, planning or scheduling is being improved. Maintenance optimization models are made up of mathematical models which focus on deriving the optimal balance between maintenance costs and benefits of maintenance or the most appropriate time to execute maintenance. Several factors are considered when attempting to achieve an optimal maintenance schedule. These factors include: safety, health, environment, maintenance cost, failure cost, opportunity cost and replacement cost (Dekker & Rommert 1998).

Maintenance optimization has been realised through the use of various modelling techniques such as decision making tools, reliability maintenance models, algorithms, simulation, mathematical programing, statistical methods and search techniques. These methods have been used individually and in some cases combined, to achieve an optimal maintenance strategy either by minimizing cost or maximising reliability/availability depending on the objective of the researcher. According to Dekker (1996), maintenance optimization process involves four aspects:

1. Description of a technical system, its function and importance.
2. Modelling of the deterioration of the system in time and possible sequences for the system.
3. A description of the available information about the system and the actions open to management
4. Objective function and an optimization technique which helps in finding the optimal balance

3.3 Classification of maintenance optimization

Maintenance optimization models can either be qualitative or quantitative. Qualitative models include TPM, RCM, and plant asset management (PAM) while quantitative models include deterministic/stochastic models such as Markov decision, Bayesian models and integer programming (Garg & Deshmukh 2006). It is important to note that maintenance optimization is only a tool to improve the overall maintenance process and therefore, to achieve an effective performance in the maintenance process, the optimization model, maintenance policies, maintenance costs and system reliability all need to be considered instantaneously (Sharma, Yadava & Deshmukh 2011). A general model for maintenance optimization is presented in Vatn *et al.*, (1996) where safety, health and environmental objectives, maintenance costs, downtime cost are all taking into consideration.

Maintenance optimization can be classified using the objective, planning horizon, decision factors and the number of components of the problem (Hilber 2008). When performing maintenance optimization, there are two common objectives often considered which are to maximize reliability or to minimize cost. These objectives are usually performed with defined constraints. In the case of reliability, the constraints could be cost and in the case of minimizing cost, the constraint can be a required level of reliability. The planning horizon for maintenance optimization can be performed in three ways, namely a one-time period, which involves optimizing maintenance for a next time period, for example, a year; multiple time periods; or long time periods ranging up to 20 years or more. In this scenario, the net present value of cost parameters is usually considered. The third is an adaptive approach that suggests a long period plan but adaptable to changes that occur in the maintenance system during that period.

Maintenance optimization can also be classified using decision factors. Such factors vary depending on the amount and kind of data available and the elements that make up the objectives of an organization. Providing a comprehensive list of the decision factors could be a difficult task. However, the common decision factors often considered in literature include: optimal maintenance intervals, optimal delay time, optimal number spare parts, optimal man power, opportunity cost and redundancy.

Maintenance optimization models vary depending on the amount of components considered for optimization. It could either be a single component or multi-component optimization model. The single component considers optimizing the most critical or expensive component in the system. It could also be a system with subcomponents which is considered as one component. The multi-component considers optimizing several components in the system each with its own different reliability characteristics simultaneously.

Table 3-1: Maintenance optimization classification adapted from (Hilber 2008)

MAINTENANCE OPTIMIZATION CLASSIFICATION	
Objective	maximize Reliability
	minimize Cost
Planning horizon	one-time period
	multiple time periods
	adaptive
Decision factors	optimal maintenance intervals
	optimal delay Time
	optimal number spare parts
	optimal man power and redundancy
	opportunity cost
Number of components	single Component
	multi-Component

Table 3-1 shows the summary of maintenance optimization classification. In an ideal optimization model, the objectives should consider all necessary decision factors listed. In reality however, most optimization models do not consider all these factors, which provide a less optimal solution to the actual optimal maintenance. This is due to the extreme difficulty in solving a model by including all the decision factors in one model. It is therefore important to choose the factors for optimization carefully. That choice could require several optimal solutions considering different decision factors (Hilber 2008). The railway industry has benefited from maintenance optimization models.

3.4 Maintenance optimization in Railway

Rolling stock is a very important aspect of a railway system. However, not much research has been done to improve maintenance operations in rolling stock. Majority of the work done focuses on railway infrastructure. It is established from literature that railway operators have shifted attention to preventive maintenance but the methods of efficiently scheduling these PM activities have been a concern to many countries (Soh, Radzi & Haron 2012). Every maintenance project will require a certain amount of resources, expertise, and crew size with required skills, as well as a predetermined start and finish date. The completion of a project will be determined by the design of the maintenance schedule with respect to allocation of resources.

Preventive maintenance scheduling problem involves is determining which preventive maintenance activities require to be scheduled in a specific period of time, which will minimize an aspect of maintenance cost. Peng *et al.*, (2011) applied a heuristic solution technique to solve the track maintenance scheduling problem. Here, a time space network model was developed with the aim of minimizing the total travel cost of maintenance teams as well as the impact of maintenance projects on railroad operation. These are formulated by three types of side constraints: mutually exclusive, time window, and precedence constraints**.** Similarly, (Budai, Huisman & Dekker 2005) proposed a heuristic search technique to solve preventive maintenance scheduling problem by minimizing the track possession costs.

Borraz-Sánchez and Klabjan (2012) identified a railway track maintenance scheduling problem. They applied human resource allocation also known as gangs to solve the problem. The authors designed a solution method which made use of very large scale neighbourhood search combined with mathematical programming for the purpose of minimizing total costs incurred by the maintenance projects within a time frame.

Genetic algorithm (GA) is another technique that has been applied to railway and rolling stock maintenance problems. Sriskandarajah *et al.*, (1998) applied GA to the maintenance overhaul scheduling problem of rolling stock at Hong Kong Mass Transit Railway Corporation. The solution was automated and embedded in a computer program, which empowered maintenance scheduler to establish an efficient yearly maintenance schedule program. The objective of the model was to satisfy maintenance requirements of various units of the trains in order to minimize the maintenance cost. García Márquez *et al.*, (2003) also applied GA to detect the failure modes after which RCM was implemented to the switch and crossing maintenance of railway infrastructure to improve railway turnouts.

Another problem in rolling stock maintenance is reducing the hold time of rolling stock during maintenance. A robust schedule constructed in a manner that a sequence of the tasks is allocated to each resource for which the makespan value can be predicted when the duration of the tasks is increased, can be used to ensure the task is complete at the planned duration. This was achieved by modelling the problem and solving with a robust genetic algorithm (Sevaux & Le Quéré 2003).

Several solutions offered to rolling stock maintenance problems have however, not taken reliability into consideration. This has brought the need to improve on these optimization models where RCM was investigated by applying it as a maintenance optimization tool. Rezvanizaniani *et al.*, (2008) applied RCM to the rolling stock of Raja Passenger Train Corporation to optimize maintenance to make maintenance cost effective and reduce unnecessary maintenance work.

Selecting the right maintenance strategy and keeping the right amount of spare parts in rolling stock can be challenging. Cheng and Tsao (2010) attempted to solve this problem by applying Analytic Network Process (ANP) to determining a suitable maintenance strategy for rolling stock. Their results show that preventive maintenance should be used more than corrective maintenance as it requires less spare part quantities and replacement interval of component of rolling stock. Yun, Han and Park (2012) applied GA and simulated annealing to determine the optimal preventive maintenance interval and optimal number of spare parts of rolling stock in order to satisfy the system availability requirements at minimum cost. The authors concluded that as the availability increases, the number of optimal spare parts reduces.

Considering the classifications of optimization discussed in 3.3, rolling stock maintenance problems can be modelled as multi-component optimization problems. A rolling stock system for example a train is made of motor coaches and trailers connected in series. Optimization of multi-component systems has been dealt with in literature to an extent. Some of the work done is presented in the next section.

3.5 Multi-component Maintenance Models

Multi-component maintenance models refer to models used to determine optimal maintenance decisions for a system that consists of more than one machine made up of many pieces of equipment that could either be dependent or independent of each other. According to Dekker *et al.*, (1997), these dependencies can either be economic, structural or stochastic, but for simplicity, only one of these dependencies is usually considered. These models often aim to determine optimal maintenance planning for systems consisting of several components that interact with each other (Park *et al.*, 2011). Minimizing maintenance cost of a multi-component in most cases may not relatively relate to maximizing reliability measures or vice versa. This is because of the difference in maintenance cost and reliability measures of the different components in the system. It is therefore important to consider the maintenance policy, cost and reliability of every component to achieve a successful optimal model.

Multi-component models can be modelled as a single or multi-objective optimization model in order to balance the need to minimize cost without reducing system reliability. This could also mean integrating the maintenance intervals with the production period of the system. Depending on the type of system, there are a number of criteria that can be identified in the sphere of maintenance activities. Some of these criteria include reliability, downtime costs, expected total costs per unit time, spare part costs and maintenance costs. Several researches have looked into improving maintenance scheduling of multi-component systems using one or more of these criteria. Laggoune *et al.,* (2009) considered a multi component system in continuous operation. The authors attempted to minimize the cost of maintenance by developing a preventive/corrective opportunistic maintenance plan subject to high production losses and economic dependence.

Chareonsuk *et al.*, 1997) proposed a model that incorporates multiple criteria for a production system containing several components to determine the optimal preventive maintenance intervals. The expected cost and reliability were taken into consideration and the problem was solved using PROMETHEE method. Levitin and Lisnianski (2000) proposed an optimization problem which minimizes the cost plan of preventive maintenance to provide the required level of system reliability. The authors applied GA to so solve the problem. Moghaddam and Usher (2011) proposed a multi-objective optimization model for a reparable and maintainable system. The objective of the model is to determine an optimal schedule for preventive maintenance and component replacement that would minimize maintenance cost while the overall system reliability is maximized over a period. The proposed method proposed by Moghaddam and Usher (2011) was adopted for the purpose of this research.

3.6 Maintenance Optimization Methods

Maintenance optimization of multi component systems is being achieved through various kinds of quantitative methods and techniques. These techniques vary with the kind of problem being addressed which eventually leads to the model and method applied for optimization. The optimization method for multi component systems can either be an exact method or a metaheurisic algorithm. The problem can either be constrained or unconstrained; deterministic or stochastic (Rothlauf 2011).

3.6.1 Exact optimization methods

Exact optimization methods are methods designed to find the real optimal solution of a problem. These methods are efficient at finding the optimal solution for small problems. The computation time and effort increases significantly as the problem becomes larger and more complex. For example, a multicomponent optimization problem with 20 components and a long planning horizon of about 60 months would take a long time to complete using exact methods. In this case, the method becomes unsuitable and heuristics becomes a better option (Nicolai & Dekker 2008). Some exact methods include analytical and numerical methods, linear and nonlinear programming, mixed integer and dynamic programing. (Lee *et al.*, 2004; Rothlauf 2011). It is important to note that nonlinear programming is the most general method of optimization that is being applied in most maintenance optimization literature.

3.6.1.1 Analytical & Numerical Models

These are models that have closed form of solutions. They use mathematical analytic functions to provide solutions to equations describing changes in a system. Analytical methods have been used as an optimization approach for maintenance optimization. Rezg, *et al.*, (2005) developed an analytical model to evaluate the average cost per time unit of a joint optimal inventory control and preventive maintenance strategy for a randomly failing production unit. The result was compared with a simulation approach used to solve the same problem. Oke (2005) presented an analytical model to measure profitability of a maintenance system, using a case study for application. The author used simulation experiments and demonstrated that maintenance profitability can be realised through the use of differential calculus.

3.6.1.2 Linear & Nonlinear Programming

Linear programming is an optimization method applied when solving problems with objective functions and constraints appearing as linear functions of the decision variables. These constraint equations could be either equality or inequality forms. Linear programming is considered a revolutionary development, which enables optimal decisions to be made in complex situations. Nonlinear programming is an optimization method used to solve problems that have objective functions and constraints that are not stated as explicit functions of the design variables. Maintenance optimization has seen the application of linear and nonlinear programming as a method for solution in several capacities (Rao & Rao 2009).

Jayakumar and Asgarpoor (2006) applied linear programming to implement a Markov decision process, which was used to determine the optimal maintenance policy that yields the maximum expected return. Ramanathan (2006) attempted to solve the problem of considering multiple criteria for inventory classification by proposing a classification scheme using a weighted linear optimization model. The model was adapted from linear programming and can be easily applied by inventory managers. Oyama and Miwa (2006) applied a modified linear program, called all-integer linear program to solve the irregularities in railway track maintenance. The result was an optimal maintenance schedule.

Chen *et al.*, (2006) presented an integrated framework of tolerance and maintenance design by formulating nonlinear optimization problems that can minimize the overall average production cost. Battistelli *et al.*, (2009) proposed an optimization procedure for choosing fundamental characteristics of a storage device to be used in a direct current railway system. The storage design problem was formulated as a nonlinear program and solved to determine the optimal references for a DC-DC bidirectional boost converter.

3.6.1.3 Mixed integer programming (MIP)

A mixed-integer program can either be a mixed-integer linear program (MILP), which is a mathematical program that involves the minimization or maximization of a linear function subject to linear constraints, where the decision variables assumes only integer values. A mathematical program with continuous and discrete variables and nonlinearities in the objective function and constraints is referred to as a mixed integer non-linear program (MINLP). In maintenance optimization, these programs have been applied to find optimum solutions.

Vassiliadis and Pistikopoulos (2001) presented an optimization framework using mixed integer nonlinear optimization model. The objective of the framework was to identify the number of PM or CM actions required over a given time horizon of interest as well as the time instants and sequence of these maintenance actions on the various components of the process system, so that the system efficiency is maximized. MILP was applied in the area of short-term maintenance scheduling of utility systems. A mathematical model was developed to evaluate the balance between labour cost, material cost and opportunity cost and this was solved to get an optimal solution (Matsuoka & Muraki 2007). Tokos and Pintarič (2012) presented a MINLP mathematical model to minimize freshwater consumption and water contaminant load in a semi-continuous process.

3.6.1.4 Dynamic programming

Dynamic programming (DP) is an optimization method applied to multi-stage decision problems. Multi-stage decision problems refer to problems where decisions are to be made sequentially at different points in time at different points in space and at different levels. Dynamic programming has the ability to decompose a multistage decision problem to a single stage decision problem. The decomposition is achieved in such a manner that the optimal solution of the original problem can be obtained from the optimal solution of the single stage decision problem. One major setback of the DP is the "curse of dimensionality". Despite this setback, DP is still a very suitable method for solving complex problems in decision making.

Zhou *et al.*, (2009) presented an opportunistic preventive maintenance scheduling algorithm for a multi-unit series system. The algorithm was based on dynamic programming and integrated imperfect effect into maintenance actions. They used simulation to optimize the maintenance practice by maximizing the short term cumulative opportunistic maintenance cost savings for the whole system. Numerical examples were also presented to show the application of the model. Khalesi *et al.,* (2011)presented a multi-objective function capable of determining the optimal locations to place distributed generations in a power distribution system. The authors applied dynamic programming method to solving the optimization problem in order to minimize power loss of the system and enhance reliability improvement and voltage profile. Frangopol and Liu (2007) applied stochastic dynamic programming to a multi-objective optimization problem of bridge network maintenance planning. A two-phase dynamic programming approach was applied to solving the complex problem. The result was an efficient combination of available maintenance actions for bridges in a highway network.

3.6.2 Metaheuristics optimization methods

Heuristics is a method of finding by trial and error. It finds good solutions to optimization problems in a reasonable amount of time. There is however, no guarantee that the solutions found are the best optimum solutions. Metaheuristics is an advanced method of heuristics, which utilizes a certain trade-off of randomization and local search techniques. Metaheuristics algorithms can be applied to solve almost any optimization problem; they are mostly inspired by nature and developed based on some abstraction of nature. The two major components of any metaheuristics algorithm are randomness for diversity of solutions and selection of best solutions, which ensures the solutions converge to optimality. Some examples of metaheuristics include: Genetic Algorithms, Simulated Annealing, Ant Algorithms, Particle swarm optimization and Fuzzy set theory (Yang 2010). For purposes of this research genetic algorithm and simulated annealing are considered for optimization, hence they are the ones discussed in the following sections.

3.6.2.1 Genetic Algorithm

Genetic algorithms (GAs) are global heuristic search techniques that utilise randomisation as well as directed smart search to seek the global optima. John Holland is recognized as the founding father of GAs. He was the first to formalise GAs as a solution method for optimization problems (Holland 1975). GAs are modelled after the genetic evolution of natural species such as inheritance, mutation, selection and crossover. The characteristic of GAs to search a population of solutions globally for an optimal makes it different from other optimization technics. GAs are well suited for solving optimization problems with mixed continuous-discrete variables and discontinuous and non-convex design spaces (Rao & Rao 2009b). In general, modelling a GA as a solution to an optimization problem consists of two main steps: (i) Defining a data structure, which consists of possible solution and (ii) Defining an objective function, which evaluates the possible solutions to select the optimum (Lapa, Pereira & de Barros 2006).

The fundamental principle of genetic algorithms involves the encoding of objective functions as arrays of bits or character strings to represent the chromosomes, the manipulation operations of strings by genetic operators and the selection according to their fitness with the aim of finding a solution to the problem. Yang (2010) provides the following procedure for carrying out GA.

- Encoding the objective functions.
- Defining a fitness function or selection criterion.
- Initializing a population of individuals'
- Evaluating the fitness of all individuals in the population.
- Creating a new population by performing crossover, mutation fitness proportionate reproduction etc.
- Evolving the population until certain stopping criteria are met.
- Decoding the result to obtain the solution to the problem.

Genetic algorithms have been successfully applied to a wide range of maintenance optimization problems. This is because of its robustness and easy customization. Bris *et al.,* (2003) applied genetic algorithm to a series parallel system to find the best maintenance policy that reduces cost. In their research, cost and availability were used as optimization criteria. Saranga (2004) systematically analysed a selection of components that require opportunistic maintenance. The author applied GA to decide whether opportunistic maintenance is cost effective compared to later grounding. Lapa *et al.*, (2006) applied GAs to present a model to optimize preventive maintenance policies based on the cost-reliability model. Konak *et al.*, (2006) presented a tutorial describing how genetic algorithms can be used to solve multi-objective optimization problems. The author discusses the components of GA in multi-objective optimization and the salient issues encountered in implementing multi-objective GAs.

Shum and Gong (2007) considered maintenance and spare part replacement frequency, purchasing strategy and maintenance workforce size as decision variables for a production system. Maintenance cost was the objective function of the model and genetic algorithm was used to optimize the preventive maintenance schedules of the system. Modified GAs can be used to optimize the time difference between the start and finish of a sequence of jobs or tasks, which is used to optimize the planning of jobs in a multi-factory environment (Chung *et al.*, 2010).

3.6.2.2 Simulated Annealing

Simulated Annealing (SA) is another broadly used metaheuristics for solving optimization problems. Its application into optimization problems was introduced by Kirkpatrick, Gelatt and Vecchi in 1983 (Kirkpatrick, Jr. & Vecchi 1983). SA is a search technique based on randomness for global optimization problems. It is a technique that imitates the annealing process in the material processing when a metal cools and freezes into a crystalline state with the minimum energy and larger crystal size so as to reduce the defects in metallic structures. The main advantage of the simulated annealing is its ability to avoid being trapped in local minima (Busetti 2003).

The Boltzmann's probability distribution states that for a thermal system with energy E and thermal equilibrium temperature T, the probability distribution is given as

$$\boldsymbol{P(E) = e^{-E/kT}} \qquad 3.1$$

Where $P(E)$ represents the probability of achieving the energy level E and k is called the Boltzmann's constant and T the temperature for controlling the annealing process. To mimic the annealing process, a new energy state is defined and the difference in energy level ΔE is calculated. The objective function is linked to the Energy E and the change in energy level ΔE is accepted or rejected based on the probability

$$\boldsymbol{P}(\Delta \boldsymbol{E}) = \boldsymbol{e}^{-\Delta E/_{kT}} \qquad \text{if } \Delta \boldsymbol{E} > \mathbf{0} \qquad 3.2$$

Simulated annealing has been used to solve several maintenance optimization problems especially for models containing non-linear decision variables. In order to minimize the operation cost along the scheduling period of generator maintenance, Saraiva *et al.,* (2011) applied simulated annealing to solve the mixed integer optimization problem. Safaei *et al.,* (2012) proposed a parallel simulated annealing algorithm combined with multi-threaded architecture to solve a bi-objective maintenance scheduling problem. The objective of the research was to minimize the multi-skilled workforce requirements over a given period of time and to minimize the total downtime of equipment as a result of maintenance. Doostparast *et al* (2013) applied simulated annealing to finding the optimal frequency and types of maintenance actions required to achieve a certain level of system availability with minimum total cost.

3.6.3 Multi-Objective Models

Multi-objective models can be applied to most real life engineering maintenance complex problems. These are problems where the objectives conflict with one another and finding an optimal solution for a single objective produce unacceptable results given the effect it has on other objectives. Therefore, multi-objective models result to a set of solutions which satisfy the objectives to a reasonable acceptable level. Multi-objective models have been applied to many maintenance problems. Kralj and Petrovic (1995) presented a multi- objective combinatorial optimization model to minimize total fuel costs, maximize reliability of expected unserved energy and minimize constraint violations. The search for an optimal solution was achieved through the use of a multi-objective branch and bound algorithm. Min *et al.*, (2009) assumed two possible maintenance actions, maintenance repair or replacement, which would result in different system reliability and maintenance cost. A multi-objective model was used to determine the optimal maintenance actions that will result in the maximum reliability with minimum cost.

Levitin and Lisnianski (2000) generalized a preventive maintenance optimization problem to multi-state systems which have an array of performance levels. The authors developed an algorithm to obtain a sequence of maintenance actions that provides the system with a desired level of reliability during its lifetime with the minimal possible cost. A universal generating function technique is applied and used to evaluate the multi-state system reliability. Verma & Ramesh (2007) present a constrained nonlinear multi-objective problem using reliability, cost, non-occurrence of maintenance periods and maintenance start times as criteria. They considered a Higher Modular Assembly, which is made up by grouping systems, subsystems and components of a large engineering plant together. The decision problem was solved by applying an elitist genetic algorithm.

3.6.4 Simulation Model

Simulation is the process of imitating a real-world process or system over a period of time from a developed mathematical model. Simulation is considered as the most flexible operations research techniques (Sharma *et al.*, 2011). Simulation has been widely used as a solution technique to maintenance optimization techniques. Sarker and Haque (2000) considered a manufacturing system with stochastic item failure, replacement and order lead times of statistically identical items and developed a simulation model to reduce maintenance and inventory costs. Duffuaa *et al.,* (2001) identified maintenance planning and scheduling as the most critical aspect of maintenance because it controls the maintenance process. The authors developed a generic conceptual model for a maintenance system which contained seven modules. The aim of the model was to lay a ground for developing a realistic simulation model.

Rezg *et al.,* (2004) proposed an integrated method for preventive maintenance and inventory control of a production line. The authors developed approximate analytical models for a single machine case considering three maintenance strategies. PROMODEL simulation software was used to simulate the production line by applying a genetic algorithm to optimize the parameters of the model. They conclude, from the results of the simulation that the joint optimization of maintenance strategy and production control policy leads to a significant reduction of the total cost. Crespo Marquez *et al.,* (2006) used simulation model to improve preventive maintenance scheduling in semi-conductor plants. They show how Monte Carlo continuous simulation modelling can be used to improve preventive maintenance scheduling. They conclude that the use of age and availability based maintenance scheduling policy maximizes the entire maintenance process and provides better result than the use of single age based maintenance scheduling policy. Hagmark and Virtanen (2007) provide an extensive method of using simulation to determine the level of reliability, availability, corrective and preventive maintenance cost of a production system at an early stage of design.

Maintenance optimization is a widely covered subject in literature. An observation made from the researches done is that every problem solved in maintenance optimization is unique in its own way as authors have adapted models suitable to the objective of the problem to be solved. It is important to understand how problems can be formulated and how to decide which model or solutions would be suitable to apply.

3.7 Modelling of Repairable Systems

Engineering systems can either be repairable or non-reparable. Non-repairable systems refer to systems in which when a failure occurs, the system is discarded because repairing the system is not economically feasible. Examples of these systems include electric bulbs, missiles and non-degradable batteries. In these systems, the reliability of the systems is required to be high and is modelled using statistical distributions such as Weibull. Repairable systems refer to systems that go through many phases of failure and repair within the duration of their design life. The reliability of these systems does not generally have to be as high as that of non-repairable systems. Reliability of repairable systems is modelled by using stochastic point process (Louit, Pascual & Jardine 2009).

The two widely used stochastic process models applied to modelling repairable systems in literature are the Homogeneous Poisson process (HPP) and the Non-Homogeneous Poisson process (NHPP). There are several other stochastic processes, which can be seen in Faulin *et al.*, (2010). A method of improving repairable systems is making use of highly reliable components for the system and applying an efficient repair or maintenance system. The two most important performance criteria for repairable system are reliability and inter-arrival failure times (Elsayed 2012). In fitting a repairable system into a distribution, it is assumed that the failures are always statistically independent and identically distributed, although this may not always be the case. When a component failure occurs in a repairable system, the remaining components have a current age. Therefore, the next failure of the component depends on its current age. Thus, the failure events at the system level are dependent. This property forms an important characteristic of a repairable system. If the times between sequential failures are increasing, then the reliability of the system is improving. If the times between sequential failures are decreasing, then the systems' reliability is degrading.

3.7.1 Failure data

Gathering the right information for reliability improvement is a very crucial and important aspect of reliability analysis. However, this process is faced with different challenges and limitations. One of the common challenges in reliability analysis is lack of adequate data to carry out proper statistical analysis. As pointed out by Louit *et al.*, (2009), the amount of data available places a limit on the capabilities of statistical methodologies used for analysis. It is believed that this problem would never disappear given that the aim of maintenance is to reduce failure occurrence. Another practice during data collection is data censoring. Censored data refers to stopping a collection of data when the unit has not failed and the exact failure time in not known. It can either be left, interval or right censored (Hamada 2008).

3.7.2 Trend Test

In analysing a repairable system, it is important to determine if there is a trend in the data set that has been gathered by analysing the changes of inter-arrival failures occurring over a certain period of time of the system. The results of this test can be used to model the system to follow either the HPP or NHPP. A system can have various monotonic or non-monotonic trends; monotonic trends means there could be reliability growth which implies times between failures are occurring longer with time. It could also be reliability degradation, which means times between failures are decreasing with time. Non-monotonic such as cyclic, bathtub curves could also be present. Statistical hypothesis test is an effective way to check inter-arrival failure times for a trend (Ionescu & Limnios 1999). Such tests include the Laplace and the Lewis Robinson trend test.

Laplace Test

This test is used to test a set of data for the null hypothesis of HPP against the alternative of NHPP. This measure under the null hypothesis is approximately standard normally distributed. The Hypothesis test as presented by Coit (2005) is

$H_0: HPP$

$H_a: NHPP$

Under H_0 and conditioning on $T_1, T_2, \ldots \ldots \ldots, T_n$ are uniformly distributed, the test statistic for a time censored data is

$$\boldsymbol{U} = \frac{\frac{\sum_{i=1}^{n} T_i}{n} - \frac{T_n}{2}}{T_n\sqrt{\frac{1}{12n}}} \qquad 3.3$$

Where

T_i is the time from a given start point to the time of each failure event

T_n is end time of the observation period

n is the number of failures

For time uncensored data, n is replaced with $n - 1$ and T_n by τ

The rejection criteria is based on the standard normal distribution assumption for U. This is given by,

Reject H_0 if $U > Z\alpha/_2$ or $U < -Z\alpha/_2$. at 95% confidence interval.

According to (Lindqvist 2006), rejecting H_0 only confirms that the data does not follow HPP. It does not necessarily imply that there exist a trend in the data hence a need to apply a renewal trend test to check if the data follows a trend.

Lewis-Robinson test

The Lewis-Robinson (LR) test is a modification of the Laplace test that tests the data for a null hypothesis of a Renewal Process (RP) using the failure inter-arrival failure times (Lindqvist 2006). The Hypothesis test as presented by Coit (2005) is

$H_0: RP$

$H_a: Not\ RP$

The LR test statistic is derived by dividing the Laplace statistic U by the coefficient of variation (CV) for the observed inter-arrival failure times.

$$\boldsymbol{LR} = \frac{\boldsymbol{U}}{\boldsymbol{CV}} \qquad 3.4$$

where CV is derived as the variance of X divided by the Mean of X

$$\boldsymbol{CV}[\boldsymbol{X}] = \frac{\sqrt{\boldsymbol{Var}[\boldsymbol{X}]}}{\bar{\boldsymbol{X}}} \qquad 3.5$$

where X is the inter-arrival times variable.

The rejection criterion is similar to that of Laplace. Which is given by,

Reject H_0 if $LR > Z\alpha/_2$ or $LR < -Z\alpha/_2$ at 95% confidence interval

3.7.3 NHPP model

Analysing a repairable system by applying a distribution analysis may not be suitable for an effective analysis of a repairable system considering the characteristics of its failure events. For this reason, a stochastic process such as the Non-Homogeneous Poison Process (NHPP) would be suitable for such analysis. The NHPP has been proven by literature to be a suitable model for data that have trend. NHPP models are mathematically straightforward and their theoretical base is well developed. The model has been tested and vastly applied in literature (Coetzee 1997). The NHPP signifies that the failure intensity function is not time dependent. A NHPP must satisfy the following conditions (Elsayed 2012):

$N(t) \geq 0$

$N(t)$ is an integer value

$[N(t), t \geq 0]$ has independent increments i.e $N(t_2) - N(t_1) \perp N(t_1)$

$if\ t_1 < t_2, then\ N(t_1) \leq N(t_2)$, and

The number of events that occur in the interval $[t_{1,t_2}]$ where $t_1 < t_2$ has a Poisson distribution with mean $\int_{t_1}^{t_2} u(t)dt$.

Therefore, the probability of having n failures in the interval $[t_1, t_2]$ is

$$\boldsymbol{P[N(t_2) - N(t_1) = n] = \frac{e^{-\int_{t_1}^{t_2} u(t)dt}\left[\int_{t_1}^{t_2} u(t)dt\right]^n}{n!}} \qquad 3.6$$

The expected number of failures in $[t_1, t_2]$ is

$$\boldsymbol{E[N(t_2) - N(t_1)] = \int_{t_1}^{t_2} u(t)dt.} \qquad 3.7$$

The reliability function of the NHPP for the interval $[t_1, t_2]$ is

$$\boldsymbol{R[t_1, t_2] = e^{-\int_{t_1}^{t_2} u(t)dt}} \qquad 3.8$$

There are two methods in literature for applying the NHPP for repairable systems, namely the power law intensity and the log linear intensity (Vlok 2013; Rigdon & Basu 1989; Ascher & Feingold 1984; Coit 2005 & Krivtsov 2007).

Power law NHPP

The power law NHPP is given by

$$\boldsymbol{u(t) = +} \qquad \boldsymbol{\gamma, \delta > 0} \text{ and } \boldsymbol{t \geq 0} \qquad 3.9$$

Where

$u(t)$ is the failure intensity, i.e. Rate of occurrence of failure

γ is the scale parameter (failure function)

δ is the shape parameter(improvement/degradation)

The parameter δ can be used to understand the reliability growth of the system. $\delta < 1$ implies that there's reliability growth and $\delta > 1$ implies that there is reliability degradation.

From the definition of NHHP, the expected number of failures for the interval t_1, t_2 is

$$\boldsymbol{E[N(t_2) - N(t_1)] = \int_{t_1}^{t_2} u(t)dt.} \qquad 3.10$$

$$\boldsymbol{E[N(t_2) - N(t_1)] = \gamma\left({T_2}^{\delta} - {T_1}^{\delta}\right),} \qquad \boldsymbol{\gamma, \delta > 0, T_2 \geq T \geq 0} \qquad 3.11$$

The reliability function for the interval t_1, t_2 is given by

$$\boldsymbol{R[t_2, t_1] = e^{-\gamma\left({T_2}^{\delta} - {T_1}^{\delta}\right)}} \qquad \boldsymbol{\gamma, \delta > 0, T_2 \geq T \geq 0} \qquad 3.12$$

Log Linear NHPP

The log linear NHPP is given by

$$\boldsymbol{v(t) = e^{\alpha_0 + \alpha_1 t}} \qquad \boldsymbol{-\infty < \alpha_0, \quad \alpha_1 < \infty, \quad t \geq 0} \qquad 3.13$$

This format of NHPP gives a good representation of a repairable system with $\alpha_1 > 0$. similarly, from the definition of NHHP, the expected number of failures for the interval t_1, t_2 is

$$\boldsymbol{E[N(t_2) - N(t_1)] = \int_{t_1}^{t_2} v(t)dt.} \qquad 3.14$$

$$\boldsymbol{E[N(t_2) - N(t_1)] = \frac{e^{\alpha_0}}{\alpha_1}\left(e^{\alpha_1 t_2} - e^{\alpha_1 t_1}\right)} \qquad 3.15$$

$$\boldsymbol{-\infty < \alpha_0, \quad \alpha_1 < \infty, \quad T_2 \geq T_1 \geq 0}$$

The reliability function for the interval t_1, t_2 is given by

$$\boldsymbol{R[t_2, t_1] = e^{-\frac{e^{\alpha_0}}{\alpha_1}\left(e^{\alpha_1 t_2} - e^{\alpha_1 t_1}\right)}} \qquad 3.16$$

$$\boldsymbol{-\infty < \alpha_0, \quad \alpha_1 < \infty, \quad T_2 \geq T_1 \geq 0}$$

3.7.4 Parameter Estimation

Parameters of NHPP can be estimated by using either the Maximum Likelihood method (MLE) or the least-square method. MLE method is a process that involves maximising the log likelihood of the power law function given by,

$$\boldsymbol{l(\lambda,\beta) = nln\gamma + nln\delta - \gamma {T_n}^{\delta} + (\delta - 1)\sum_{i=1}^{n} lnT_i} \qquad 3.17$$

Such that,

$$\mathbf{max}(\hat{\gamma},\hat{\delta}):\ l(\gamma,\delta) = \mathrm{l}(\hat{\gamma},\hat{\delta}) \qquad 3.18$$

For log linear NHPP

$$\boldsymbol{l(\alpha_0,\alpha_1) = n\alpha_0 + \alpha_1 \sum_{i=1}^{n} T_i - \frac{e^{\alpha_0 T_n - 1}}{\alpha_1}} \qquad 3.19$$

Such that

$$\mathbf{max}(\widehat{\alpha_0},\widehat{\alpha_1}) : l(\alpha_0,\alpha_1) = l(\widehat{\alpha_0},\widehat{\alpha_1}) \qquad 3.20$$

The least square method involves minimizing the difference between the observed number of failures and the expected number of failures using the following function for the power law NHPP

$$\mathbf{min}(\hat{\gamma},\hat{\delta}) = \sum_{i=1}^{n}[E[N(0 \to T_i)] - N(0 \to T)]^2 \qquad 3.21$$

For log linear NHPP

$$\mathbf{min}(\widehat{\alpha_0},\widehat{\alpha_1}) = \sum_{i=1}^{n}[E[N(0 \to T_i)] - N(0 \to T_i)]^2\ 3. \qquad 3.22$$

The least square method is a preferable parameter estimation method because it leads to more appropriate parameters than the MLE (Vlok 2013).

The process of selecting an appropriate model is summarised in Figure 3.1

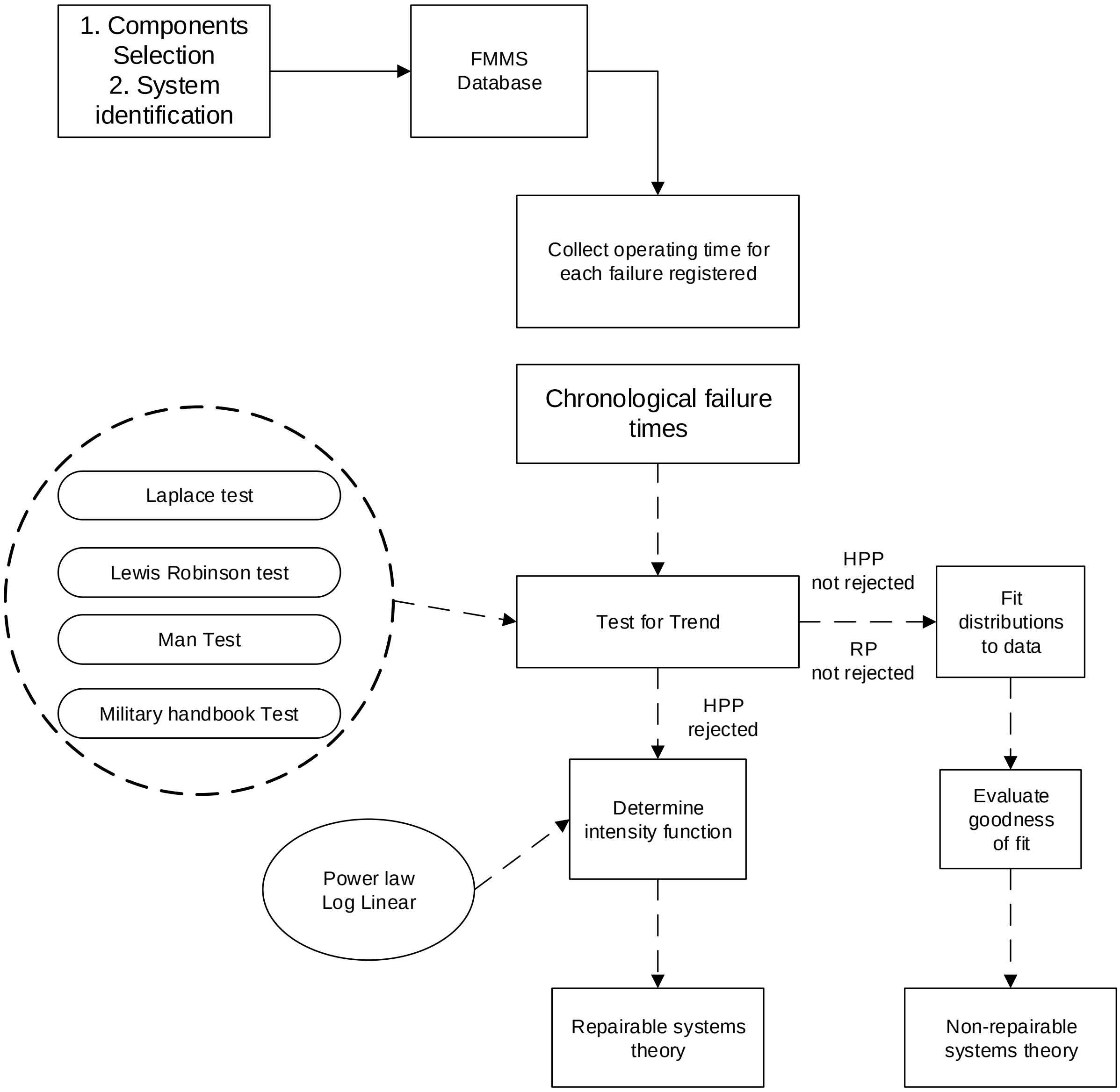


Figure 3.1: A framework for selecting a decision model for maintenance adapted from Louit, Pascual & Jardine (2009)

Kim and Singh (2010) applied a power law NHPP to model an aging model by a proper choice of parameter β. The research focus is on estimating the proper β parameter for power generators for reliability measurement. Ryan *et al.*, (2011) considered a NHPP power law process and applied it to single repairable and a multiple repairable system. A Bayesian inferential approach was used to model failure times and failure counts. They conclude that a power law process is effective in analysing multiple repairable systems.

Reliability prediction is an area in literature that has gained much argument and attention. Reliability is not a parameter that is easily predictable on the basis of the laws of nature or of statistical analysis of past data. It is important to note that when forecasting reliability, any change in the physical system or in the change of operations will alter the prediction outcomes. It is therefore important to appreciate that the predictions of reliability can seldom be considered as better than rough estimates and that the achieved reliability can be considerably different to the predicted value (O'Connor & Kleyner 2011).

3.8 Age reduction models

Different maintenance strategies have been discussed in chapter 2. Each of these strategies has a level to which they reduce the age of a system when applied. This level is known as the age reduction factor which is also known as improvement factor. Several researchers have developed ways in which this factor can be estimated. Moghaddam (2008) presented a mathematical function that can be used to estimate age reduction factors. The author suggested a practical procedure of gathering failure data and fitting a NHPP to estimate the age reduction factor. Cheng *et al.,* (2007) argue that not all maintenance actions has a reduction effect on the system age, rather maintenance may only have an effect on the degradation rate. Based on this, the author developed an optimal periodic preventive maintenance policy by minimizing the expected cost.

3.9 Chapter Conclusion

Improving maintenance through optimization has been an area of continuous research. Several approaches have been taken to achieve maintenance objectives. These approaches vary relative to the objective of the company. Maintenance optimization problems are solved either by applying exact or metaheuristics methods. Over the years, authors have used nonlinear programming to present optimization problems. It is evident from literature that cost minimization or reliability maximization is the focus of most researchers. A system can either be modelled as a HPP model or a NHPP model where a Laplace trend test and the Lewis Robinson test are performed to help apply the appropriate model to the data set. The importance and effect of age reduction factor to the system cannot be ignored when maintenance is performed to a system.

Figure 3.2 presents a broad classification of maintenance management models. As seen in the figure, there are several optimization models, nevertheless only a few relevant to this research has been discussed with emphasis given to genetic algorithm and simulated annealing as they are used later in this study. A literature survey showing the reviewed articles and some applications of these models is presented in Appendix 1.

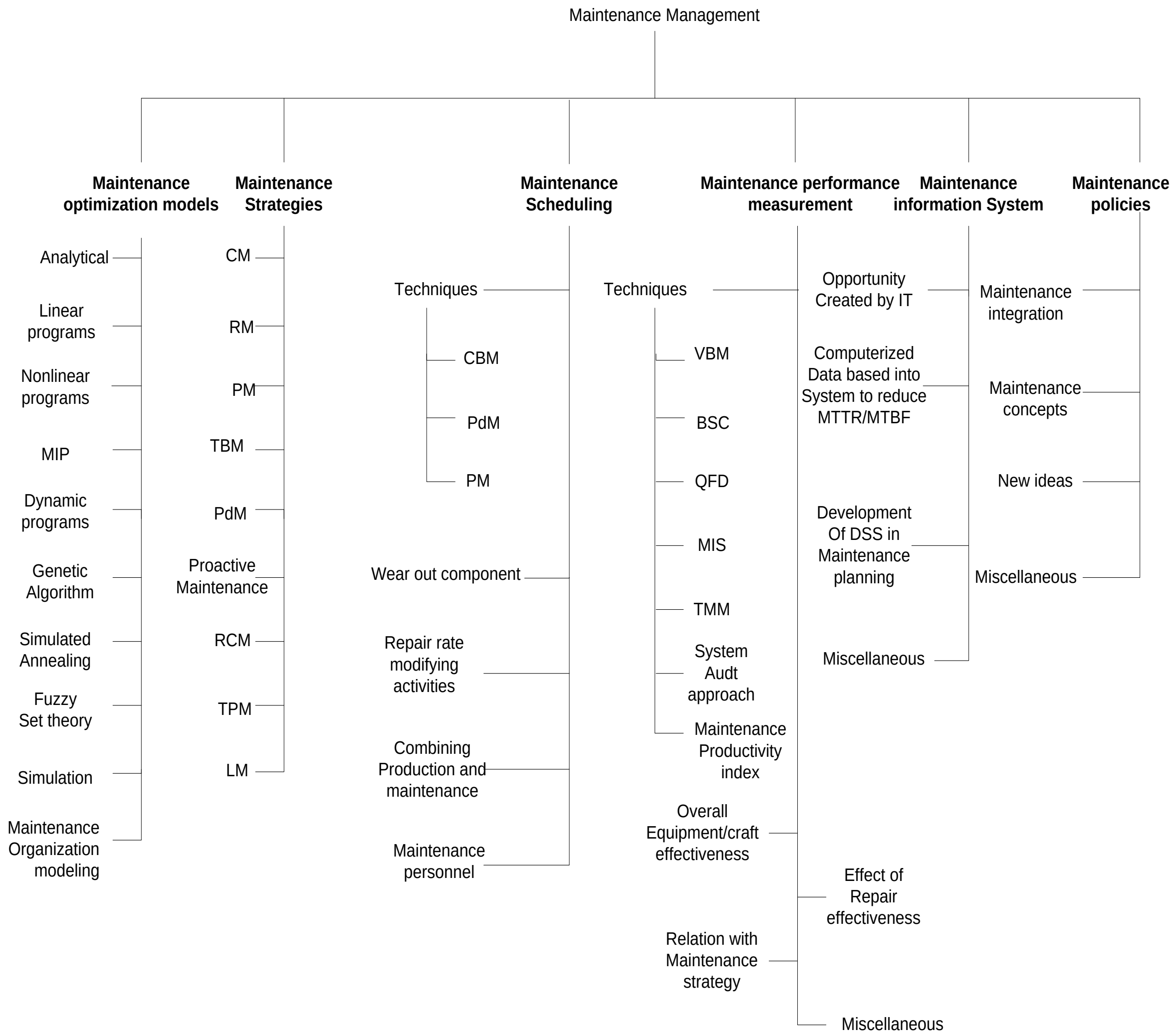


Figure 3.2: Maintenance management classification tree showing various sub areas based on Garg & Deshmukh (2006)

Keys: AHP: Analytic Hierarchy Process; MCDM: Multiple Criteria Decision Making; MIP: Multi-integer Programming; OIF: Operational Inspection Frequency; CM; Corrective Maintenance; Reactive Maintenance; PM: Preventive Maintenance; TBM: Time-based Maintenance; PdM: Predictive Maintenance; RCM: Reliability Centred Maintenance; TPM: Total Productive Maintenance; LM: Lean Maintenance; VBM: Vibration Based Maintenance; BSC: Balances Score Card; QFD: Quality Function Deployment; MIS: Maintenance Information Systems; TMM: Total Maintenance Management

CHAPTER 4: DECISION MODEL FOR ROLLING STOCK

4.1 Introduction

Chapter 3 reviewed literature on maintenance decision models. This chapter presents a decision support model for maintenance scheduling improvement and discusses the rolling stock components selection criteria as well as estimating the reliability parameters. The reliability character of the system and model assumptions is presented in this chapter. The proposed model is developed and the methods of solution are proposed.

4.2 Model Formulation

There are several objectives of maintenance as discussed in chapter 2. From literature, it is established that preventive maintenance and corrective maintenance are the two widely used strategies for rolling stock to achieve these objectives. Each of these strategies has different effect on the age of the system when they are used. When developing a decision model for rolling stock, it should be clear what the objective (maximize/minimize) of the model is. The planning horizon for the model is significant in that if the planning period is very short or too long, the model could likely produce unacceptable results. Therefore, it is important to consider the average life span of rolling stock components when defining the planning horizon.

The system configurations for the model can be defined at this stage. These configurations include the number of components, relevant cost associated with the maintenance process and the reliability parameters. The decision variables used to achieve the objective of the models are defined as well. These configurations could be used to form either a linear, nonlinear or mixed inter programming problem. Solution techniques such as exact methods or metaheuristics methods are proposed to solve the decision problem. Figure 4.1 presents a process flow chart for developing a decision support model for rolling stock using reliability and cost of rolling stock components. Simulation models are not applicable in this framework in that random events are required to mimic different maintenance scenarios to select the optimal solution. Therefore, simulation models would not be discussed further in view of the scope of this research.

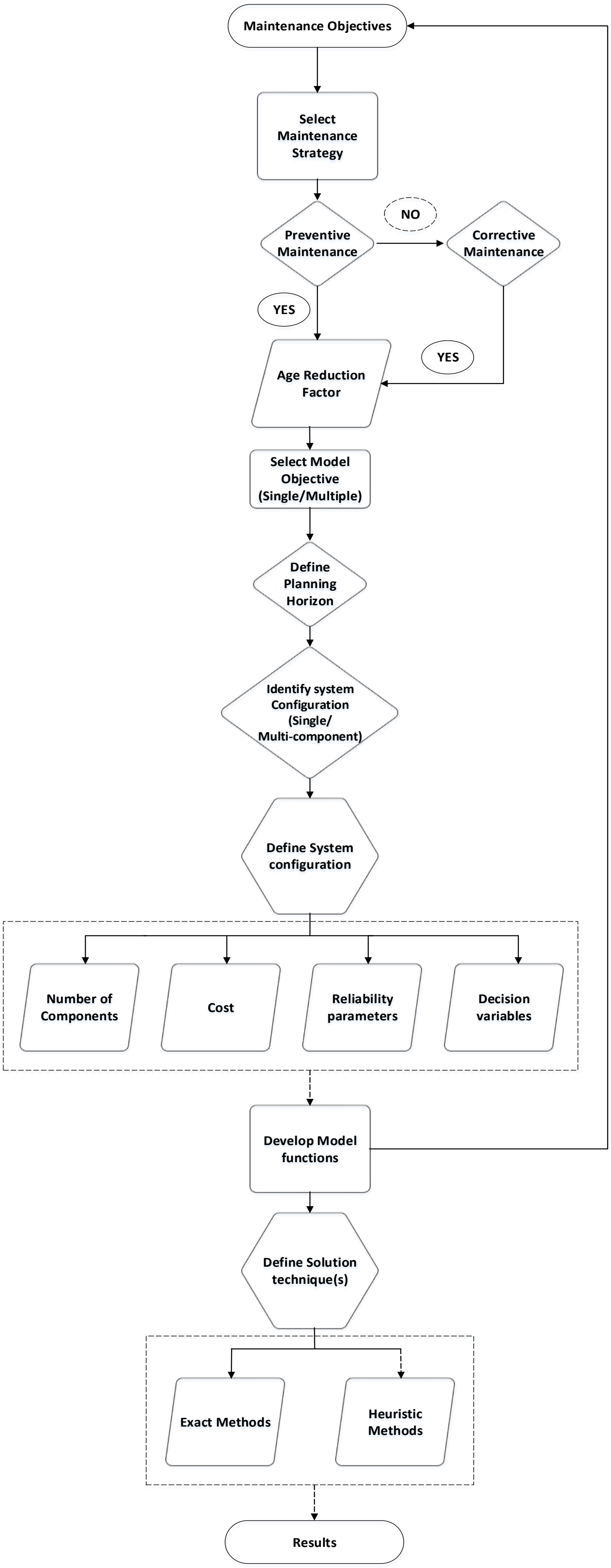


Figure 4.1: Flow chart for developing Decision model

To determine the optimal maintenance schedules for a rolling stock system, the approach proposed by Moghaddam and Usher (2011) is applied by modifying the model for rolling stock components. The cost of maintenance and the reliability of the system are used as the objective functions criteria to find an optimal solution that will minimize maintenance cost and maximize the reliability of the system. The parameters and decision variables are defined in the next section.

4.2.1 System Definitions

The parameters for the system are defined as follows:

N: Number of components

T: Length of planning horizon

J: Number of intervals

γ_i: Failure function parameter of component i

δ_i: Improvement/degradation parameter of component i

${\alpha^{pm}}_i$: Age reduction factor of preventive maintenance on component i

F_i: Failure cost of component i

M_i: Cost preventive maintenance for component i

R_i: Cost of replacement for component i

Z: Opportunity cost of downtime of the system

RR: Required reliability of the system of components

Decision variables

$X_{i,j}$: Effective age of component i at the start of period j

$X'_{i,j}$: Effective age of component i at the end of period j

$$m_{i,j} \quad = \begin{cases} 1 & \text{if component i at period j is maintained} \\ 0 & \text{otherwise} \end{cases}$$

$$r_{i,j} \quad = \begin{cases} 1 & \text{if component i at period j is maintained} \\ 0 & \text{otherwise} \end{cases}$$

If we consider a repairable rolling stock system consisting of N components and each component in the system is subject to failure, and the system deteriorates with an increasing rate of occurrence of failure of $u_i(t)$, where t represents actual time, ($t > 0$). Assuming the component failure corresponds to a power law non-homogeneous Poisson process (NHPP) which signifies that the failure rate is not a function of time. The power law failure intensity also known as the rate of occurrence of failure (ROCOF) is expressed as follows (Moghaddam & Usher 2011).

$$\boldsymbol{u_i(t)} = \gamma_i \delta_i t^{\delta_i - 1} \qquad \text{for } i = 1, \ldots, N \tag{4.1}$$

Where γ_i and δ_i are the parameters of component i and $\gamma_i > 0,\ \delta_i > 0$.

To determine a desirable schedule for future maintenance for each component over a defined planning period $(0, T)$, the planning period $(0, T)$ is divided into J separate intervals of length T/J. We define three possible actions that could have taken place at the end of period j. These actions are preventive maintenance (PM), component replacement and do nothing. The activity performed on the component in period j would have an effect on the “effective age” and “failure intensity” of the component and overall system. If we assume that the time required for this maintenance activities are negligible when compared to the size of the interval, we can assume that there is still a cost for performing an action either maintenance or replacement. Let the initial age for each component be equal to zero, let $X_{i,j}$ represent the effective age of component i at the start of period j and $X^!_{i,j}$ represent the effective age of component i at the end of period j, then:

$$\boldsymbol{X^!_{i,j} = X_{i,j} + \frac{T}{J}} \qquad \text{For } \boldsymbol{i = 1, \ldots, N; j = 1, \ldots, T} \tag{4.2}$$

If component i is maintained at the end of period j, the PM action effectively reduces the age of component i for the start of the next period by an age reduction factor $\alpha^{pm}{}_i$ of component i.

$$\boldsymbol{X_{i,j+1}} = \boldsymbol{\alpha^{pm}}_{\boldsymbol{i}} \times \boldsymbol{X^{!}_{i,j}} \quad \text{For } \boldsymbol{i} = \mathbf{1}, \dots, \boldsymbol{N}; \boldsymbol{j} = \mathbf{1}, \dots, \boldsymbol{T} \text{ and } (\mathbf{0} \leq \boldsymbol{\alpha^{pm}}_{\boldsymbol{i}} \leq \mathbf{1}) \tag{4.3}$$

The parameter $\alpha^{pm}{}_i$ represents the age reduction factor of component i. This factor shows the inconstant effect of PM on the effective age of the components of the ageing system. Furthermore, this means when $\alpha^{pm}{}_i = 0$, PM improves the system and returns it to a new state and when $\alpha^{pm}{}_i = 1$, PM has absolutely no effect on the component and the component remains in its bad state. Consequently at the end of period j, the rate of occurrence of failure for component i would be $u_i(X^{!}_{i,j})$ and drops to $u_i(X_{i,j+1})$ and the start of period $j+1$. This is as a result of the effect of the maintenance action performed on component i. Figure 4.2 shows the effect maintenance on the rate of occurrence of failure.

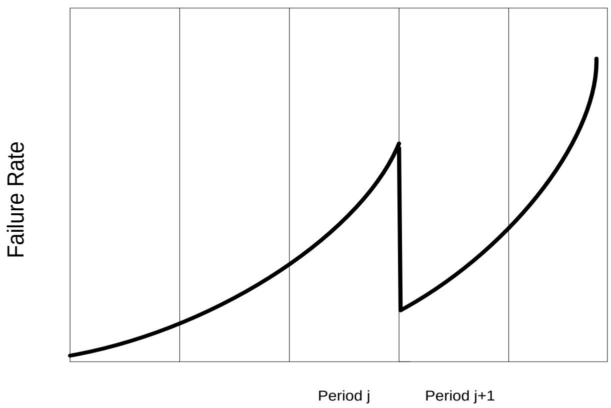


Figure 4.2: Effect of period j maintenance on rate of occurrence of failure on component (Moghaddam, Usher 2011)

The rate of occurrence of failure of the component would reset to $u_i(0)$ from $u_i(X^{!}_{i,j})$ when component i is replaced at the end of period j with a new component, see Figure 4.3. Therefore:

$$\boldsymbol{X_{i,j+1}} = \mathbf{0} = \quad \text{For } \boldsymbol{i} = \mathbf{1}, \dots, \boldsymbol{N}; \quad \boldsymbol{j} = \mathbf{1}, \dots, \boldsymbol{T} \tag{4.4}$$

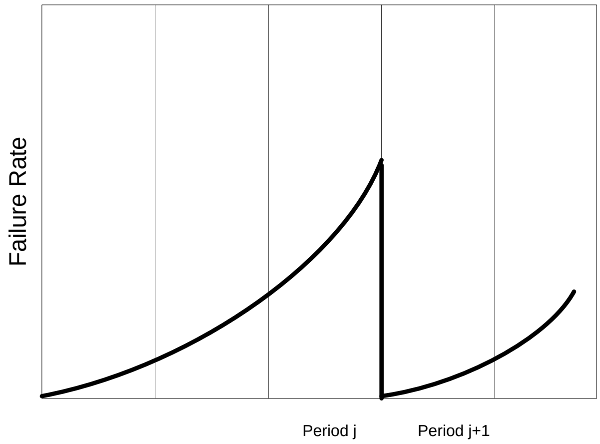


Figure 4.3: Effect of period j replacement on rate of occurrence of failure on component (Moghaddam, Usher 2011)

If no action is taken on component i in period j, then the rate of occurrence of failure of component i remains the same as that of the previous period

$$\boldsymbol{X^{!}_{i,j} = X_{i,j} + \frac{T}{J}} \qquad \text{for} \qquad \boldsymbol{i = 1, \ldots, N}; \quad \boldsymbol{j = 1, \ldots, T} \qquad 4.5$$

$$\boldsymbol{X_{i,j+1} = X^{!}_{i,j}} \qquad \text{for} \qquad \boldsymbol{i = 1, \ldots, N}; \quad \boldsymbol{j = 1, \ldots, T} \; 4.6$$

$$\boldsymbol{u_i(X_{i,j+1}) = u_i(X^{!}_{i,j})} \quad \text{for} \qquad \boldsymbol{i = 1, \ldots, N}; \quad \boldsymbol{j = 1, \ldots, T} \qquad 4.7$$

4.2.2 Cost of Maintenance

The maintenance cost refers to the total cost associated with all actions carried out on all the components of the system for every period. This cost is a function of each of either a PM or replacement action, therefore. It includes the sum of cost of failure, PM cost, replacement cost and opportunity cost.

Cost of failure

When equipment fails to perform its required function, a failure is said to have occurred. As a result of this, there is loss in production cost and service levels. To calculate this cost, we first need to calculate the expected number of failures for component i in period j and multiply by the failure cost of component i, the cost of failure of component i in period j is calculated as

$$\boldsymbol{F_{i,j} = F_i \times E[N_{i,j}]} \qquad \text{for} \qquad \boldsymbol{i = 1, \ldots, N}; \quad \boldsymbol{j = 1, \ldots, T} \qquad 4.8$$

Where F_i is the cost of failure of component i and $E[N_{i,j}]$ is the expected number of failures of component i in period j. Therefore, from equation 3.11,

$$\boldsymbol{E[N_{i,j}] = \int_{X_{i,j}}^{X^!_{i,j}} u_i(t)dt} \text{ for } \quad \boldsymbol{i = 1, \ldots, N}; \quad \boldsymbol{j = 1, \ldots, T} \qquad 4.9$$

This implies that

$$\boldsymbol{E[N_{i,j}] = \int_{X_{i,j}}^{X^!_{i,j}} \gamma_i \delta_i t^{\delta_i - 1} dt = \gamma_i \left[\left(X^!_{i,j}\right)^{\delta_i} - (X_{i,j})^{\delta_i} \right]} \qquad \text{for } \boldsymbol{i = 1, \ldots, N}; \quad \boldsymbol{j = 1, \ldots, T} \qquad 4.10$$

So $F_{i,j}$ becomes

$$\boldsymbol{F_{i,j} = F_i \times \gamma_i \left[\left(X^!_{i,j}\right)^{\delta_i} - (X_{i,j})^{\delta_i} \right]} \quad \text{for} \quad \boldsymbol{i = 1, \ldots, N}; \quad \boldsymbol{j = 1, \ldots, T} \qquad 4.11$$

Maintenance cost

The maintenance cost refers to the cost M_i incurred at the end of period when component i is maintained in period j. It takes into consideration the labour cost, material cost and administrative costs. The cost of maintenance performed on component i in period j is $M_{i,j}$ and is calculated as

$$\boldsymbol{M_{i,j} = M_i} \text{ for } \boldsymbol{i = 1, \ldots, N}; \quad \boldsymbol{j = 1, \ldots, T} \qquad 4.12$$

Replacement Cost

Sometimes, it could be economical to replace a component rather than maintaining it for the purpose of ensuring high reliability of the system. A cost of R_i is incurred at the end of a period if component i is replaced with a new component. Therefore, the cost of replacing the component i in period j is $R_{i,j}$ and is calculated as

$$\boldsymbol{R_{i,j} = R_i} \text{ for } \boldsymbol{i = 1, \ldots, N}; \quad \boldsymbol{j = 1, \ldots, T} \qquad 4.13$$

Opportunity Cost

In a realistic system, when a rolling stock system is scheduled for maintenance or component replacement, there is usually a loss associated with stopping the system. Thus, it is assumed that an opportunity cost of downtime Z is charged in period j if any component is maintained or replaced in that period. Then, the opportunity cost in each period can be calculated based on the revenue cost lost as a result of a cancellation or delay of a system being in service.

Total cost

The total cost is the total sum of all the cost defined for all component i in period j and is expressed as:

$$\textbf{\textit{Total Cost}} = \sum_{i=1}^{N}\sum_{j=1}^{T}\left\{F_i \times \gamma_i\left[\left(X_{i,j}^{!}\right)^{\delta_i} - \left(X_{i,j}\right)^{\delta_i}\right] + M_i.m_{i,j} + R_i.r_{i,j}\right\} + \sum_{j=1}^{T} Z \qquad 4.14$$

4.2.3 System reliability

In this model, it is assumed the components are arranged in series (see 5.3) and the reliability function for component i in the period j is defined as

$$R_{i,j} = e^{-E[N_{i,j}]dt} = e^{-\left[\int_{X_{i,j}}^{X_{i,j}^{!}} u_i(t)dt\right]} \qquad 4.15$$

$$R_{i,j} = e^{-\left[\gamma_i\left[\left(X_{i,j}^{!}\right)^{\delta_i} - \left(X_{i,j}\right)^{\delta_i}\right]\right]} \qquad 4.16$$

The System reliability at the end of period j is given as,

$$R_j = \prod_{i=1}^{N} e^{-\left[\gamma_i\left[\left(X_{i,j}^{!}\right)^{\delta_i} - \left(X_{i,j}\right)^{\delta_i}\right]\right]} \qquad 4.17$$

It is worth noting that the reliability function can be modified and adapted to any system with a different configuration such as parallel, series, k-out-of-n etc. as the case may be. Unlike the cost, the reliability of the system is measured at an instant. For example, the reliability of the system would be the reliability $\boldsymbol{R_j}$ at the end of every period. In order to maximize the reliability of every period, the product of the achieved reliability in each period for the planning horizon would be used as the objective function.

4.2.4 Decision model

The parameters, decision variables, cost functions and reliability equations have been defined, the decision model is presented as a multi-objective optimization problem to minimize cost and maximize reliability. The purpose of this model is to show the possible trade-offs between maintenance cost and achievable reliability and also to present the relative preventive maintenance schedule. The model was adapted from Moghaddam (2008) and is defined as:

Decision model

Min Total Cost

$$= \sum_{i=1}^{N}\sum_{j=1}^{T}\left\{F_i \times \gamma_i\left[\left(X_{i,j}^{!}\right)^{\delta_i} - \left(X_{i,j}\right)^{\delta_i}\right] + M_i.m_{i,j} + R_i.r_{i,j}\right\} + \sum_{j=1}^{T} \mathrm{Z}$$

Max Reliability

$$= \prod_{i=1}^{j} R_j$$

Subject to:

1	$X_{i,1} = 0$	$i = 1, \dots .. N$
2	$X_{i,j} = (1 - m_{i,j-1})(1 - r_{i,j-1})X_{i,j-1}^{!}$ $+ m_{i,j-1}\left(\alpha^{pm}{}_i \times X_{i,j-1}^{!}\right)$	$i = 1, ., N$ and $j = 2, \dots ., T$
3	$X_{i,j}^{!} = X_{i,j} + \frac{T}{J}$	$i = 1, \dots ., N$ and $j = 1, \dots ., T$
4	$m_{i,j} + r_{i,j} \leq 1$	$i = 1, \dots ., N$ and $j = 1, \dots ., T$
5	$m_{i,j}, r_{i,j} = 0$ or 1	$i = 1, \dots ., N$ and $j = 1, \dots ., T$
6	$X_{i,j}, X_{i,j}^{!} \geq 0$	$i = 1, \dots ., N$ and $j = 1, \dots ., T$

4.18

Constraints explained

1. The first constraint specifies that the initial age for each component is equal to zero
2. The second constraint specifies that if a component is replaced in the previous period then $r_{i,j-1} = 1$, $m_{i,j-1} = 0$, so the effective age $X_{i,j} = 0$. Similarly, if a component is maintained in the previous period then $r_{i,j-1} = 0$, $m_{i,j-1} = 1$, so the effective age $X_{i,j} = \alpha^{pm}{}_i \times X^!_{i,j-1}$. And if no action takes place in the previous period, $r_{i,j-1} = 0$, $m_{i,j-1} = 0$, so the effective age $X_{i,j} = X^!_{i,j-1}$
3. The remaining constraints relate to Section 4.2.1

The reliability maximisation function ensures that the reliability of every period is maximized.

4.3 Solution Methodology

The decision model presented in equation 4.18 is a mixed-integer nonlinear optimization problem. Three different methods of solution are proposed, namely Microsoft Excel® evolution algorithm solver, Genetic Algorithm and Simulated Annealing. These methods have been discussed in literature as good solution methods for complex optimization problems. Each of these methods is used to find an optimum solution to the problem using the case study as an application.

4.3.1 Excel Solver

Microsoft Excel® has the ability to solve optimization problems. This is achieved by making use of the excel solver tool which minimizes or maximizes a function using either the simplex linear programming, Generalized Reduced Gradient (GRG), nonlinear or the evolutionary algorithm methods (Microsoft 2009 & Oppenheimer 2009). The excel solver uses the local search technique which involves searching until a local optimum is identified. The excel solver has a limit of 200 decision variables for both nonlinear problems. It can also perform only single objective problems. For this reason, a much advanced solver capable of solving multi-objective problems is required.

LINGO is a powerful solver tool designed to solve linear, nonlinear, quadratic and integer optimization models using either the branch and bound algorithm or the GRG algorithm (LINDO systems 2014). Excel and LINGO is combined to solve a special case where the multi-objective optimization problem is turned into a single optimization problem. This is achieved by turning the maximisation function of the reliability into a constraint. An add-in is combined with excel to enable it solve multi-objective optimization problems. GANetXL is an optimization add-in for Microsoft Excel®. GANetXL uses genetic algorithms to solve complex optimization and search problems. Refer to Savić *et al.*, (2011) for more on the GANetXL add-in.

4.3.2 Genetic Algorithm

As mentioned in 3.1.8, GAs is efficient at solving wide range of analytical problems. Their ability to search from a very large population of potential solutions for a global optimum solution makes GA a suitable method of solution. The GA process can be summarized as shown in Figure 4.4. The generational genetic algorithm is used; the algorithm is presented in Appendix 2a.

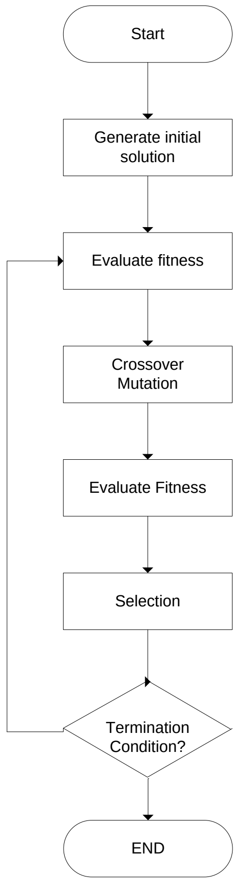


Figure 4.4: Genetic algorithm flow diagram (Yun, Han & Park 2012)

4.3.2.1 Solution representation

The initial step in applying genetic algorithm is to represent the solutions by encoding the solutions as strings. To represent the solution of the proposed problem, a matrix with length of $N \times T$ components for N components and T periods where each cell in that matrix contains 0, 1 or 2 corresponds to three different actions, namely do nothing, preventive maintenance and replacement actions as a chromosome used by genetic algorithms is defined.

4.3.2.2 Fitness functions

The objective of the fitness function is to enable evaluation of good solutions by ranking a solution over other solutions. The fitness function returns an integer value called the fitness value which shows the level of optimality of the solution. A good fitness function is associated with the objective function of the GA. Considering that model presented in equation (4.18) has two objectives, the following different fitness functions are used.

$$\textbf{Fitness}_{\mathbf{1}} = \boldsymbol{w_1}(\textbf{Total Cost/Cost}_{\mathbf{max}})+\boldsymbol{w_2}\ (\textbf{-Reliability}) \qquad 4.19$$

$$\textbf{Fitness}_{\mathbf{2}} = \textbf{Total Cost/Cost}_{\mathbf{max}}) + \left|\textbf{Reliability-Required Reliability}\right| \qquad 4.20$$

The first fitness function is based on the weighted summation method, which implies that the normalized total cost and reliability functions are summed with the condition $w_1 + w_2 = 1$. See Obayashi (2007) for more on weighted sum method. This fitness function compares different Pareto optimal fronts and gradually converts the multi-objective problem into a single-objective problem. For this to occur, the cost function needs be normalised. This is done by using a normalization coefficient which is defined by $1/Cost_{max}$ The coefficient is interpreted as the maximum possible cost incurred by the system which is achieved if all components are replaced over the planning horizon. The second fitness function minimizes the total cost and absolute values of subtraction of overall reliability and required reliability of the system. Cost normalization coefficient is also used to normalize total cost term in order to make the same magnitude for both parts.

4.3.2.3 Crossover procedures

The objective of the crossover procedure is to create new solutions called offspring from two parent solutions. These offspring inherit some beneficial properties of both parents it was created from in order to facilitate its spread all through the population. The crossover procedure used for the model suggested by Moghaddam (2008) is defined as follows:

a. Two-Point Inverse Crossover: In this type of crossover, two random numbers are first generated between 1 and $N \times T$. An offspring is made from selected parents by copying in reverse order all elements outside the position of the generated random numbers from the second parents. This type of crossover ensures a different offspring is made if the chosen parents are identical.
b. NT-Point Crossover: This type of crossover copies the even genes from the first parents and the odd genes from the second parent. Based on this , the genetic algorithm is designed in such a manner that the Two-point inverse crossover is used when the two solutions selected are equal and the NT-Point Crossover is used to produce new solutions if the initial selected solutions are not equal.

4.3.2.4 Mutation procedure

The mutation procedure is used to modify some string elements in the offspring solutions which increase the genetic diversity in the problem. A special type of mutation procedure was suggested by Moghaddam (2008) for the solution of the optimization problem. The procedure accounts for the opportunity cost of any action that takes place. A random number between 1 and $N \times T$ is generated. The corresponding gene to the offspring solution is changed to 0 if the string is equal to 1 or 2, or it is changed to 1 or 2 if it string is equal to 0 for each of the components. This mutation procedure produces schedules with the tendency of maintenance and replacement activities occurring at the same periods for all components.

4.3.3 Simulated Annealing

Simulated annealing is a popular tool for solving discrete and continuous optimization problems in many application areas. Its ability to employ a random search that accepts changes that can either decrease or increase the objective function of say a minimisation problem gives it an advantage. The SA process can be summarized as shown in Figure 4.5 and the algorithm is presented in Appendix 2b.

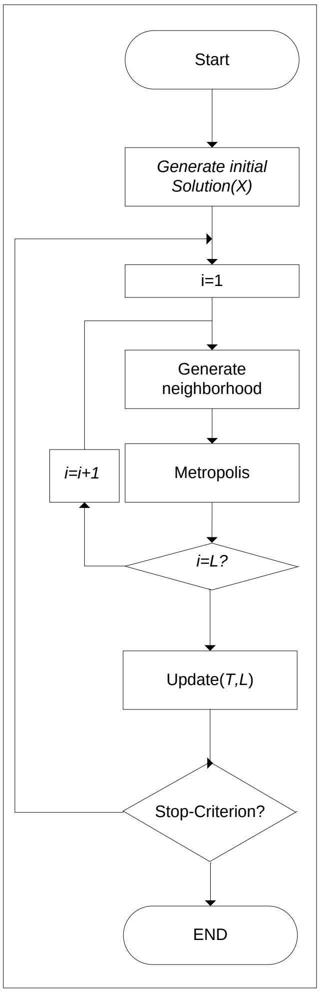


Figure 4.5: Simulated annealing flow diagram (Yun, Han & Park 2012)

4.4 Chapter Conclusion

The methodology for developing the decision support was defined and the decision support model for maintenance scheduling was developed as a multi-objective optimization problem which minimises the total cost over a certain defined period and simultaneously maximises the reliability over the same period. Excel, Genetic algorithm and simulated annealing were the different solution methods proposed.

CHAPTER 5: CASE STUDY

5.1 Introduction

For the purpose of testing the developed decision support model in chapter 4, a rolling stock maintenance case study was selected. The Salt River Rolling stock maintenance facility of Metrorail was selected for this purpose. This chapter gives an overview of the company Metrorail. It further describes the context of the maintenance process in Metrorail. The current maintenance scheduling process at the case study is discussed and the problems faced in maintenance planning and scheduling are highlighted. The parameter required for model application where estimated and the case study was applied to the developed model.

5.2 Metrorail

Metrorail is a division of the Passenger Rail Agency of South Africa (PRASA) rail operations which manages urban metro (PRASA 2009). Metrorail is South Africa's biggest provider of passenger and commuter rail services. Metrorail operates in four of South Africa's provinces, namely Kwa-zulu Natal, Cape Town, Gauteng and Eastern Cape. Each of these regions operates independently with each having its own maintenance depot where it takes responsibility for the maintenance of both infrastructure and rolling stock assets. Metrorail operates in 468 stations, 317 of these stations belong to them while the others belong to Transnet Freight Rail which is another rail company.

The rolling stock fleet of Metrorail consists of approximately 406 train sets. These train sets vary in size between 8 and 14 coaches per train set and have the capacity to carry about 100 people per trip and 2 million passengers daily collectively. This accounts for 15% of the people who use public transport daily in South Africa (Metrorail South Africa 2007). Most of the rolling stock of Metrorail are quite old, built between 1958 and 1985. This age is responsible for frequent failures recorded among the rolling stock fleet. Efforts have been made to upgrade the rolling stock through the accelerated rolling stock investment programme (PRASA 2010).

Metrorail started as a business unit of Transnet before the consolidation. Metrorail lost its independence in 2006 and was transferred into SARCC (South African Commuter Corporation), which then became PRASA (Passenger Rail Agency of South Africa)

(Metrorail South Africa 2007). During this transfer, majority of the large rail engineering services were separated from Metrorail and they remained within Transnet. These services include maintenance of wheel sets and overhaul of motor coaches and trailers (Rommelspacher 2012). Metrorail rolling stock maintenance operations include inspecting train sets, ordering defect parts and replacing them. Most of the parts are outsourced from external vendors, therefore making maintenance operation vulnerable to the delivery times of the vendors. The traction motor however is serviced and overhauled within Metrorail.

5.3 Case Study

As discussed in 5.2, each region operates independently from other regions. The Western Cape is divided into three regions, namely North, Central and South regions. These regions are serviced by two maintenance facilities and one over haul maintenance facility. For geographical proximity and frequent access to required data, the maintenance facility of Metrorail rolling stock at the Salt River depot which is located in the city centre of Cape Town was used as a case study for this research. Henceforth the name Metrorail depot refers to the Salt River Rolling Stock Depot. Figure 5.1 shows the organization structure at the Salt River rolling stock maintenance depot.

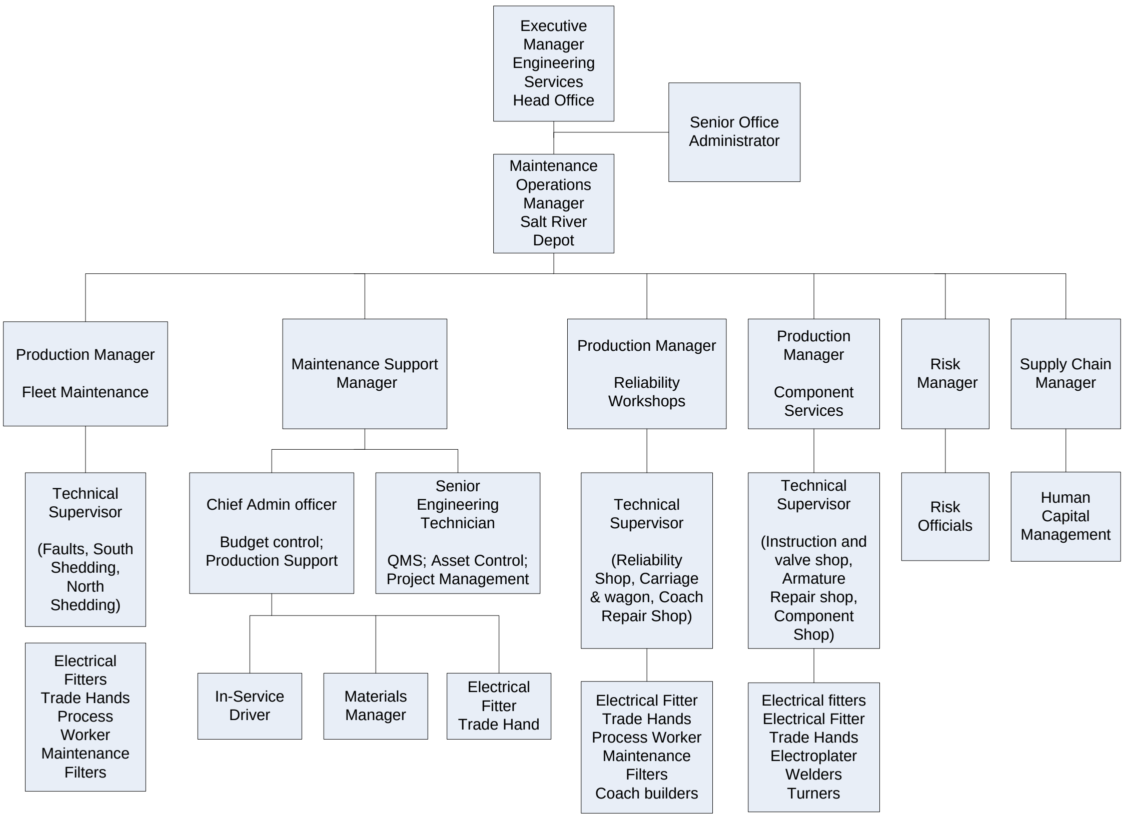


Figure 5.1: Metrorail Salt River Maintenance Operations

Metrorail depot is divided into two major divisions: Infrastructure and Rolling Stock. Infrastructure deals with maintenance procedures for signal, power supply and rail tracks while Rolling stock deals with maintenance of all rolling stock equipment. The rolling stock division has seven production function departments, namely shedding, Coach building, Carriage and wagon, repair shop, reliability shop, faults and availability/components store. Each of these departments has different responsibility and depend on each other as shown in Figure 5.2. The planning office and Engineering office is responsible for planning and scheduling activities in each of these departments. A brief description of the functions of these departments is given.

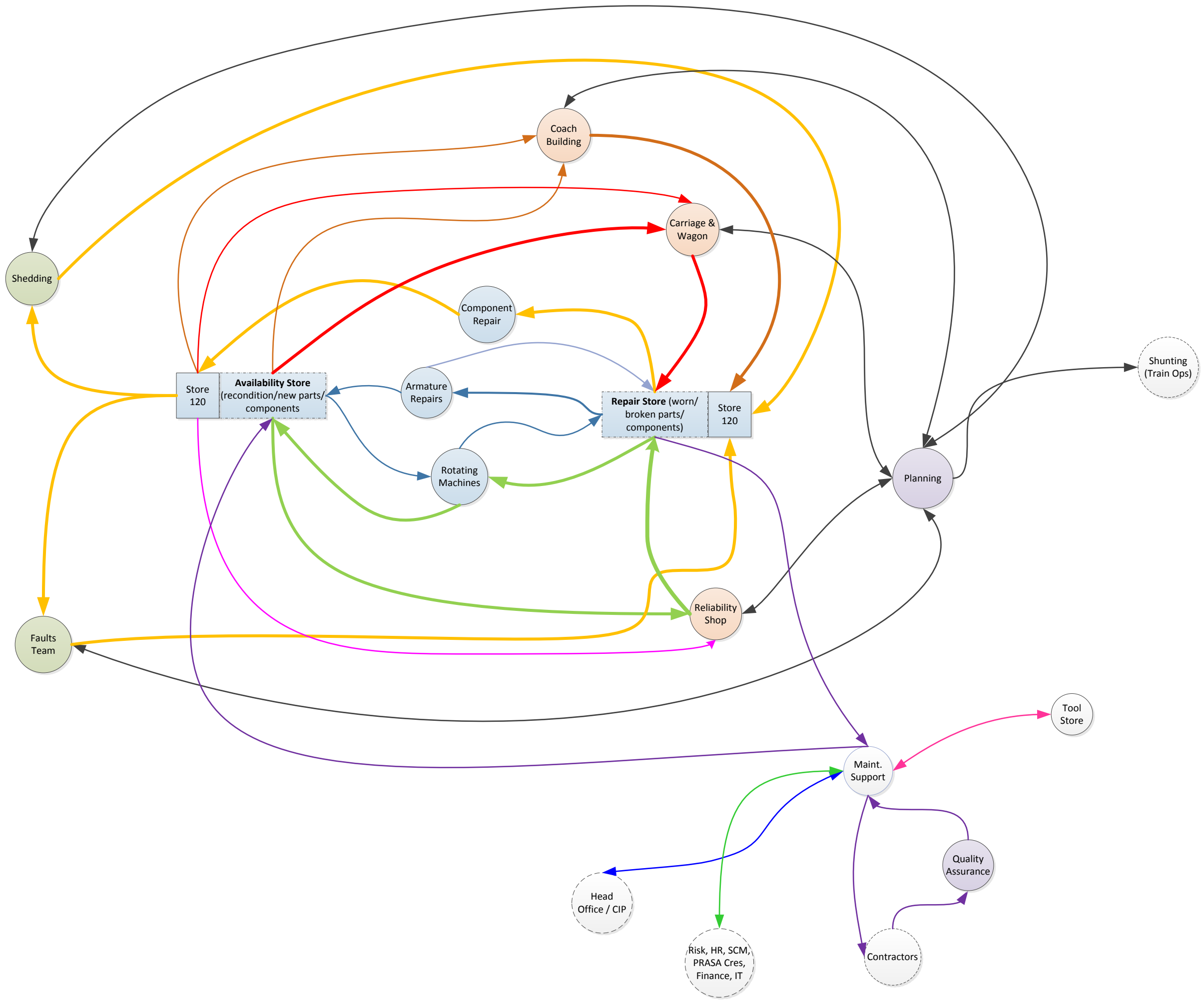


Figure 5.2: Inter-relations between departments (Rommelspacher 2012)

Shedding

This is where trains scheduled for maintenance are received. It could either be scheduled or unplanned. It consists of eight pits which are used according to the importance and urgency of maintenance requirements. In the event that a coach is assessed and needs major replacement of parts, the coach is stopped from service and sent to the repair shop for repairs. The availability store and repair shop provide support by supplying required materials for maintenance to shedding (Murray 2013).

Availability/components store

The availability store is where all raw materials and spares are stored. There are two types, namely material stores and store 120 or the repair store. The material store contains all the raw material needed for maintenance and rebuilding components while the repair store keeps all the inventory of the components that has been stripped, cleaned and repaired (Thembinkosi 2013).

Reliability shop

The reliability shop is responsible for replacing rotating equipment on a stopped motor coach. The coach is lifted and the failed component is removed and transferred to the repair shop. Once repair is complete, the parts are transferred back to the reliability shop to be coupled back to the coach (Venter 2013).

Repair shop

The repair shop performs maintenance activities on rotating components from the reliability shop. These components are stripped down and repaired then followed by a testing and it's sprayed and assembled back before a quality assessment is performed. The repaired components are then used as a spare for the motor coach (Resnthal 2013).

Coach building

A stopped coach is scheduled to the coach shop if it needs refurbishment of seats. It can be a motor coach or a plain trailer. If the coach consists of major damage, it is sent to be repaired at the repair shop. The coach shop relies on the availability components store for replacement components.

Carriage and wagon

This department performs maintenance work on plain trailers. Components that require heavy repair which cannot be rectified during shedding are sent to carriage and wagon. The repaired parts are tested by the overhaul unit before being sent to the repair stores. The material store provides support for required raw materials for the repairs (Boer 2013).

Faults Team

A stopped coach is scheduled to the fault department if there is specific electrical work to be done.

5.3.1 Coaches and trailers

Metrorail currently has 386 motor coaches. These are made up of different types of motor coach, namely 5M2A, 8M, 10M3 and 10M5. Table 5.5-1 presents the number of each coach available. These coaches differ in type of braking system, traction motor type, control systems, structural frame, speed and compressor type. 5M2A was selected for this research because it is consists about 60% of the entire motor coaches of the Salt River depot.

Table 5.5-1: Number of each type of motor coach available

Motor Coach Type	Amount
5M2A	228
8M	48
10M3	22
10M5	88

5.3.2 Maintenance Strategy for rolling stock

According to Rommelspacher (2012), time directed maintenance (TDM) and Run-To-Failure (RTF) are the maintenance strategies being applied at Metrorail. The TDM is established using the overall average number of kilometres travelled. This is converted to days by dividing the total kilometres travelled by the kilometres travelled per day. The TDM has been scheduled into three different intervals, namely Passenger Safety and Comfort (PS&C), Intermediate Shed and Full Shed. This occurs every 2 weeks, 4 weeks and 8 weeks respectively. This schedule was determined in 1998, based on the main agreement between the SARCC and Metrorail (Malinga 2013). It was calculated using the operating conditions, procedures as well as equipment conditions. This system is quite old and could be simplified to enable the system become more flexible.

Unplanned failure occurs within the system. However, it is somewhat difficult to differentiate the fraction of the unplanned failures in RTF relative to the failures that are allowed to take place. Equipment or components that deteriorated in an unpredictable manner were addressed using RTF. As mentioned earlier, some of the failures are unplanned and therefore lead to CM. It is important to mention that Metrorail Engineering department is looking into changing the maintenance strategy to Predictive Maintenance. At the time of this research, the Original Equipment Manufacturers (OEM) manual is used for maintenance procedures.

5.3.3 Maintenance Management System

Metrorail uses a combination of Fleet Maintenance Management System (FMMS), General Query Language (GQL) and SAP® enterprise software to manage its maintenance operations. FMMS is used to schedule maintenance while GQL gives an output of the data of maintenance outcomes. FMMS is used to generate work orders and completed jobs and pending jobs are captured into the system. FMMS is used to generate the list of all the coaches, history of faults (service and maintenance), resource used, materials used and cost. FMMS generates the yearly schedule which triggers every coach when it is due for any of the maintenance cycles. SAP® is used for costing purposes. It is used for procurement, spare parts inventory and every other cost associated with maintenance.

5.3.4 Failure data

The failure history and patterns of motor coaches can be populated from FMMS. This information can be used to determine components reliability and failure distribution. The system captures in service failures, amount of resources used and cost. The system is managed by the planning office. Failures are input into the system using fault codes established by the planning office. These faults code are not very descriptive due to the reason that they were developed using the 5M2A coaches. As explained in section 5.3.1, the configurations differ and using these codes for the 8Ms and 10Ms does not always match the exact fault. The actual fault is mostly discovered when the system is stripped down and this information is not always updated in the system (Southgate 2013).

5.3.5 Maintenance Cost

The total operating cost is calculated using the SAP system. The FMMS is also used to capture maintenance cost. However currently the costing on the system is not properly done and is only used as a benchmark for ascertaining the cost of maintenance of components.

5.3.6 Maintenance Planning and scheduling

The planning office is responsible for planning and scheduling maintenance. As mentioned in 5.3.2, the maintenance is scheduled into three different intervals. The maintenance cycle begins with a full shed, followed by a Passenger Safety and Comfort (PS&C) maintenance, intermediate maintenance, Passenger Safety and Comfort (PS&C) then a full shed again. This can be seen in Figure 5.3: Metrorail maintenance interval. Each train set has been configured on the FMMS system to trigger once it is due for any of the maintenance cycles. The details of this maintenance process are presented in Appendix 3 (Southgate 2013).

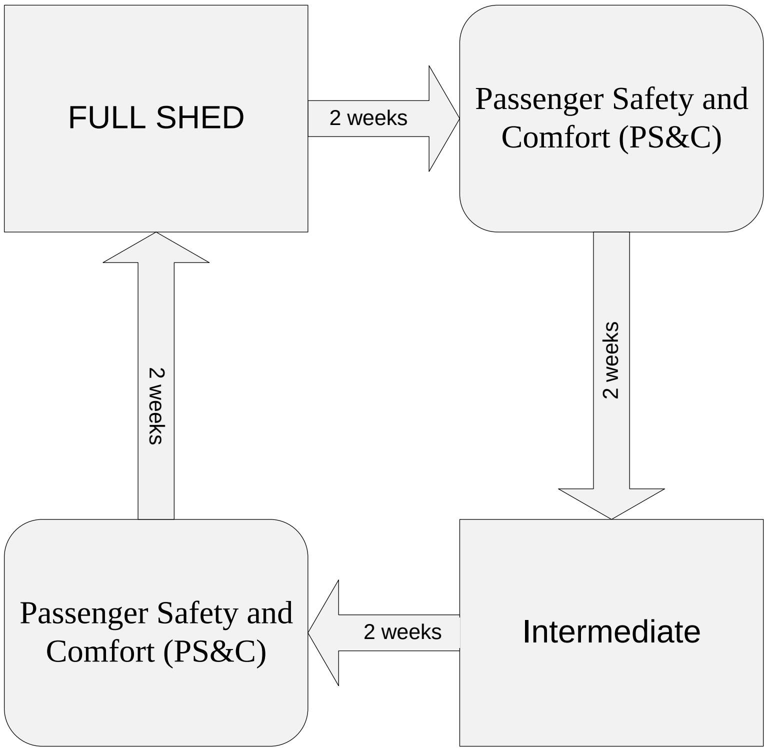


Figure 5.3: Metrorail maintenance interval

5.3.7 Problems faced in maintenance planning and scheduling

The current coaches are at least 25 years old. The method of maintenance is therefore obsolete and it is assumed that improvement can be made to the process. There has been an increase in the demand for rail travel which increases the required availability. This has an impact on maintenance scheduling as trains need to be maintained as quickly and efficiently as possible to have them available to run their schedules. If a coach is stopped due to a failure, it affects its availability and there is a need to assign other train sets to its route which increases the rate of wear and tear and failure therefore affecting the reliability. Some coaches go through an unbalanced maintenance cycle when they are swopped around because they now absorb the maintenance cycle of the motor coach they are attached to.

Another problem faced is the issue of spare parts availability of components. The unavailability of spare parts components when required increases maintenance time to repair which can eventually affects availability of rolling stock. Most importantly, it is assumed that unnecessary maintenance activities are being carried out in the current maintenance shedding cycle discussed in 5.3.6. These 2 weeks interval maintenance instances result in high maintenance cost. This is the problem this research is proposing to solve by developing a maintenance schedule that will reduce maintenance cost and maintain a high reliability.

5.4 Case study Application

A decision model for rolling stock has been defined in 4.3. To apply this model to the case study, the components are selected and the reliability parameters are estimated. Other required data for the case study application are also defined.

5.4.1 Components Selection

A train consists of several components with different reliability characteristics. As discussed in paragraph 5.3.1, the 5M2A was selected for the purpose of this research. Ideally, each component should be considered for application to the model but getting the failure and cost parameter for each component became unrealistic given the time frame of the research. It became necessary to select critical components and use their data to model the system. In order to be able to select the components to determine the input data for the model, a 5M2A motor coach was grouped into different sub-systems. The full list of components groupings was populated from FMMS and grouped into different sub-system shown in Figure 5.4.

As discussed in section 5.3.1, a 5M2A train set has three motor coaches and 8 trailers on average. The motor coaches are positioned at the beginning, middle and end of the train set. In-service failure history was gathered from the FMMS for the last 10 years, where 30 motor coaches were selected at random and these failures were grouped into the different sub system categories. The data was analysed to determine the most frequent failure patterns. From the analysis, the auxiliary machines components and the traction motor showed the most occurrence of failure and were selected for application to the model. It is assumed that using the reliability and cost parameters of these components for the model would produce a result that can be used for maintenance planning and scheduling of other components in other subsystems. The result of the analysis can be viewed in Appendix 4.

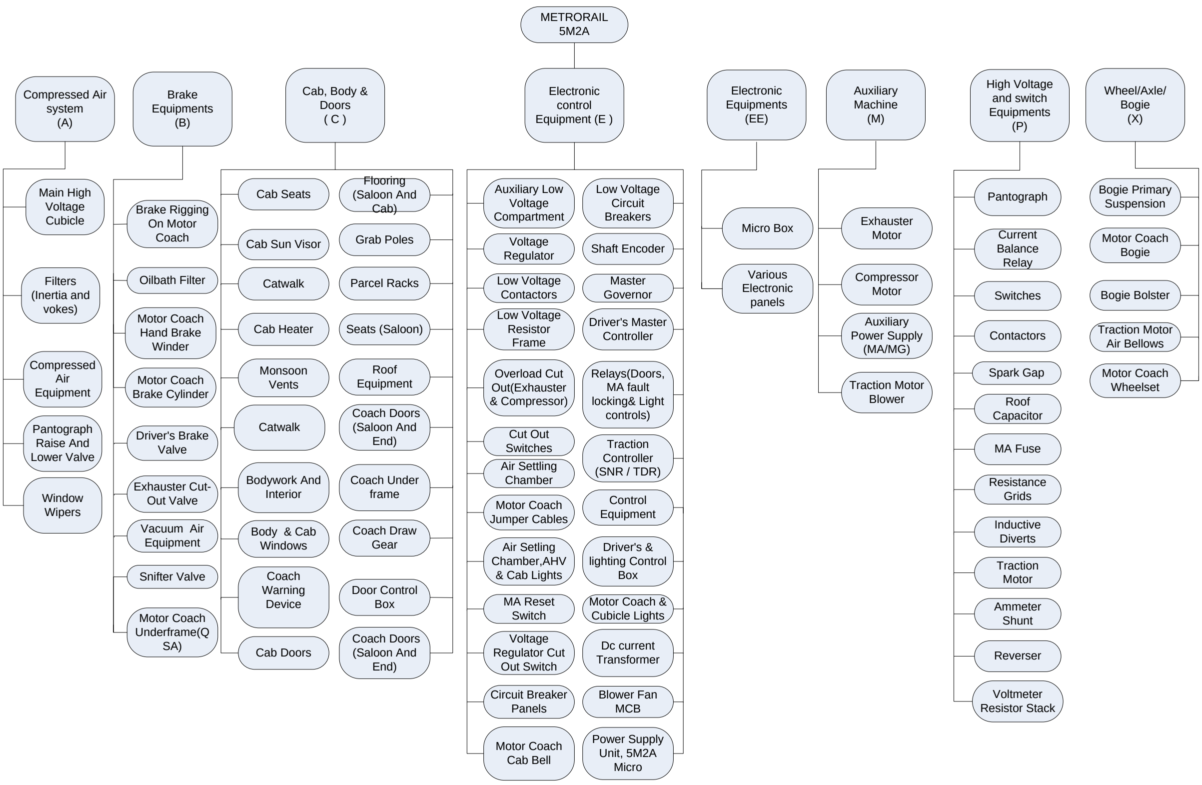


Figure 5.4: Metrorail 5M2A Motor Coach subsystems

5.4.2 Reliability of components

Reliability is defined as the probability of a component performing a required operational function successfully under given condition for a defined time interval. The probability is a function of the failure characteristics of the system. The components in auxiliary machines are connected in series and parallel, see Figure 5.5 for reliability block diagram of the Mixed-Parallel form.

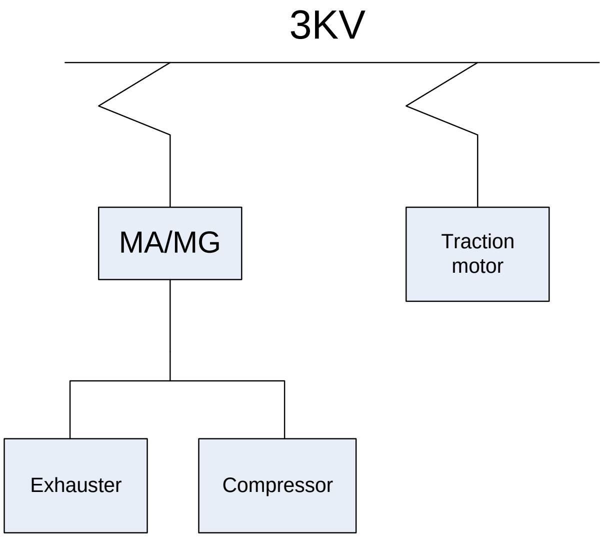


Figure 5.5: Reliability diagram of components

For the purpose of reliability analyses, these components are assumed to be connected in series given the effect they have on each other. This means the failure of any of these components during operation would cause the rolling stock to stop during operation and it can be said that the overall reliability and availability are affected. Hence to achieve high system reliability, the reliability of each of these components must be relatively high.

The auxiliary components upon failure can be repaired and returned to an operational state. As a result of this, the system can be called a repairable system and can be modelled using either the HPP or NHPP models depending on the failure characteristics (Ionescu & Limnios 1999; Carlos *et al.*, 2013 & Vlok 2013). The failure times for the components were gathered and statistical analysis was carried out. Figure 5.6 shows a summary of the analysis carried out on the data.

Figure 5.6: Data analysis process

The selected components are Exhauster, Compressor, MA/MG and traction motor, the global time of the failure trend for the components is expressed in graphical form and presented in Figure 5.7.

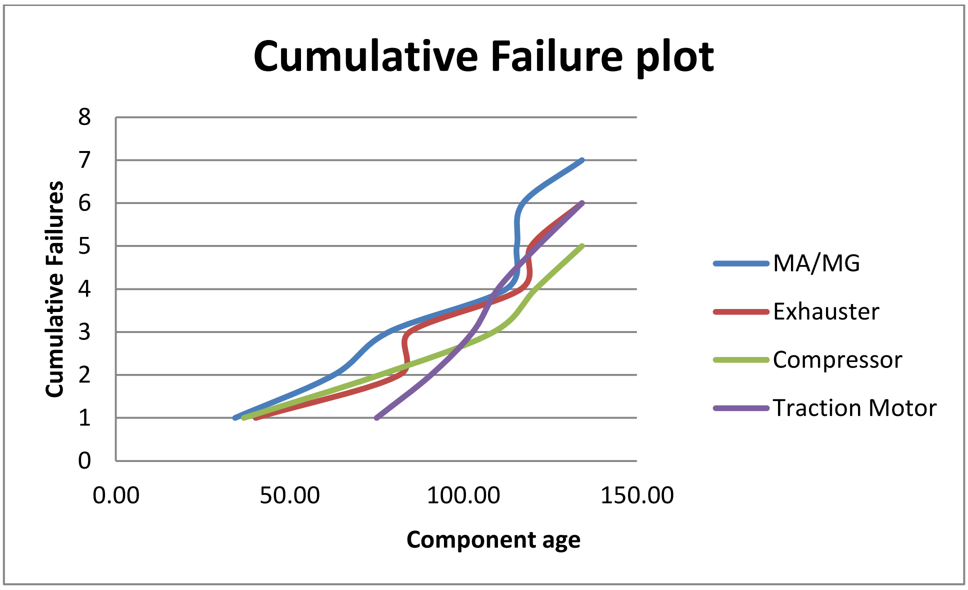


Figure 5.7: Cumulative time Failure plot

Taking a look at the plot in Figure 5.7, it is difficult to conclude which components are degrading or improving. A trend test is therefore needed to ascertain the extent to which the data tends to. Hence, Laplace and Lewis Robinson trend test is carried out on the data set to determine its reliability trend. From the Laplace test, it was inconclusive what the trend of the data was. Hence, a Lewis –Robinson test was performed to confirm if the data follows a HPP process or not. It was observed that the failure data showed degrading reliability trend and can be modelled as a NHPP model. Applying the Log-Linear NHPP and Power Law NHPP processes is often used to model repairable systems' reliability. The method of least squares for parameter estimation is used to estimate the parameters for a log linear and power law failure intensity function. The results for the Laplace, Lewis-Robinson and parameter estimations are presented in Table 5.1.

Table 5-2: Result of Laplace and Least Square test

MA/MG				
Laplace Statistic		1.8066		
Lewis-Robinson		2.5510		
		Power Law		Log Lin
	γ	0.002376738	α_0	-4.400985779
	δ	1.620982079	α_1	0.017130117
EXHAUSTER				
Laplace Statistic		1.8364		
Lewis-Robinson		2.3057		
		Power Law		Log Lin
	γ	0.000119814	α_0	-4.092286102
	δ	2.212852684	α_1	0.012729043
COMPRESSOR				
Laplace Statistic		1.6284		
Lewis-Robinson		3.3404		
		Power Law		Log Lin
	γ	0.002626395	α_0	-4.122128589
	δ	1.529811075	α_1	0.010686844
TRACTION MOTOR				
Laplace Statistic		2.4408		
Lewis-Robinson				
		Power Law		Log Lin
	γ	2.2679E-05	α_0	-4.872727374
	δ	2.551833431	α_1	0.021986366

5.4.3 Parameters for case study

As discussed earlier, the model and solution is applied to the case study. The parameters estimated in Table 5.1 are used. Due to the time limitations of performing an experiment on the case study to estimate the age reduction factor for each component, a fixed factor of 0.7 was assumed as the age reduction factor for all the components. This means, if preventive maintenance is performed on any component, the effective age of the component is reduced by 30%. The opportunity cost of the system was calculated as R500, 000 (Conradie &

Treurnicht 2012). A total planning horizon of 36 months was considered. The parameters are presented in table 5.2. Given the complexity of the model, MATLAB R2012b programming environment was used to program the genetic algorithm, simulated annealing and the proposed fitness functions. Different combination of values between 0 and 1 were used for fitness function 1. The various required reliability value are applied to the second fitness function to give non-dominated (i.e. different Pareto optimal front) as solutions to the multi-objective optimization problem.

The problem is then solved using GA and the extreme points of the objective functions are obtained in the case of fitness function 1 and 2. The process is repeated using simulated annealing. The parameters for the GA and SA are shown in table 5.3.

Table 5-3: Parameters for Case study

	T	36 months					
	$\boldsymbol{Z_j}$ (Rands)	500, 000					
N	Component	γ_i	δ_i	${\alpha^{pm}}_i$	F_i Rands	M_i Rands	R_i Rands
1	Auxiliary Power Supply (MA/MG)	0.00238	1.6210	0.7	400720	20,000	320,000
2	Exhauster Motor	0.00012	2.2129	0.7	210720	65,000	85,000
3	Compressor Motor	0.00263	1.5298	0.7	222720	40,000	120,000
4	Traction Motor	0.00002	2.5518	0.7	340720	70,000	210,000

Table 5-4: Genetic Algorithm and Simulated Annealing Parameters

<table>
<tr><th colspan="2">Genetic Algorithm</th><th colspan="2">Simulated Annealing</th></tr>
<tr><td>Number of generations</td><td>500</td><td>Initial Temperature</td><td>100000</td></tr>
<tr><td>Population Size</td><td>2000</td><td>Final Temperature</td><td>0.01</td></tr>
<tr><td>Probability of selection</td><td>0.2</td><td rowspan="2">Decreasing rate</td><td rowspan="2">0.99</td></tr>
<tr><td>Probability of crossover</td><td>0.4</td></tr>
<tr><td>Probability of mutation</td><td>0.4</td><td></td><td></td></tr>
</table>

5.5 Chapter Conclusion

The Salt River Rolling stock maintenance facility of Metrorail was identified as suitable case study to apply the decision model for improving rolling stock maintenance schedule. The case study operates four different types of motor coaches out of which the 5M2A were chosen because they make up a larger part of the fleet. TDM and RTF are the maintenance strategies currently being applied at Metrorail based on an agreement the company made in 1998. There are on-going plans to move to a different type of maintenance strategy. The failure history of components are captured by the companies FMMS while cost are captured by SAP. These two systems are the source of the data collected for the decision support model. Maintenance is scheduled into three different intervals, namely PS&C, intermediate maintenance, and full shed. Given the increasing demand for rail travel and the age of the trains, these intervals are no longer efficient to achieve availability and cost requirements. The critical components selected from the case study for application are the MA/MG, compressor, exhauster and traction motor. The parameters for these components were estimated and applied to the model to calculate the possible optimal maintenance schedules for the optimal reliability and cost.

CHAPTER 6: RESULTS, INTERPRETATION OF RESULTS AND DISCUSSION

6.1 Introduction

In the previous chapter, the optimization problem was formulated, parameters estimated and three proposed method of solution presented. In this chapter, the case study strategy is represented as a solution, the results from the application of the proposed model to the case study data are presented. The result from different solution methods are presented and compared. The results are also interpreted and discussed.

6.2 Case Study maintenance Strategy

As discussed in chapter 5, the case study currently applies full preventive maintenance every eight weeks. Table 6.1 shows the maintenance schedule. By applying this maintenance schedule to the model, the results of the application is summarised as follows: The product of system reliability is 5.91% with an average reliability of 92.5% and the total cost for this schedule is R13 380 864.7. System reliability is shown in Figure 6.1.

Table 6-1: Preventive maintenance schedule for case study

Month/ Comp	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
MA/MG	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M
EXH	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M
COM	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M
TM	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M	-	M

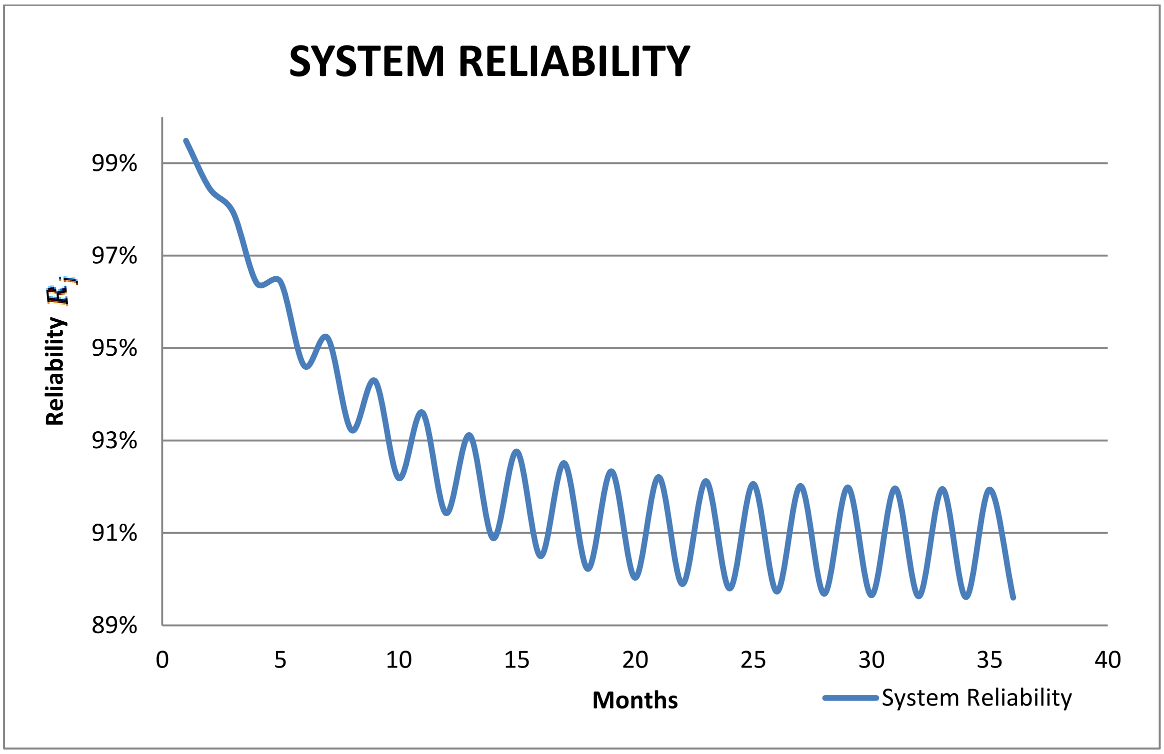


Figure 6.1: System reliability for maintenance strategy of case study.

6.3 Three possible scenario outcomes

During the model formulation in 4.2, it was discussed that the model is based on three possible actions, namely preventive maintenance, component replacement and do nothing. Here, the results of these three actions are presented with their relative cost and system reliability over the planned period of 36 months.

6.3.1 No maintenance

If no maintenance is performed over the planning period of 36 months, the reliability of the system depreciates with time, eventually, the system breaks down and the cost of failure begins to increase exponentially. In figure 6.2, the system reliability and the cost is presented. In this case, the product of the system reliability for each period is 2.44601E-12 with an average system reliability of 55.69% for the 36 months planning period and the total cost for doing nothing is R8 181 959.93. The cost is as a result of the cost of failure incurred as the system begins to deteriorate.

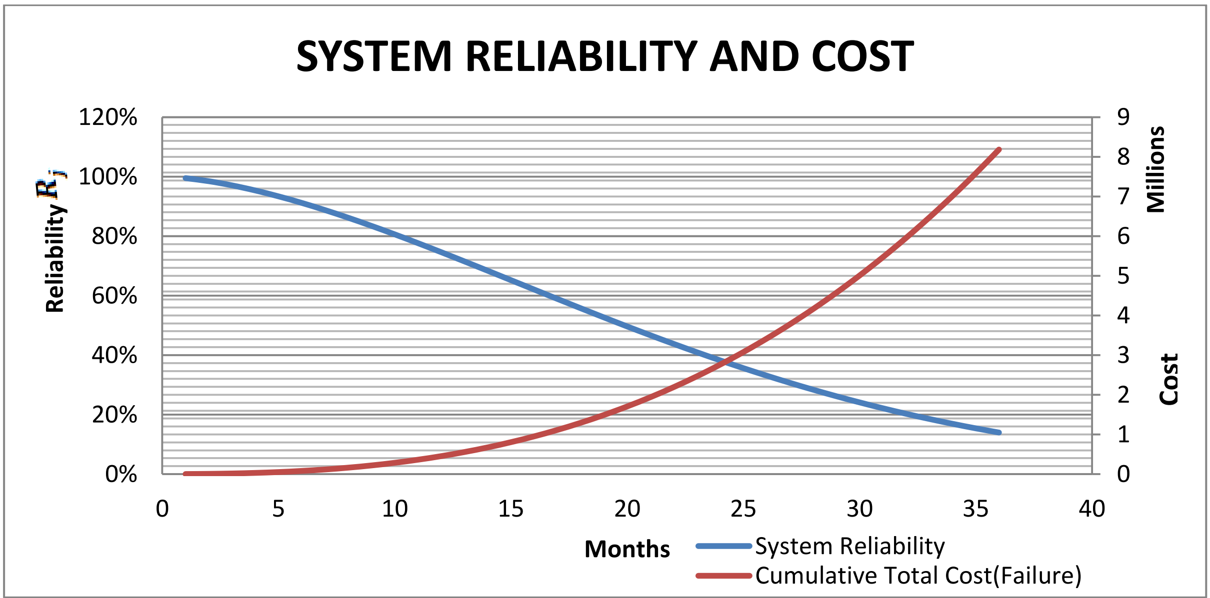


Figure 6.2: System reliability and cost for each period without maintenance or replacement

6.3.2 Maintenance

In a scenario where maintenance is carried out in every period over the planning period, the reliability of the system depreciates with time and eventually gets to a breaking point in which maintenance effect on reliability becomes insignificant. This is shown in figure 6.3. In this case the product of the system reliability over the planned period of 36 months is 31.25% with an average reliability of 96.82% and the total cost for performing this maintenance action every period is R25 377 743.73.

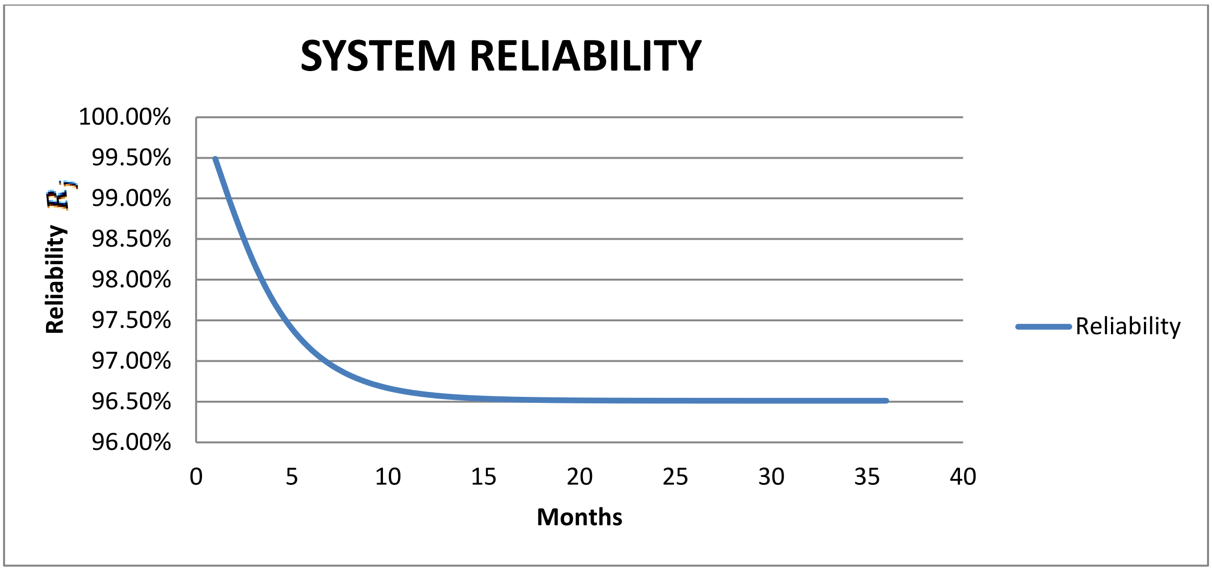


Figure 6.3: System reliability for maintenance action over planning period

6.3.3 Replacement

In this scenario where each component is replaced at the end of every period, the reliability of the system remains constant as a result of the system being returned to a new state at the end of every period. Thus, the reliability of the system stays constant over every period. In this case the product of the system reliability over the planned period of 36 months is 83.09% with an average reliability of 99.5% and the total cost for performing this replacement action every period is R44 516 531.94.

The function of the decision support model is to find the optimal combination of these activities that meets the objectives of the decision maker. These can either be to maximize reliability or minimize cost. The following section presents examples using the case study as an application to the decision support model for rolling stock.

6.4 Results using Excel

6.4.1 EXCEL/LINGO solutions

LINGO is combined with excel to solve the optimization problem. The multi-objective problem was converted to a single objective problem by making the reliability objective function a constraint. It took approximately 19 minutes to solve the optimization problem for each scenario with 568 variables and 426 constraints. Several required reliability (RR) were considered as constraints. The reliability is a function of the product of the system reliability for each period of the planning horizon. The result is shown in Table 6.2 and the Pareto optimal front is presented in Figure 6.4.

Table 6-2: EXCEL/LINGO Pareto optimal solutions

RR (%)	Reliability (%)	Cost (Rands)
1	1.08	4 785 914.07
5	5.22	5 498 620.11
10	10.24	6 127 046.92
20	20.01	7 739 697.62
30	30.25	8 556 277.43
40	40.11	10 386 215.52
50	50.00	13 202 504.88
60	60.22	17 464 308.74
70	70.00	23 682 618.46
80	80.02	35 033 902.66

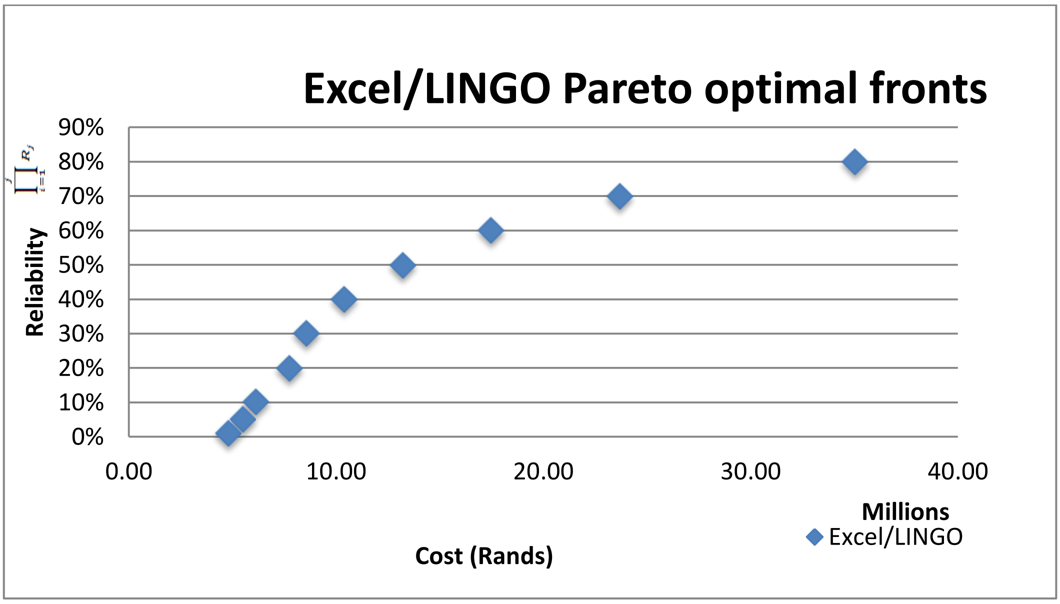


Figure 6.4: Excel/LINGO Pareto optimal fronts

Each of the solutions produced a corresponding maintenance and replacement schedule. The expected system reliability was also calculated for each solution. The solution for a RR of 50% was selected as an example to show the maintenance and replacement schedule as well as the system reliability. The optimal solution for the RR of 50% was a reliability of 50% at a cost of R13 202 504.88. The maintenance and replacement schedules are shown in Table 6.3.

Table 6-3: Pareto optimal preventive maintenance and replacement schedule for EXCEL/LINGO (R = 50%, C = R13 202 504.88)

Month/ Comp	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
MA/MG	-	-	R	-	-	-	R	-	M	-	R	-	-	R	-	-	M	-	R	M	-	-	R	-	-	R	-	R	-	-	R	-	-	R	-	-
EXH	-	-	R	-	-	-	R	-	-	-	R	-	-	R	-	-	R	-	-	R	-	-	R	-	-	-	-	R	-	-	R	-	-	-	-	-
COM	-	-	R	-	-	-	R	-	R	-	R	-	-	R	-	-	R	-	M	R	-	-	R	-	-	R	-	R	-	-	R	-	-	R	-	-
TM	-	-	-	-	-	-	-	-	R	-	-	-	-	M	-	-	-	-	-	R	-	-	-	-	-	R	-	-	-	-	R	-	-	M	-	-

The achieved reliability of 50% is a product of the reliability of the system at the end of each period, as discussed in Section 5.4.3. The system reliability for each period for the RR of 50% is shown in Figure 6.5.

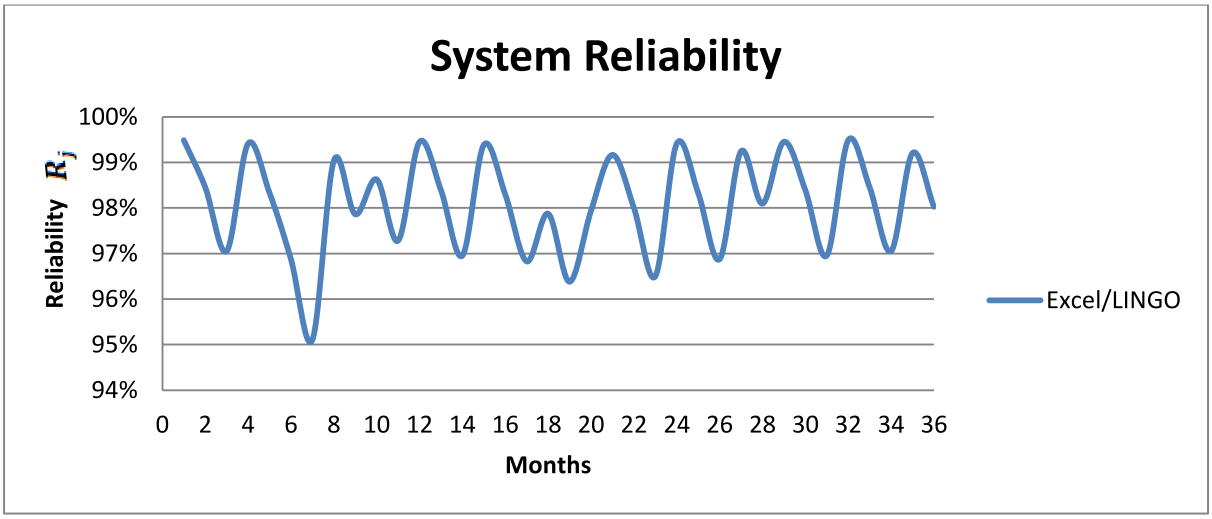


Figure 6.5: System reliability using EXCEL/LINGO (R = 50%, C = R13 202 504.88)

The system reliability shows that the reliability of the system lies between 95.1% and 99.5% over the defined planning period of 36 months. The average reliability over the planning period is 98.1%. The significant drop in reliability in period 7 is as a result of no maintenance/replacement actions for 3 consecutive periods.

6.4.2 EXCEL/GANetXL Solutions

The GANetXL Excel add-in was applied to solve the multi-objective problem. The solution time for each run was approximately 27 minutes. A multi-objective optimization problem does not give one optimal solution. Rather, it produces several optimal points called the Pareto optimal points which could contain weak and strong solutions. The two extremes of the average reliability solution for the model are 55.96% at a cost of R 8 181 959.93 where no action takes place throughout out the planning period and 99.5% at the cost of R 44 516 531.94 if each component is replaced every period as seen in Section 6.3.1 and 6.3.3. A few of the Pareto optimal solutions are shown in Table 6.4. The first four solutions indicate that performing no maintenance, i.e. RTF, may not necessarily be the best strategy when cost is considered.

Table 6-4: EXCEL/GANetXL Pareto Optimal solutions

Reliability (%)	Cost (Rands)
1.07%	3 867 368
5.43%	4 956 713
10.04%	5 653 488
20.13%	6 687 479
30.28%	8 592 190
40.39%	10 173 263
50.00%	12 550 430
60.05%	15 995 631
70.04%	22 138 803
80.02%	34 663 846

The Pareto front for the GANetXL solution is shown in Figure 6.6. Screen shots of the GANetXL Excel add-in application can be viewed in Appendix 5.

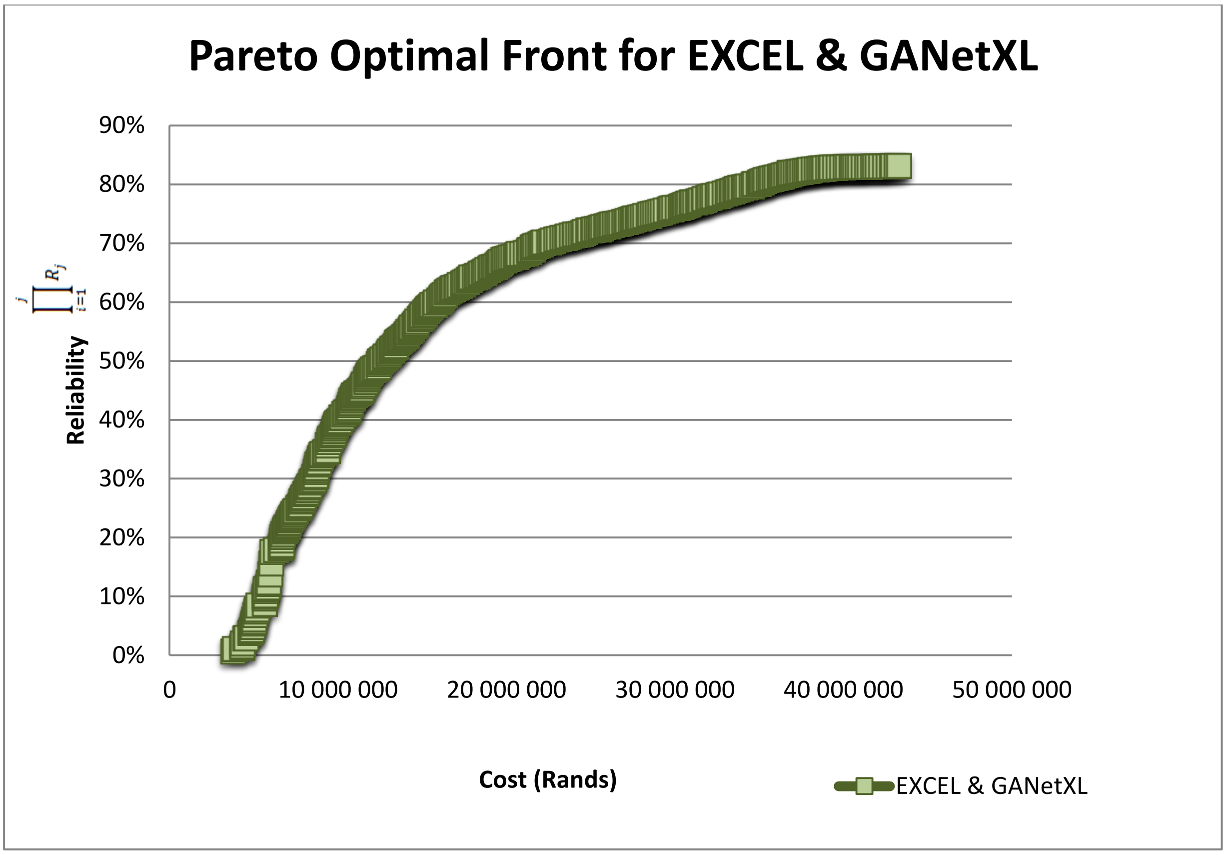


Figure 6.6: Pareto optimal front from EXCEL and GANetXL

Similarly, a point was selected from the Pareto front as an example. An optimal solution of 50% reliability gave an optimal cost of R12 550 430. The maintenance and replacement schedules are shown in Table 6.5 while the system reliability for each period is shown in Figure 6.7.

Table 6-5: Pareto optimal preventive maintenance and replacement schedule for EXCEL/GANetXL (R=50%, C= R12 550 430)

Month/ Comp	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
MA/MG	-	-	R	-	-	R	-	-	R	-	-	-	R	-	-	R	-	R	-	M	-	R	-	-	-	R	-	-	R	-	M	-	R	-	-	-
EXH	-	-	R	-	-	R	-	-	R	-	-	-	R	-	-	-	-	R	-	-	-	R	-	-	-	R	-	-	M	-	R	-	-	-	-	-
COM	-	-	R	-	-	R	-	-	R	-	-	-	R	-	-	R	-	R	-	R	-	R	-	-	-	R	-	-	R	-	R	-	R	-	-	-
TM	-	-	-	-	-	R	-	-	-	-	-	-	R	-	-	-	-	M	-	-	-	R	-	-	-	-	-	-	R	-	-	-	-	-	-	-

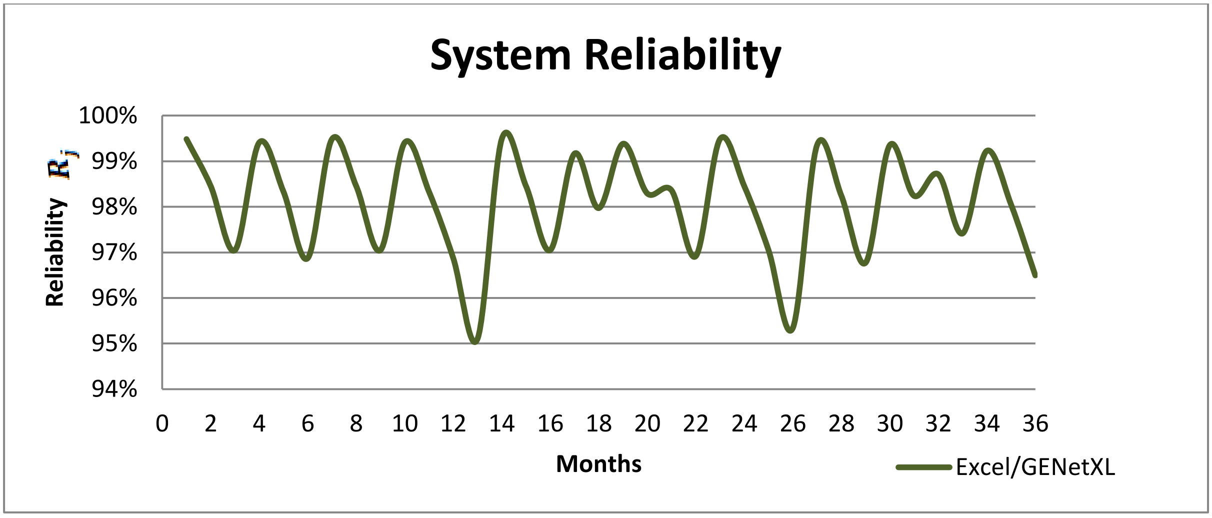


Figure 6.7: System reliability using EXCEL/GANetXL (R=50%, C= R12 550 430)

The system reliability for each period shows that the reliability of the system lies between 95.1% and 99.5%. The average reliability over the planning period is 98.1%. The significant drop in reliability in period 13 and 26 is as a result of no maintenance/replacement actions for 3 consecutive periods respectively.

6.4.3 Comparison of Both Solutions

Both the LINGO and GANetXL when combined with Excel gave similar results when applied to the multi-objective model. Figure 6.8 shows a comparison between the two Pareto optimal fronts using the two methods. It can be seen that GANetXL solutions produces better quality cost solutions in most scenarios. It is also important to compare the system reliability for these two solutions. This is presented in Figure 6.9; the two solutions have an average system reliability of 98.1%. The GANetXL solution had a drop in reliability during period 13 and 26 while the LINGO solution only dropped at period 7. The cost savings in the GANetXL solution can be seen as components are allowed to spend longer times in service before being maintained or replaced.

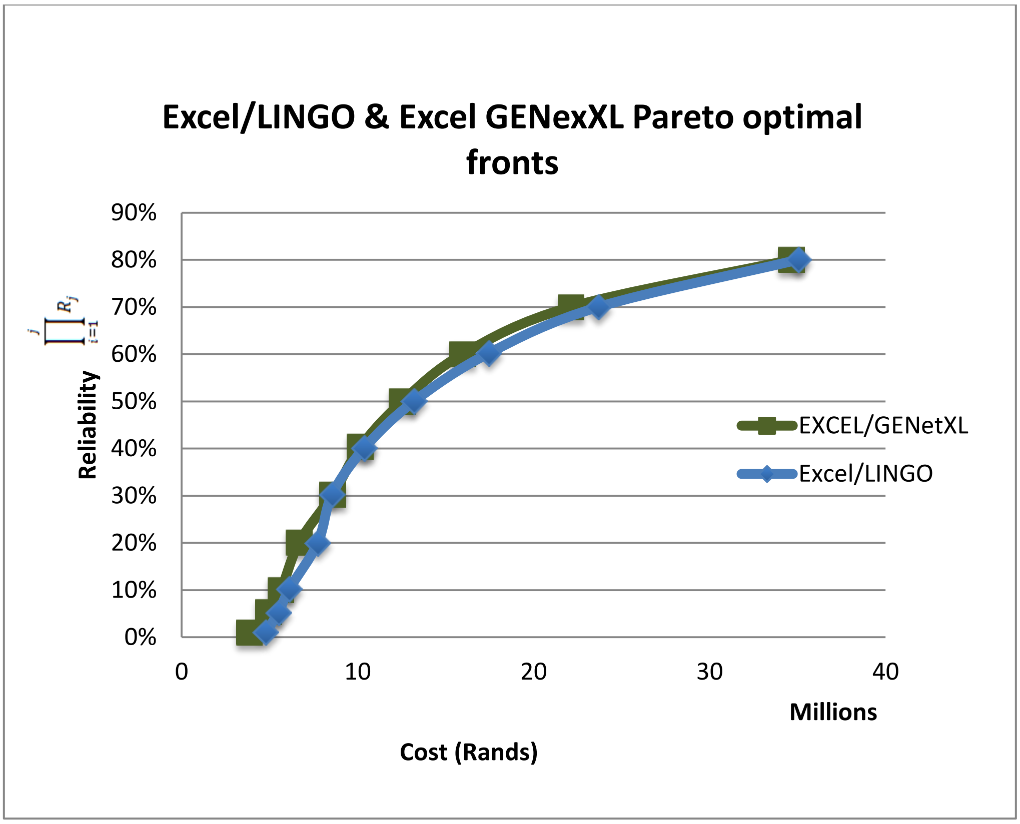


Figure 6.8: Excel/LINGO & Excel GANetXL Pareto optimal fronts

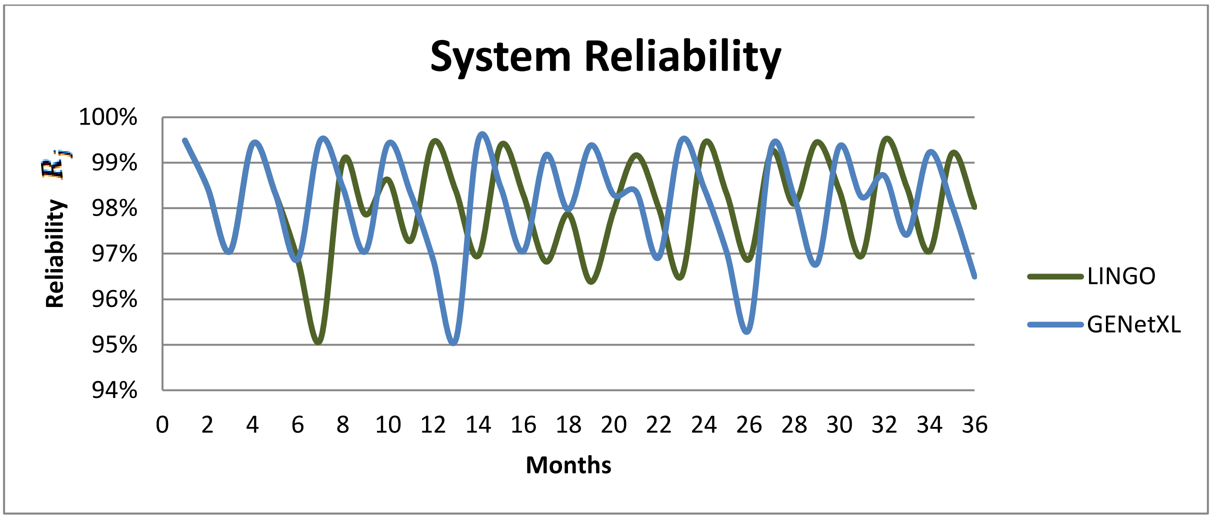


Figure 6.9: Excel/LINGO & Excel GANetXL System reliability (R=50 %,)

6.5 Genetic Algorithm Results

6.5.1 Fitness 1

As presented in 5.5.2.2, two fitness functions were used for optimization; fitness function 1, which was based on the weighted sum was applied. Several values for w_1 and w_2 were used with the condition $w_1 + w_2 = 1$. MATLAB was used to develop the algorithm to solve the problem. It took an average of 4 minutes to solve each run in MATLAB. The fitness functions, crossover, mutation and genetic algorithm procedures are presented in appendix 6. The Pareto front for the optimal solutions is shown in Table 6.6**.** The extreme case of $w_1 = 0\, , w_2 = 1$ gave cost solution of R15 514 691.73 and a reliability of 59.31 % while when $w_1 = 1\, , w_2 = 0$, the cost of solution was R4 312 358.56 at 1.53% reliability.

Table 6-6: Genetic Algorithm Pareto optimal solutions for fitness function 1

Weights		GA fitness function 1	
W1	W2	Reliability (%)	Cost (Rands)
0	1	59.31	15 514 691.73
0.1	0.9	56.73	14 709 662.44
0.2	0.8	55.39	14 300 771.20
0.3	0.7	50.30	12 623 229.98
0.4	0.6	48.68	12 180 892.05
0.5	0.5	41.66	10 648 812.21
0.6	0.4	35.69	9 392 747.83
0.7	0.3	23.70	7 294 953.53
0.8	0.2	12.40	5 879 213.63
0.9	0.1	6.87	5 077 228.59
1	0	1.53	4 312 358.56

The Pareto optimal front of fitness function 1 obtained by genetic algorithm is presented in Figure 6.10.

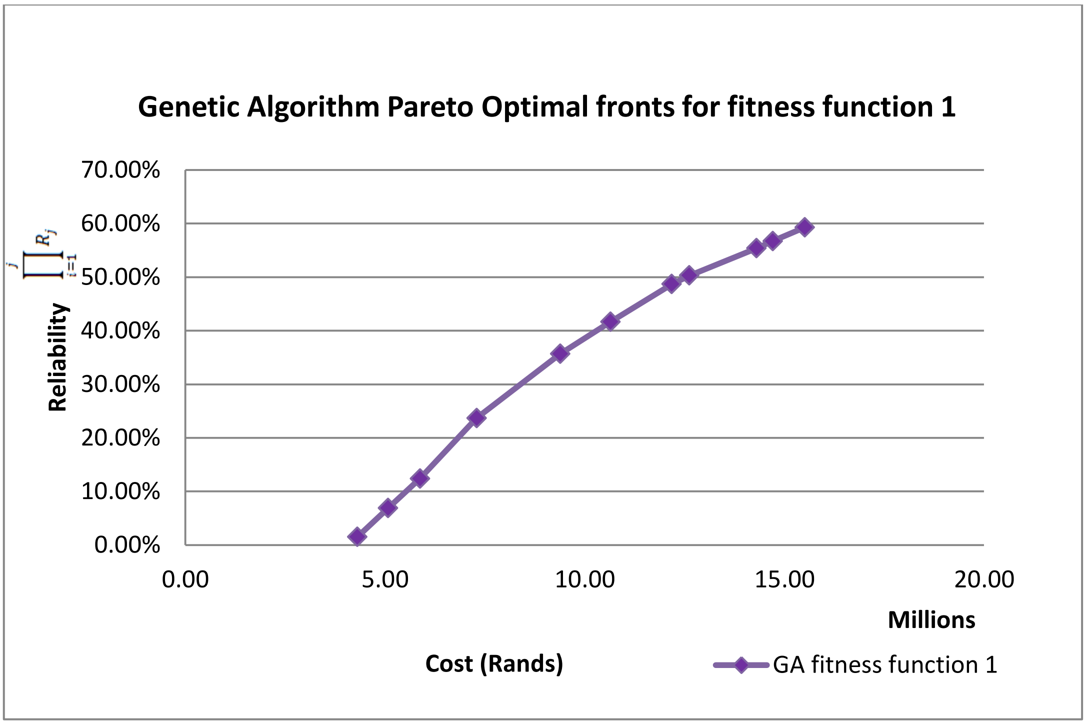


Figure 6.10: Genetic Algorithm Pareto Optimal fronts for fitness function 1

An example of the optimal maintenance and replacement schedule for the weight of $w_1 = 0.3$ and $w_2 = 0.7$ is shown in table 6.7. The optimal cost solution is R12 623 229.98 and the reliability is 50.3% and the system reliability is shown in Figure 6.11.

Table 6-7: Pareto optimal preventive maintenance and replacement schedule for GA fitness 1 (W1=30%, W2=70%)

Month/ Comp	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
MA/MG	-	-	R	-	-	R	-	-	R	-	-	-	R	-	-	R	-	R	-	M	-	R	-	-	-	R	-	-	R	-	M	-	R	-	-	-
EXH	-	-	R	-	-	R	-	-	R	-	-	-	R	-	-	-	-	R	-	-	-	R	-	-	-	R	-	-	-	-	R	-	-	-	-	-
COM	-	-	R	-	-	R	-	-	R	-	-	-	R	-	-	R	-	R	-	R	-	R	-	-	-	R	-	-	R	-	R	-	R	-	-	-
TM	-	-	-	-	-	R	-	-	-	-	-	-	R	-	-	-	-	R	-	-	-	R	-	-	-	-	-	-	R	-	-	-	-	-	-	-

As shown from the result for fitness one, several optimal solutions are found and depending on the objective of the maintenance engineer, any of these points can be taken as an optimal solution. From the Pareto optimal fronts, achieving a higher reliability means the cost would be increased as more replacement activities are scheduled to take place. Also it is important to mention that as a result of the opportunity cost; activities are occurring at the same period.

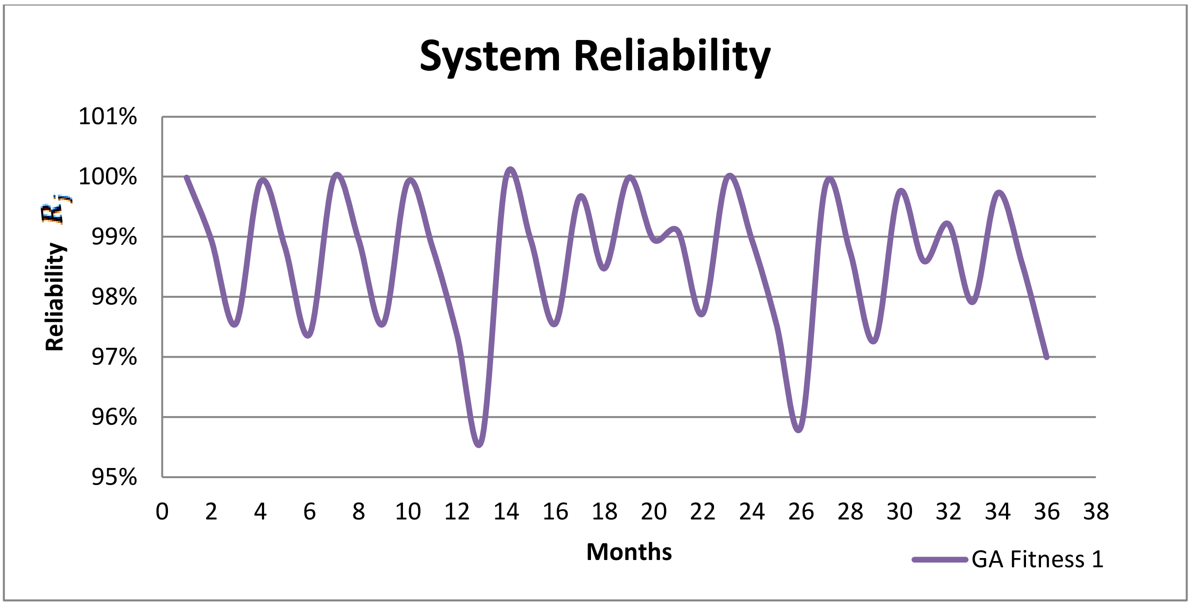


Figure 6.11: System reliability for fitness 1 (W1=30%, W2=70%)

The system reliability for fitness 1 example solution shows the reliability of the system lies between 95.1% and 99.5%. The average reliability over the planning period is 98.1%. The significant drop in reliability in period 13 and 26 is as a result of no maintenance/replacement actions for 3 consecutive periods.

6.5.2 Fitness 2

Similarly, the second fitness function which minimizes the total cost and absolute values of subtraction of overall reliability and required reliability of the system was also used to determine the optimal cost for several required system reliability using genetic algorithms. The Pareto front for the optimal solutions is presented in Table 6.8. Different values of required reliability were considered. The extreme required reliability of 1% and 60% gave an optimal result of 1.30% reliability with a cost of R4 309 246.00 and a reliability of 59.35% at cost of R17 820 424.55 respectively.

Table 6-8: Genetic Algorithm Pareto optimal solutions of fitness function 2

RR (%)	Reliability (%)	Cost (Rands)
1	1.30	4 309 246.00
5	5.72	5 010 997.00
10	10.34	5 429 839.51
20	19.65	7 728 180.50
30	29.97	9 081 778.12
40	39.98	11 078 530.15
50	50.30	12 834 562.76
60	58.28	15 715 231.10

The Pareto optimal front of fitness function 2 obtained by genetic algorithm is presented in Figure 6.12. An example of the optimal maintenance and replacement schedule for the required reliability of 50% is presented in Table 6.9. The optimal cost solution was R12 834 562.76 with a reliability of 50.3%. As mentioned in the previous solution, this reliability is a product of the system reliability over the planned period of 36 months. Hence, the system reliability is shown in Figure 6.13.

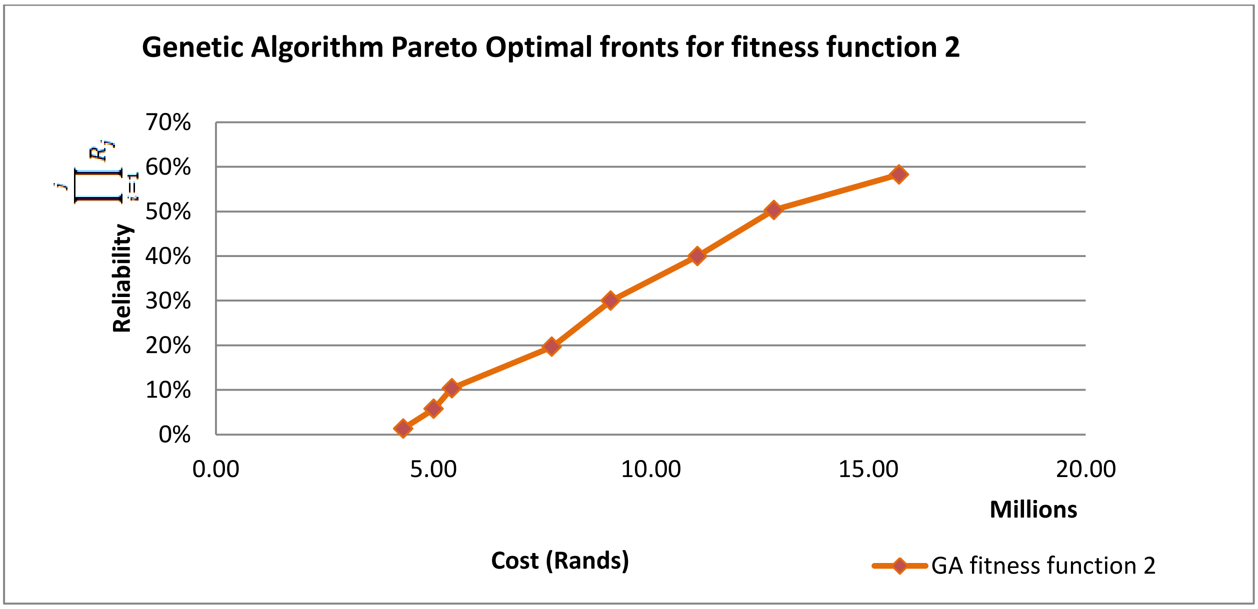


Figure 6.12: Genetic Algorithm Pareto Optimal fronts for fitness function 2

Table 6-9: Pareto optimal preventive maintenance and replacement schedule for GA fitness 2 (R=50.3%, C= R12 834 562.76)

Month/ Comp	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
MA/MG	-	-	R	-	-	-	R	-	R	-	-	R	-	R	-	-	R	-	-	-	R	-	-	R	-	-	R	-	-	R	-	-	R	-	-	-
EXH	-	-	R	-	-	-	M	-	R	-	-	-	-	R	-	-	R	-	-	-	R	-	-	-	-	-	R	-	-	R	-	-	R	-	-	-
COM	-	-	R	-	-	-	R	-	R	-	-	R	-	R	-	-	R	-	-	-	R	-	-	R	-	-	R	-	-	R	-	-	R	-	-	-
TM	-	-	R	-	-	-	-	-	R	-	-	-	-	R	-	-	R	-	-	-	-	-	-	M	-	-	R	-	-	R	-	-	R	-	-	-

The Pareto optimal fronts results from fitness function 2 also give optimal choices for a set of required reliability. The effect of the opportunity cost is also seen in fitness function 2 maintenance and replacement schedules.

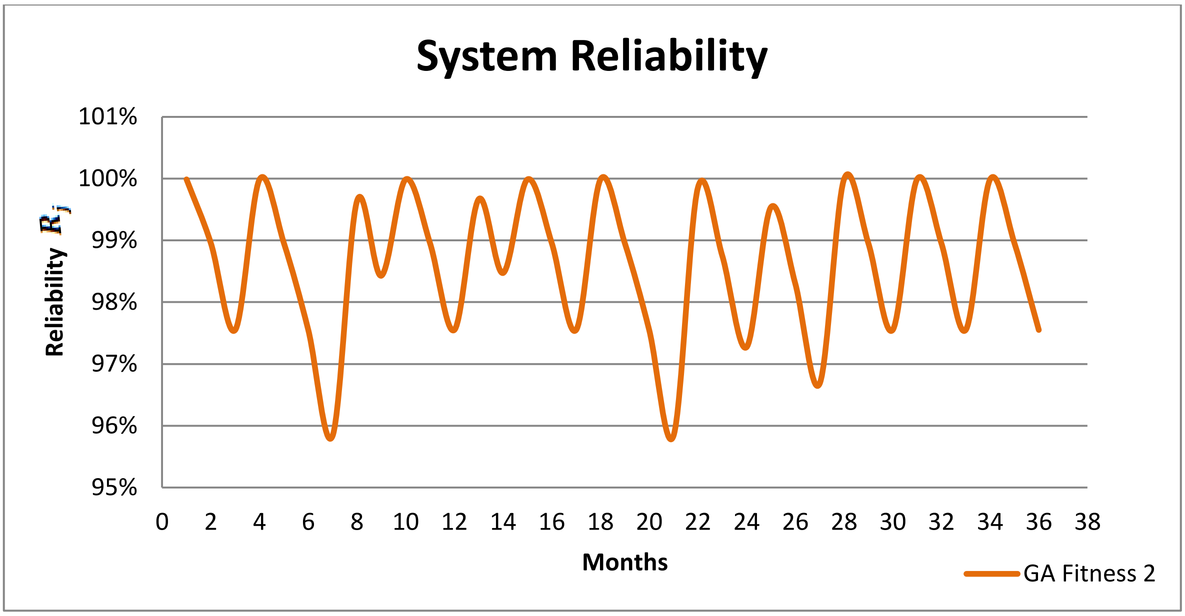


Figure 6.13: System reliability for fitness 2 (R=50.3%, C= R12 834 562.76)

The system reliability for fitness 2 example solution shows similar results to fitness function 1 results. The reliability of the system lies between 95.3% and 99.5%. The average reliability over the planning period is 98.1%. The significant drop in reliability in period 7 and 21 is as a result of no maintenance/replacement actions for 3 consecutive periods.

6.5.3 Comparison of fitness functions

The two fitness functions solutions for the genetic algorithm are compared. The result shows a deviation in the results produced by the two fitness functions. Fitness function 1 produced cost results lower to fitness function 2 with similar reliability. Figure 6.14 shows a comparison between the two Pareto optimal fronts using the genetic algorithm method.

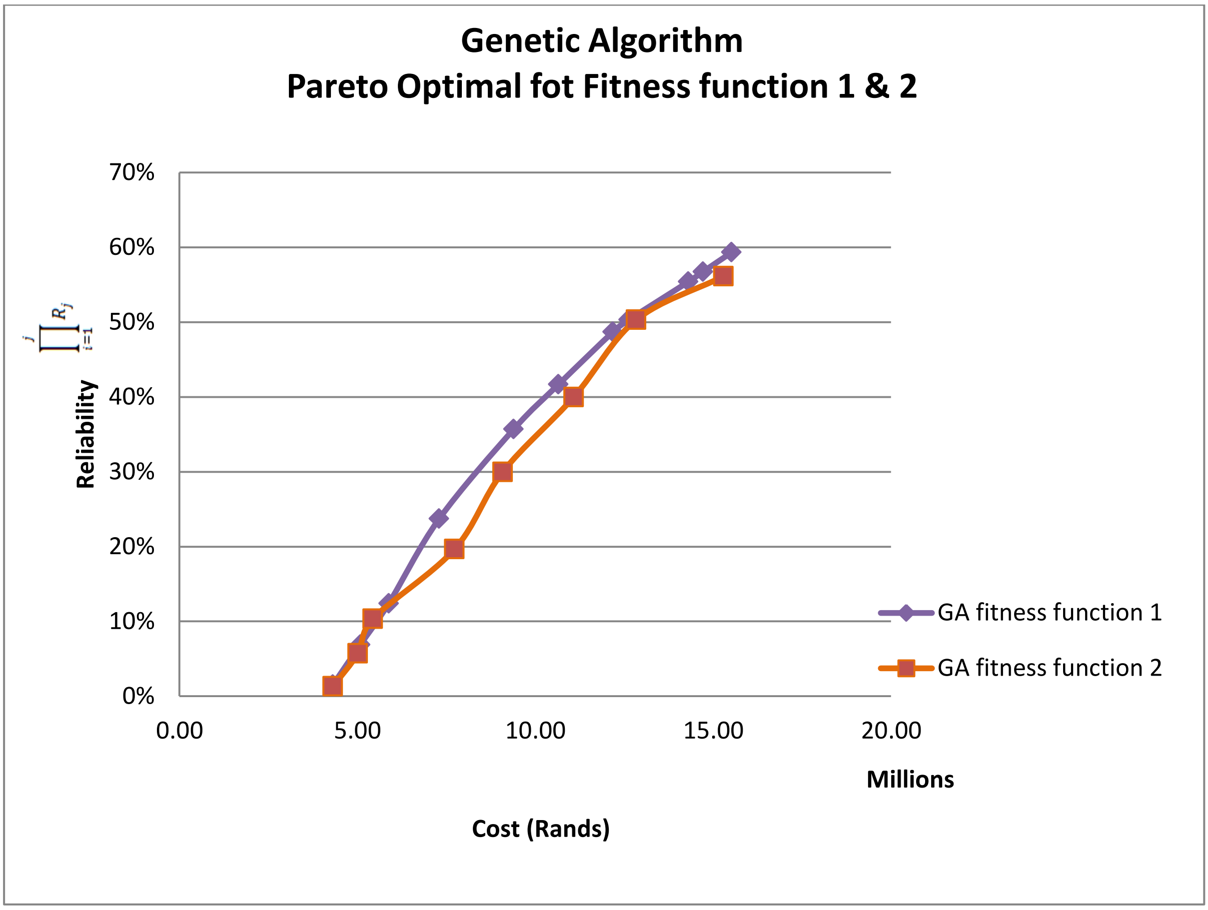


Figure 6.14: Genetic Algorithm Pareto Optimal fronts for fitness function 1 & 2

Another result worth comparing is the system reliability of the examples used in both fitness functions. By comparing these examples, it is seen that the least system reliability in fitness 1 is lower at 95.1% than the least reliability in fitness 2 over the planning period which is 95.3%. Figure 6.15 shows the two system reliability for the example used in fitness 1 and fitness 2. From the comparison, one can understand why the cost solutions in fitness 2 are higher. These plots are good at making optimal maintenance planning decisions for the components of rolling stock.

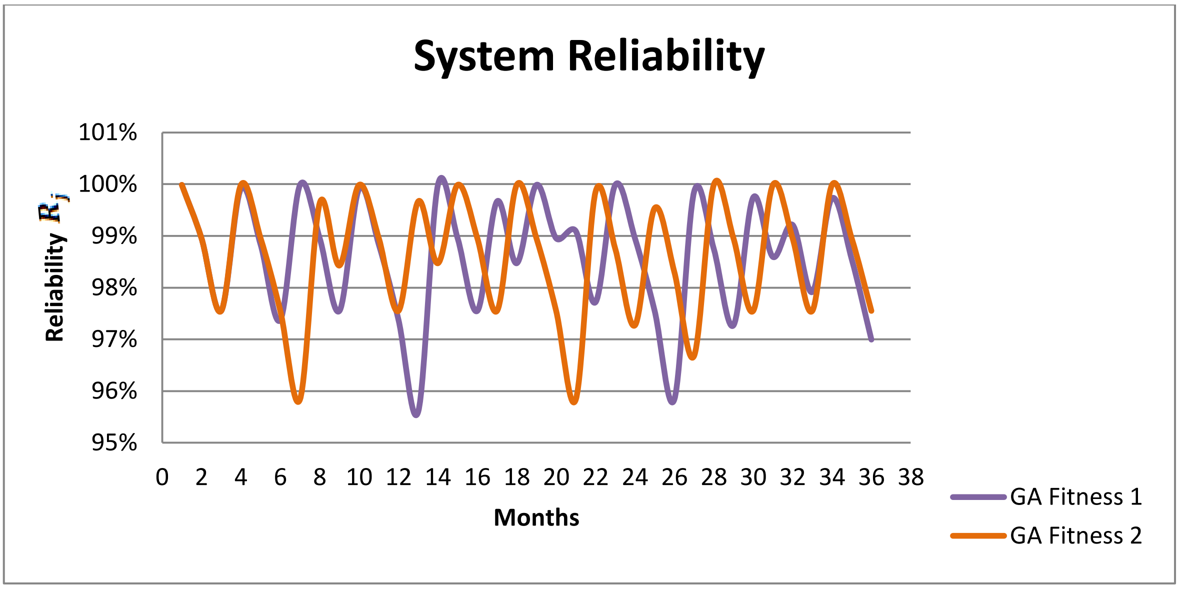


Figure 6.15: Genetic Algorithm System reliability for both fitness functions

6.6 Simulation Annealing Results

6.6.1 Fitness 1

The same process carried out in 6.5 was done using simulated annealing as the method of solution. Two fitness functions where used for optimization fitness function 1, which was based on the weighted sum, was applied. Several values for w_1 and w_2 were used with the condition $w_1 + w_2 = 1$. MATLAB was used to develop the algorithm procedure used to solve the problem. It took an average of 3 seconds to solve each run in MATLAB. The simulated annealing algorithm, fitness functions and transition procedures are presented in Appendix 7. The Pareto front for the optimal solutions is presented in Table 6.10 below**.** The extreme case of $w_1 = 0$, $w_2 = 1$ gave cost of R25 097 496.84 and a reliability of 58.89 % while when $w_1 = 1$, $w_2 = 0$, the solution was R 9 480 544.18 million at 0.13% reliability.

Table 6-10: Simulated Annealing Pareto optimal solutions for fitness function 1

Weights		SA fitness function 1	
W1	W2	Reliability (%)	Cost (Rands)
0	1	58.89	25 097 496.84
0.1	0.9	56.39	23 025 911.13
0.2	0.8	55.32	21 927 413.73
0.3	0.7	51.62	20 043 091.06
0.4	0.6	49.14	19 510 603.23
0.5	0.5	41.13	17 223 278.64
0.6	0.4	36.28	15 751 822.59
0.7	0.3	22.26	13 430 841.88
0.8	0.2	12.48	12 375 805.50
0.9	0.1	7.00	11 319 045.97
1	0	0.13	9 480 554.18

The Pareto optimal front of fitness function 1 obtained by simulated annealing is presented in Figure 6.15. An example of the optimal maintenance and replacement schedule for the weight of $w_1 = 0.3$ and $w_2 = 0.7$ is shown in Table 6.11. The optimal cost solution is R20 043 091.06 and the reliability is 51.62%. Similarly, this reliability is a product of the system reliability over the planned period. The system reliability is shown in Figure 6.17.

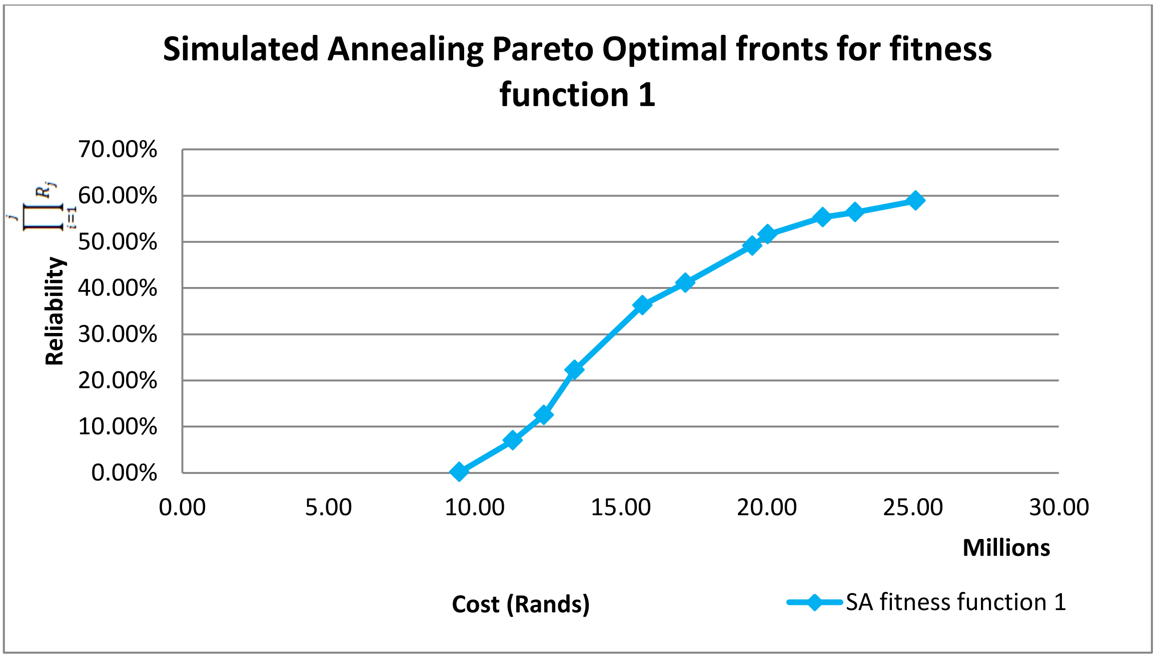


Figure 6.16: Simulated Annealing Pareto Optimal fronts for fitness function 1

Table 6-11: Pareto optimal preventive maintenance and replacement schedule for SA fitness 1 (W1=30%, W2=70%)

Month /Comp	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
MA/MG	M	-	-	R	-	-	R	-	-	M	R	M	M	R	R	-	M	M	-	R	-	-	R	-	R	M	R	-	M	M	-	R	-	-	-	R
EXH	M	-	-	R	-	-	R	-	-	M	R	M	M	R	R	-	M	M	-	R	-	-	R	-	R	M	R	-	M	M	-	R	-	-	-	R
COM	M	-	-	R	-	-	R	-	-	M	R	M	M	R	R	-	M	M	-	R	-	-	R	-	R	M	R	-	M	M	-	R	-	-	-	R
TM	M	-	-	R	-	-	R	-	-	M	R	M	M	R	R	-	M	M	-	R	-	-	R	-	R	M	R	-	M	M	-	R	-	-	-	R

The Pareto optimal fronts results from fitness function 1 produced several optimal choices for a set of required reliability. The effect of the opportunity cost is also seen in fitness function 1's maintenance and replacement schedules.

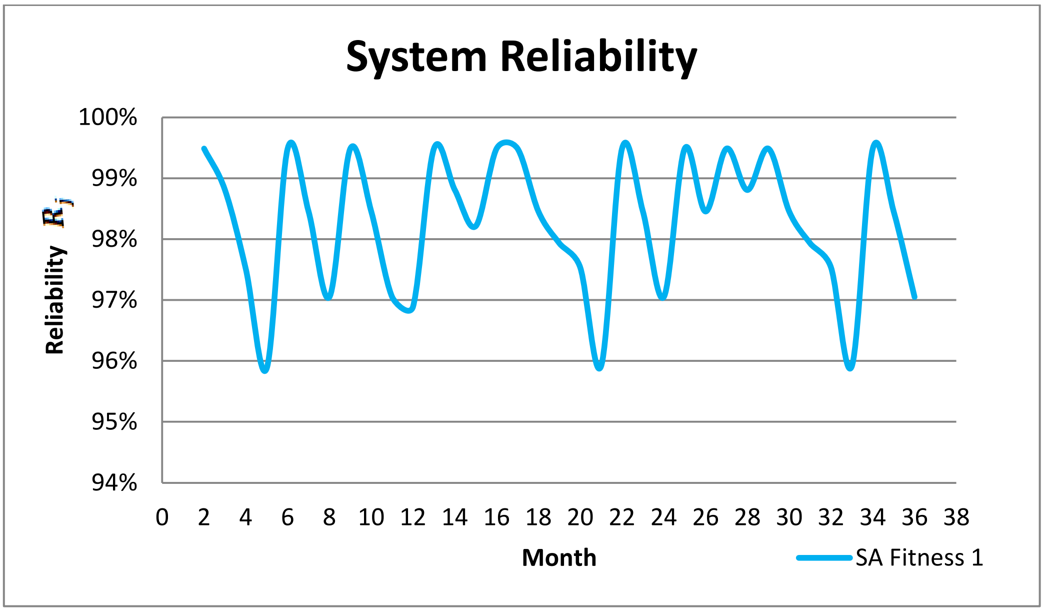


Figure 6.17: System reliability for fitness 1 (W1=30%, W2=70%)

The system reliability shows that the reliability of the system lies between 95.88% and 99.5%. The average reliability over the planning period is 98.1%. The significant drop in reliability in period 5, 20 and 32 is as a result of maintenance actions and no actions for consecutive periods.

6.6.2 Fitness 2

Similarly the second fitness function which minimizes the total cost and absolute values of subtraction of overall reliability and required reliability of the system, was also used to determine the optimal cost for several required system reliability. The Pareto front for the optimal solutions is presented in Table 6.12. Different required reliability was considered. The extreme required reliability of 1% and 60% gave an optimal result of 1.38% reliability with a cost of R7 881 797.21 and a reliability of 60.04% at cost of R20 365 958.19 respectively.

Table 6-12: Simulated Annealing Pareto optimal solutions of fitness function 2

RR (%)	Reliability (%)	Cost (Rands)
1	1.38	7 881 797.21
5	5.13	9 406 584.50
10	9.90	11 792 460.24
20	20.97	12 117 395.25
30	30.98	15 105 484.52
40	42.45	16 219 033.21
50	51.62	17 787 577.04
60	60.04	20 365 958.19

The Pareto optimal front of fitness function 2 obtained by simulated annealing is presented in Figure 6.18. An example of the optimal maintenance and replacement schedule for the required reliability of 50% is presented in Table 6.13. The optimal cost solution of R17 787 577.04 04 was gotten to achieve a reliability of 51.62%. As mentioned in previous solutions, this reliability is a product of the system reliability over the planned period. Hence, the system reliability is shown in Figure 6.19.

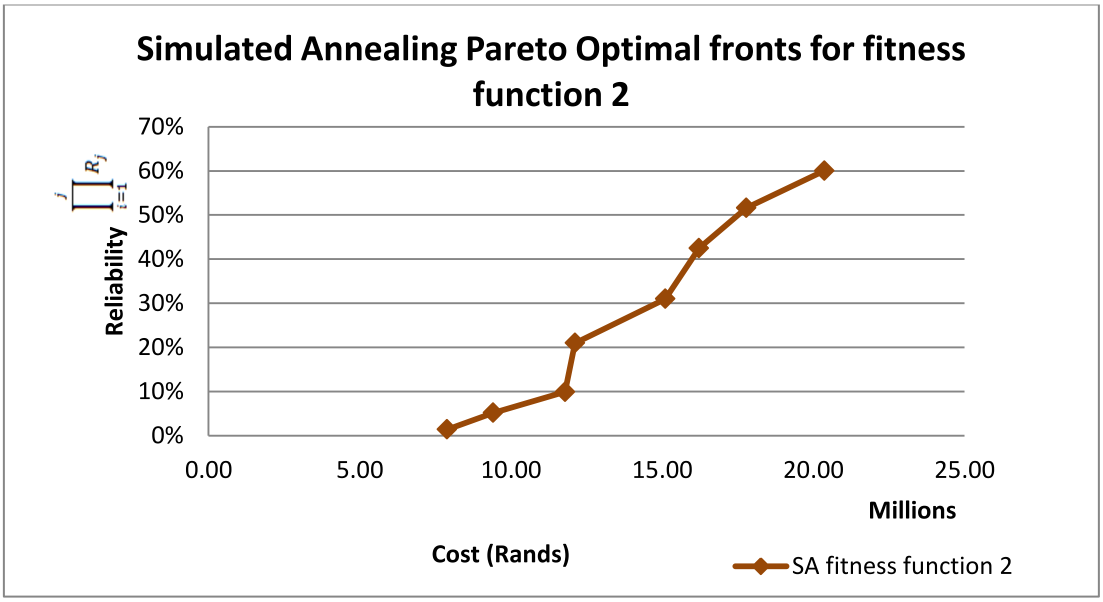


Figure 6.18: Simulated Annealing Pareto Optimal fronts for fitness function 2

Table 6-13: Pareto optimal preventive maintenance and replacement schedule for SA fitness 2 (R=51.67%, C= R17 787 577.04)

Month/ Comp	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
MA/MG	-	-	M	R	R	-	R	-	M	R	-	-	-	R	M	R	M	-	R	-	-	-	R	-	R	M	-	-	R	-	-	R	-	M	-	-
EXH	-	-	M	R	R	-	R	-	M	R	-	-	-	R	M	R	M	-	R	-	-	-	R	-	R	M	-	-	R	-	-	R	-	M	-	-
COM	-	-	M	R	R	-	R	-	M	R	-	-	-	R	M	R	M	-	R	-	-	-	R	-	R	M	-	-	R	-	-	R	-	M	-	-
TM	-	-	M	R	R	-	R	-	M	R	-	-	-	R	M	R	M	-	R	-	-	-	R	-	R	M	-	-	R	-	-	R	-	M	-	-

The Pareto optimal fronts results from fitness function 2 also give optimal choices for a set of required reliability. The effect of the opportunity cost is also seen in fitness function 2 maintenance and replacement schedules.

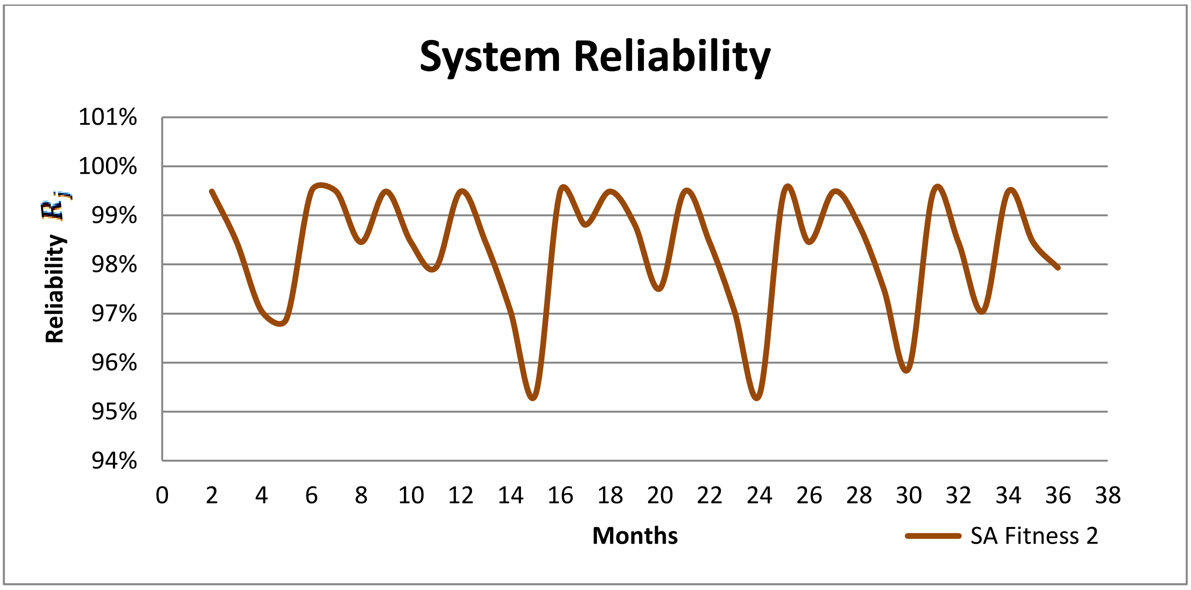


Figure 6.19: System reliability for fitness 2 (R=51.67%, C= R17 787 577.04)

The system reliability for fitness 2 example solution shows similar results to fitness function 1 results. The reliability of the system lies between 95.3% and 99.5%. The average reliability over the planning period is 98.2%. The significant drop in reliability in period 14 and 22 is as a result of no maintenance/replacement actions for 3 consecutive periods while the drop in period 29 is as a result of maintenance actions followed by no actions for consecutive periods.

6.6.3 Comparison of fitness functions

The two fitness function gave similar results when applied to the multi-objective model. Figure 6.20 shows a comparison between the two Pareto optimal fronts using the simulated annealing method. It can be seen that fitness 2 which minimizes the total cost given a required reliability of the system produces better quality cost solutions in most scenarios.

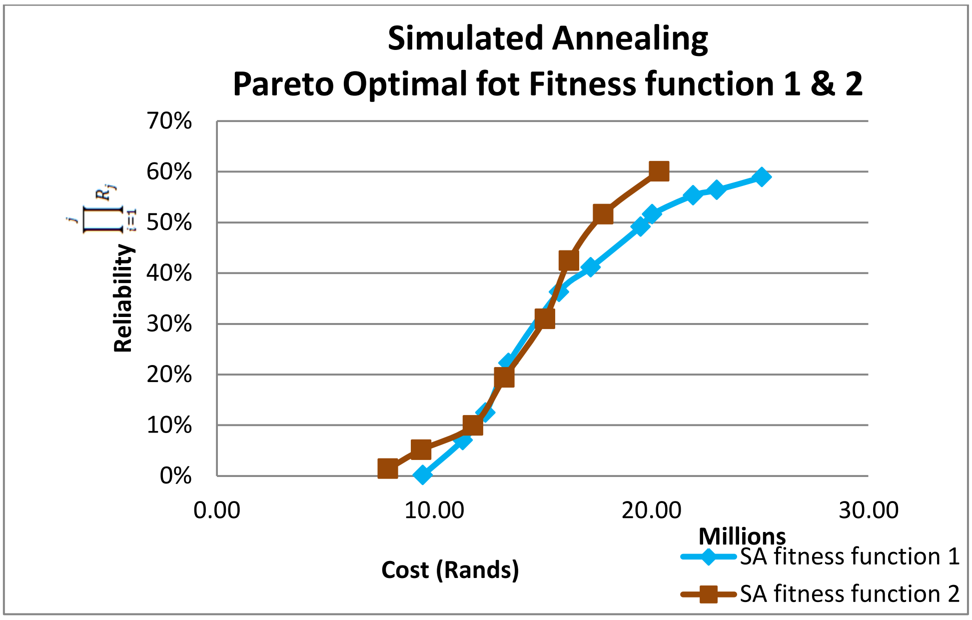


Figure 6.20: Simulated Annealing Pareto Optimal fronts for fitness function 1 & 2

Comparing the example given in both scenarios, the least system reliability in fitness 1 is higher than the least reliability in fitness 2 over the planning period. Figure 6.21 shows the two system reliability for the optimal solution of 51.67% reliability. This explains the reason in higher cost when fitness 1 was applied. These plots can be used by a rolling stock planning office to plan the maintenance schedule for the components of rolling stock.

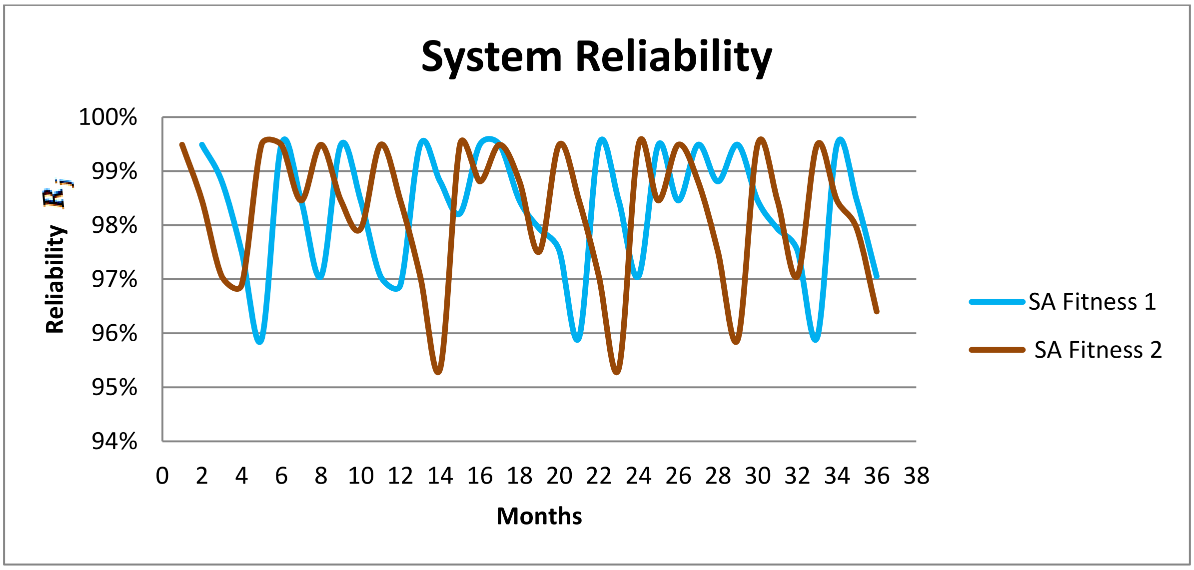


Figure 6.21: Simulated Annealing System reliability for both fitness functions

6.7 Analysis of all solutions

All solutions from all the methods are being compared and discussed. Figure 6.22 shows the Excel, Genetic algorithm and simulated annealing solutions, the Excel and Genetic algorithm results are very similar. However, that is not the case with the simulated annealing solutions. The deviation in the cost solutions is high as a result of more scheduled maintenance and replacement activities.

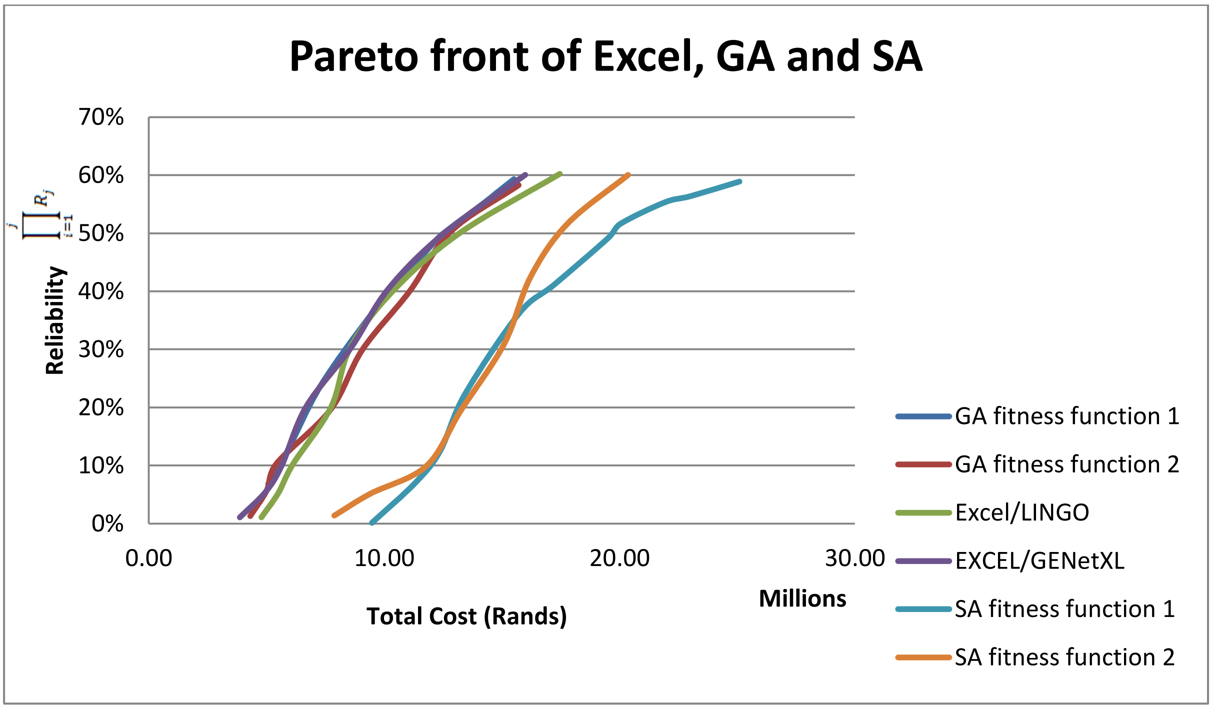


Figure 6.22: Pareto front of Excel, GA and SA

The example values for each of the solution methods are compared in Table 6.14

Table 6-14: Comparison of all solution methods

Required Reliability	Solution method	Reliability	Total Cost	Average Reliability	Gap	CPU time
50%	Excel/GANetXL	50.00%	12 550 430.00	98.1		27
	Genetic Algorithm	50.30%	12 834 562.76	98.1	2.26%	4
	Excel/LINGO	50.00%	13 202 504.88	98.1	5.20%	19
	Simulation Annealing	51.62%	17 787 577.04	98.2	41.73%	0

The comparison of the example solutions show that the exact method takes longer to solve and will require a longer computational time as the problem becomes bigger. The simulated annealing solutions could be considered to be poor when compared with the other solutions. It can be argued that the simulated annealing results show that scheduling more maintenance activities cost more and doesn't necessarily add much value to the reliability of the system.

The results achieved are compared with the results of the current maintenance schedule to determine if the model indeed improves reliability. In Table 6.15**,** a comparison of the case study and achieved results is presented. From this comparison, it can be concluded that there is noticeable improvement in reliability in the Excel and Genetic algorithms as these solutions produce schedules with higher reliability with lower cost

Table 6-15: Comparison of Case study and optimal results

	Case Study	Excel/LINGO	Excel/GA NetXL	GA fit 1	GA fit 2	SA fit 1	SA fit 2
Reliability	**5.9%**	**50.0%**	**50.0%**	**50.3%**	**50.3%**	**51.6%**	**51.6%**
Average Reliability	**92.5%**	**98.1%**	**98.1%**	**98.1%**	**98.1%**	**98.1%**	**98.2%**
Total Cost(R)	**13,380,864**	**13,202,504**	**12,550,430**	**12,623,229**	**12,834,562**	**20,043,091**	**17,787,577**

6.8 Chapter Conclusion

The solution to the case study applications has been presented. The Excel methods show very similar solutions to the problem with different optimal solutions. The limitation of exact methods can be seen with the improvements made in the GANetXL solutions. The metaheuristics approach, however, produced interesting results. The genetic algorithm found similar solutions to the LINGO and GANetXL solutions while the simulated annealing found different solutions. These solutions can be considered to be weak solutions since they give higher cost solutions for similar reliability solutions in the previous models. However, an interesting observation is that more activities do not relate to higher reliability.

The solutions achieved show improvement in reliability and cost when compared with the current maintenance schedule of the case study. The effect of the opportunity cost was seen in every solution as it tends to schedule maintenance/replacement actions of components to occur at the same time in a period. In the example schedules presented, there were more replacement activities because the effect of maintenance on the age of the equipment was not sufficient to increase reliability.

CHAPTER 7: CONCLUSIONS AND RECOMMENDATIONS

In this chapter, conclusions are drawn with regard to the research project. The chapter begins with general conclusions then specific conclusions are also given. A discussion on the contribution of this research to both theory and practice is presented. This is followed by an evaluation with the objectives and hypothesis of the research. Finally recommendations and suggestions for future research are made.

7.1 Specific conclusions

- Scheduling of rolling stock can be improved using reliability parameters and cost of rolling stock components.
- For the model to be effective, input data needs to be as accurate as possible. Therefore, rail companies need to ensure that failure history and cost of maintenance/ replacement of every component of rolling stock are properly documented to ensure reliability prediction and accurate cost forecasting.
- The impact of maintenance strategies determine the behaviour of the model in that if the impact of the selected strategy on reliability is low, the model tends to allow more replacements to occur to keep reliability high, and therefore this factor must be selected or calculated carefully.

7.2 Achievement of Research Objectives and Hypothesis

The purpose of this research was to develop a decision support model based on reliability of components and cost associated with maintenance of rolling stock to improve maintenance scheduling of rolling stock. This objective has been achieved. In chapter 5, a decision support model that was based on reliability and cost was developed. The output of this model was a maintenance schedule that can be used to achieve a specific reliability at an optimum cost.

The second objective was to apply the model to a case study which can help improve maintenance planning and scheduling in rail companies. This objective was achieved by applying the decision model to Metrorail’s maintenance facility at Salt River, Cape Town. From the conclusions made in chapter 6, it is clear that the use of reliability and cost as objective criteria resulted into a more efficient maintenance schedule. The results show that the impact of continuous preventive maintenance’s on reliability reduces with time.

7.3 Contribution to real world practice

The developed decision support model, which was successfully applied to the case study, can contribute to the field of maintenance management in rolling stock. The model, although considered for the rolling stock environment, can also be easily modified to suit any other multi-component system. The investigation has also highlighted the significance of data documentation and appropriate model formulating for repairable multi-component systems. The optimal maintenance schedules can be used to control stock levels of components at an efficient level.

7.4 Recommendations for Future Work

- In this research, reliability measures and cost were considered as objective criteria to improve maintenance scheduling of rolling stock. It can be useful to apply other criteria, for example availability, stock levels, maintenance time, to develop a model to achieve the same purpose of improving maintenance scheduling.
- The decision support model can be expanded by applying more than one maintenance strategy.
- As discussed in paragraph 5.2, four components were selected for application to the decision model. It can be useful to carry out a more detailed analysis to obtain the cost and failure times for every component on a motor coach and apply it to the model for a more practical result.
- In this research, only the NHPP power law was used for the decision support model. It can be useful to apply other repairable system models like log linear and compare the results achieved using other models with the one used with the NHPP power law model. It can also be useful to consider adding the non-repairable components of rolling stock to the model, which would mean using other modelling techniques.
- Considering the variations in the result using the simulated annealing method, it can be useful to apply other metaheuristics solution methods to solve the model and compare the results with the ones achieved using genetic algorithms.

BIBLIOGRAPHY

Afefy, I.H. 2010, "Reliability-Centered Maintenance Methodology and Application: A Case Study", *Engineering*, vol. 2, no. 11, pp. 863.

Altuger, G. & Chassapis, C. 2009, "Multi criteria preventive maintenance scheduling through Arena based simulation modelling", *Simulation Conference (WSC), Proceedings of the 2009 Winter*, pp. 2123.

Al-Turki, U. 2009, "Maintenance Planning and Scheduling" in , eds. M. Ben-Daya, S.O. Duffuaa, A. Raouf, J. Knezevic & D. Ait-Kadi, Springer London, , pp. 237-262.

Ambika, P.P. 2009, *Maintenance Decision Support Models for Railway Infrastructure using RAMS & LCC Analyses*, Luleå University of Technology.

Anderson, R.T. & Neri, L. 1990, *Reliability-Centered Maintenance: management and engineering methods*, Elsevier applied science.

Apeland, S. & Scarf, P.A. 2003, "A fully subjective approach to modelling inspection maintenance", *European Journal of Operational Research*, vol. 148, no. 2, pp. 410-425.

Ascher, H. & Feingold, H. 1984, "Repairable systems reliability: Modelling, inference, misconceptions and their causes", *Lecture Notes in Statistics*, vol. 7.

Battistelli, L., Ciccarelli, F., Lauria, D. & Proto, D. 2009, "Optimal design of DC electrified railway stationary storage system", *Clean Electrical Power, 2009 International Conference on*IEEE, , pp. 739.

Bevilacqua, M. & Braglia, M. 2000, "The analytic hierarchy process applied to maintenance strategy selection", *Reliability Engineering & System Safety*, vol. 70, no. 1, pp. 71-83.

Boer, P. 2013, *Carraige and Wagon*, Metrorail Salt River.

Borraz-Sánchez, C. & Klabjan, D. 2012, *Strategic Gang Scheduling for Railroad Maintenance*, CCITT, Center for the Commercialization of Innovative Transportation Technology, Northwestern University.

Bris, R., Châtelet, E. & Yalaoui, F. 2003, "New method to minimize the preventive maintenance cost of series–parallel systems", *Reliability Engineering & System Safety*, vol. 82, no. 3, pp. 247-255.

Budai, G., Huisman, D. & Dekker, R. 2005, "Scheduling preventive railway maintenance activities", *Journal of the Operational Research Society*, vol. 57, no. 9, pp. 1035-1044.

Busetti, F. 2003, "Simulated annealing overview", *World Wide Web URL* *www.geocities.com/francorbusetti/saweb.pdf*, .

Chareonsuk, C., Nagarur, N. & Tabucanon, M.T. 1997, "A multicriteria approach to the selection of preventive maintenance intervals", *International Journal of Production Economics*, vol. 49, no. 1, pp. 55-64.

Chen, Y., Ding, Y., Jin, J. & Ceglarek, D. 2006, "Integration of process-oriented tolerancing and maintenance planning in design of multistation manufacturing processes", *Automation Science and Engineering, IEEE Transactions on*, vol. 3, no. 4, pp. 440-453.

Cheng, C., Chen, M. & Guo, R. 2007, "The optimal periodic preventive maintenance policy with degradation rate reduction under reliability limit", *Industrial Engineering and Engineering Management, 2007 IEEE International Conference on* IEEE, , pp. 649.

Cheng, Y. & Tsao, H. 2010, "Rolling stock maintenance strategy selection, spares parts' estimation, and replacements' interval calculation", *International Journal of Production Economics*, vol. 128, no. 1, pp. 404-412.

Cheng, Y., Yang, A.S. & Tsao, H. 2006, "Study on rolling stock maintenance strategy and spares parts management", *7th World Congress on Railway Research, Montreal*.

Chien, Y. & Chen, J. 2010, "Optimal spare ordering policy for preventive replacement under cost effectiveness criterion", *Applied Mathematical Modelling*, vol. 34, no. 3, pp. 716-724.

Chung, S., Lau, H., Choy, K., Ho, G. & Tse, Y. 2010, "Application of genetic approach for advanced planning in multi-factory environment", *International Journal of Production Economics*, vol. 127, no. 2, pp. 300-308.

Chung, S.H., Lau, H.C.W., Ho, G.T.S. & Ip, W.H. 2009, "Optimization of system reliability in multi-factory production networks by maintenance approach", *Expert Systems with Applications*, vol. 36, no. 6, pp. 10188-10196.

Coetzee, J.L. 1997, "The role of NHPP models in the practical analysis of maintenance failure data", *Reliability Engineering & System Safety*, vol. 56, no. 2, pp. 161-168.

Coit, D.W. 2005, "Repairable systems reliability trend tests and evaluation", .

Conradie, P. & Treurnicht, N. 2012, "Exploring Critical Failure Modes in the Rail Environment and the Consequential Costs of Unplanned Maintenance", *Computers and Industrial Engineering 42*.

Crespo Marquez, A., Gupta, J.N. & Ignizio, J.P. 2006, "Improving preventive maintenance scheduling in semiconductor fabrication facilities", *Production Planning & Control*, vol. 17, no. 7, pp. 742-754.

de Moura Xavier, José Carlos, de Andrade Azevedo, I., de Sousa Junior, Wilson Cabral & Nishikawa, A. 2013, "Rate of occurrence of failures based on a nonhomogeneous Poisson process: an ozone analyzer case study", *Environmental monitoring and assessment*, vol. 185, no. 2, pp. 1463-1471.

Dekker, R., Wildeman, R.E. & van der Duyn Schouten, Frank A 1997, "A review of multi-component maintenance models with economic dependence", *Mathematical Methods of Operations Research,* vol. 45, no. 3, pp. 411-435.

Dekker, R. 1996, "Applications of maintenance optimization models: a review and analysis", *Reliability Engineering & System Safety,* vol. 51, no. 3, pp. 229-240.

Dekker, R. & Scarf, P.A. 1998, "On the impact of optimisation models in maintenance decision making: the state of the art", *Reliability Engineering & System Safety,* vol. 60, no. 2, pp. 111-119.

Doostparast, M., Kolahan, F. & Doostparast, M. 2013, "Optimisation of PM scheduling for multi-component systems – a simulated annealing approach", *International Journal of Systems Science,* , pp. 1-9.

Duarte, J., Garbatov, Y., Zio, E. & Sorensen, J. 2010, "Framework for maintenance planning" in CRC Press, , pp. 33-52.

Duffuaa, S. & Al-Sultan, K. 1997, "Mathematical programming approaches for the management of maintenance planning and scheduling", *Journal of Quality in Maintenance Engineering,* vol. 3, no. 3, pp. 163-176.

Duffuaa, S., Ben-Daya, M., Al-Sultan, K. & Andijani, A. 2001, "A generic conceptual simulation model for maintenance systems", *Journal of Quality in Maintenance Engineering,* vol. 7, no. 3, pp. 207-219.

Duffuaa, S.O., Duffuaa, S.O., Raouf, A. & Campbell, J.D. 1999, *Planning and Control of Maintenance Systems: Modelling and Analysis,* Wiley.

Elsayed, E.A. 2012, *Reliability engineering,* Wiley Publishing.

Faulin, J., Juan, A.A., Alsina, S.S.M. & Ramirez-Marquez, J.E. 2010, *Simulation Methods for Reliability and Availability of Complex Systems,* Springer.

Frangopol, D.M. & Liu, M. 2007, "Bridge network maintenance optimization using stochastic dynamic programming", *Journal of Structural Engineering,* vol. 133, no. 12, pp. 1772-1782.

García Márquez, F.P., Schmid, F. & Conde Collado, J. 2003, "A reliability centered approach to remote condition monitoring. A railway points case study", *Reliability Engineering & System Safety,* vol. 80, no. 1, pp. 33-40.

Garg, A. & Deshmukh, S.G. 2006, "Maintenance management: literature review and directions", *Journal of Quality in Maintenance Engineering,* vol. 12, no. 3, pp. 205-238.

Ghayebloo, S. & Shahanaghi, K. 2010, "Determining maintenance system requirements by viewpoint of reliability and lean thinking: a MODM approach", *Journal of Quality in Maintenance Engineering,* vol. 16, no. 1, pp. 89-106.

Ghosh, D. & Roy, S. 2009, "Maintenance optimization using probabilistic cost-benefit analysis", *Journal of Loss Prevention in the Process Industries*, vol. 22, no. 4, pp. 403-407.

Hagmark, P. & Virtanen, S. 2007, "Simulation and calculation of reliability performance and maintenance costs", *Reliability and Maintainability Symposium, 2007. RAMS'07. Annual*IEEE, , pp. 34.

Hamada, M.S., Wilson, A., Reese, C.S. & Martz, H. 2008, *Bayesian Reliability,* Springer.

Hilber, P. 2008, "Maintenance optimization for power distribution systems", .

Holland, J.H. 1975, *Adaptation in natural and artificial systems: An introductory analysis with applications to biology, control, and artificial intelligence.* U Michigan Press.

Ionescu, D.C. & Limnios, N. 1999, *Statistical and Probabilistic Models in Reliability,* Birkh{\a}user Boston.

Jayakumar, A. & Asgarpoor, S. 2006, "Maintenance optimization of equipment by linear programming", *Probability in the Engineering and Informational Sciences*, vol. 20, no. 01, pp. 183-193.

Jin, X., Li, L. & Ni, J. 2009, "Option model for joint production and preventive maintenance system", *International Journal of Production Economics*, vol. 119, no. 2, pp. 347-353.

Kalbande, D., Sawlekar, S. & Thampi, G. 2010, "Total Productive Maintenance: A Case Study In Manufacturing Industry", *Journal of Industrial Engineering,* .

Kelly, A. 2006, *Strategic Maintenance Planning,* Elsevier Science.

Khalesi, N., Rezaei, N. & Haghifam, M. 2011, "DG allocation with application of dynamic programming for loss reduction and reliability improvement", *International Journal of Electrical Power & Energy Systems*, vol. 33, no. 2, pp. 288-295.

Kianfar, F. 2005, "A numerical method to approximate optimal production and maintenance plan in a flexible manufacturing system", *Applied Mathematics and Computation*, vol. 170, no. 2, pp. 924-940.

Kim, H. & Singh, C. 2010, "Reliability modeling and simulation in power systems with aging characteristics", *Power Systems, IEEE Transactions on*, vol. 25, no. 1, pp. 21-28.

Kirkpatrick, S., Jr., D.G. & Vecchi, M.P. 1983, "Optimization by simmulated annealing", *Science*, vol. 220, no. 4598, pp. 671-680.

Klutke, G.A., Kiessler, P.C. & Wortman, M.A. 2003, "A critical look at the bathtub curve", *Reliability, IEEE Transactions on*, vol. 52, no. 1, pp. 125-129.

Konak, A., Coit, D.W. & Smith, A.E. 2006, "Multi-objective optimization using genetic algorithms: A tutorial", *Reliability Engineering & System Safety*, vol. 91, no. 9, pp. 992-1007.

Kralj, B. & Petrovic, R. 1995, "A multiobjective optimization approach to thermal generating units maintenance scheduling", *European Journal of Operational Research,* vol. 84, no. 2, pp. 481-493.

Krivtsov, V.V. 2007, "Practical extensions to NHPP application in repairable system reliability analysis", *Reliability Engineering & System Safety,* vol. 92, no. 5, pp. 560-562.

Laggoune, R., Chateauneuf, A. & Aissani, D. 2009, "Opportunistic policy for optimal preventive maintenance of a multi-component system in continuous operating units", *Computers & Chemical Engineering,* vol. 33, no. 9, pp. 1499-1510.

Lapa, C.M.F., Pereira, C.M.N.A. & de Barros, M.P. 2006, "A model for preventive maintenance planning by genetic algorithms based in cost and reliability", *Reliability Engineering & System Safety,* vol. 91, no. 2, pp. 233-240.

Lee, E.K., Cha, K. & Shi, J. 2004, "Optimization Techniques and their Suitability and Robustness for IMRT Planning", *MEDICAL PHYSICS*AMER ASSOC PHYSICISTS MEDICINE AMER INST PHYSICS STE 1 NO 1, 2 HUNTINGTON QUADRANGLE, MELVILLE, NY 11747-4502 USA, , pp. 1762.

Levitin, G. & Lisnianski, A. 2000, "Optimization of imperfect preventive maintenance for multi-state systems", *Reliability Engineering & System Safety,* vol. 67, no. 2, pp. 193-203.

Levitt, J. 2003, *Complete Guide to Preventive and Predictive Maintenance,* Industrial Press.

LINDO systems, 2014, , *LINGO 14.0 - Optimization Modeling Software for Linear, Nonlinear, and Integer Programming*. Available: www.lindo.com.

Lindqvist, B.H. 2006, "On the statistical modeling and analysis of repairable systems", *Statistical science,* , pp. 532-551.

Liu, J., Wang, W. & Golnaraghi, F. 2010, "An enhanced diagnostic scheme for bearing condition monitoring", *Instrumentation and Measurement, IEEE Transactions on,* vol. 59, no. 2, pp. 309-321.

Louit, D.M., Pascual, R. & Jardine, A.K. 2009, "A practical procedure for the selection of time-to-failure models based on the assessment of trends in maintenance data", *Reliability Engineering & System Safety,* vol. 94, no. 10, pp. 1618-1628.

Lyonnet, P. 1991, *Maintenance planning: Methods and mathematics,* CRC Press.

Malinga, S. 2013, *Maintenance Schedule Intervals*, Salt River.

Mathew, S. 2004, "Optimal inspection frequency: A tool for maintenance planning/forecasting", *International Journal of Quality & Reliability Management,* vol. 21, no. 7, pp. 763-771.

Matsuoka, S. & Muraki, M. 2007, "Short-term maintenance scheduling for utility systems", *Journal of Quality in Maintenance Engineering,* vol. 13, no. 3, pp. 228-240.

Mechefske, C.K. & Wang, Z. 2003, "Using fuzzy linguistics to select optimum maintenance and condition monitoring strategies", *Mechanical Systems and Signal Processing*, vol. 17, no. 2, pp. 305-316.

Metrorail South Africa 2007, , *Welcome to Metrorail*. Available: http://www.metrorail.co.za/About.html [2013, 09/10].

Microsoft, 2009, , ***Introduction to optimization with the Excel Solver tool*** [Homepage of Microsoft], [Online]. Available: http://office.microsoft.com/en-za/excel-help/introduction-to-optimization-with-the-excel-solver-tool-HA001124595.aspx [2014, .

Min, L.X., Yong, W.J., Yuan, Y. & Yan, X.W. 2009, "Multiobjective optimization of preventive maintenance schedule on traction power system in high-speed railway", *Reliability and Maintainability Symposium, 2009. RAMS 2009. Annual*IEEE, , pp. 365.

Mobley, R.K. 2011, *Maintenance Fundamentals*, Elsevier Science..

Moghaddam, K.S. 2008, "Preventive maintenance and replacement scheduling: models and algorithms", .

Moghaddam, K.S. & Usher, J.S. 2011, "A new multi-objective optimization model for preventive maintenance and replacement scheduling of multi-component systems", *Engineering Optimization*, vol. 43, no. 7, pp. 701-719.

Murray, S. 2013, *Shedding*, Metrarail Salt River.

Murthy, D., Atrens, A. & Eccleston, J. 2002, "Strategic maintenance management", *Journal of Quality in Maintenance Engineering*, vol. 8, no. 4, pp. 287-305.

Nahas, N., Khatab, A., Ait-Kadi, D. & Nourelfath, M. 2008, "Extended great deluge algorithm for the imperfect preventive maintenance optimization of multi-state systems", *Reliability Engineering & System Safety*, vol. 93, no. 11, pp. 1658-1672.

Nicolai, R.P. & Dekker, R. 2008, *Optimal maintenance of multi-component systems: a review*, Springer.

Obayashi, S. 2007, *Evolutionary Multi-Criterion Optimization: 4th International Conference, EMO 2007, Matsushima, Japan, March 5-8, 2007, Proceedings*, Springer.

O'Connor, P. & Kleyner, A. 2011, *Practical Reliability Engineering*, Wiley.

Oke, S. 2005, "An analytical model for the optimisation of maintenance profitability", *International Journal of Productivity and Performance Management*, vol. 54, no. 2, pp. 113-136.

Oppenheimer, D. 2009, , ***New and Improved Solver*** [Homepage of Microsoft], [Online]. Available: http://blogs.office.com/2009/09/21/new-and-improved-solver/ [2014, .

Oyama, T. & Miwa, M. 2006, "Mathematical modeling analyses for obtaining an optimal railway track maintenance schedule", *Japan journal of industrial and applied mathematics,* vol. 23, no. 2, pp. 207-224.

Park, G., Yun, W.Y., Han, Y. & Kim, J. 2011, "Optimal preventive maintenance intervals of a rolling stock system", *Quality, Reliability, Risk, Maintenance, and Safety Engineering (ICQR2MSE), 2011 International Conference on*IEEE, , pp. 427.

Paz, N.M. & Leigh, W. 1994, "Maintenance scheduling: issues, results and research needs", *International Journal of Operations & Production Management,* vol. 14, no. 8, pp. 47-69.

Peng, F., Kang, S., Li, X., Ouyang, Y., Somani, K. & Acharya, D. 2011, "A heuristic approach to the railroad track maintenance scheduling problem", *Computer‐Aided Civil and Infrastructure Engineering,* vol. 26, no. 2, pp. 129-145.

PRASA 2010, , *Annual Report 2010/2011*. Available: http://www.prasa.com/Documents/AnnualReport2011.pdf [2013, 09/10].

PRASA 2009, , *Passenger Rail Agency of South Africa: About Us*. Available: http://www.prasa.com/About.aspx [2013, 09/10].

Ramanathan, R. 2006, "ABC inventory classification with multiple-criteria using weighted linear optimization", *Computers & Operations Research,* vol. 33, no. 3, pp. 695-700.

Rao, S.S. & Rao, S. 2009a, *Engineering optimization: theory and practice,* John Wiley & Sons.

Rao, S.S. & Rao, S.S. 2009b, *Engineering Optimization: Theory and Practice,* Wiley.

Resnthal, T. 2013, *Repair Store*, Metrorail Salt River.

Rezg, N., Xie, X. & Mati, Y. 2004, "Joint optimization of preventive maintenance and inventory control in a production line using simulation", *International Journal of Production Research,* vol. 42, no. 10, pp. 2029-2046.

Rezg, N., Chelbi, A. & Xie, X. 2005, "Modeling and optimizing a joint inventory control and preventive maintenance strategy for a randomly failing production unit: analytical and simulation approaches", *International Journal of Computer Integrated Manufacturing,* vol. 18, no. 2-3, pp. 225-235.

Rezvanizaniani, S., Valibeigloo, M., Asghari, M., Barabady, J. & Kumar, U. 2008, "Reliability Centered Maintenance for rolling stock: A case study in coaches' wheel sets of passenger trains of Iranian railway", *Industrial Engineering and Engineering Management, 2008. IEEM 2008. IEEE International Conference on*IEEE, , pp. 516.

Rigdon, S.E. & Basu, A.P. 1989, "The power law process: a model for the reliability of repairable systems", *Journal of Quality Technology,* vol. 21, no. 4.

Rommelspacher, K.O. 2012, *The recommendation and validation of an appropriate physical asset management policy for Prasa's Metrorail division*, Stellenbosch University. Faculty of Engineering. Dept. of Industrial Engineering.

Rothlauf, F. 2011, *Design of modern heuristics: principles and application,* Springer.

Roux, O., Duvivier, D., Quesnel, G. & Ramat, E. 2010, "Optimization of preventive maintenance through a combined maintenance-production simulation model", *International Journal of Production Economics*, .

Ryan, K.J., Hamada, M.S. & Shane Reese, C. 2011, "A Bayesian Hierarchical Power Law Process Model for Multiple Repairable Systems with an Application to Supercomputer Reliability", *Journal of quality technology,* vol. 43, no. 3, pp. 209-223.

Safaei, N., Banjevic, D. & Jardine, A.K. 2012, "Multi-threaded simulated annealing for a bi-objective maintenance scheduling problem", *International Journal of Production Research,* vol. 50, no. 1, pp. 63-80.

Saraiva, J.T., Pereira, M.L., Mendes, V.T. & Sousa, J.C. 2011, "A simulated annealing based approach to solve the generator maintenance scheduling problem", *Electric Power Systems Research,* vol. 81, no. 7, pp. 1283-1291.

Saranga, H. 2004, "Opportunistic maintenance using genetic algorithms", *Journal of Quality in Maintenance Engineering,* vol. 10, no. 1, pp. 66-74.

Sarker, R. & Haque, A. 2000, "Optimization of maintenance and spare provisioning policy using simulation", *Applied Mathematical Modelling,* vol. 24, no. 10, pp. 751-760.

Savić, D.A., Bicik, J. & Morley, M.S. 2011, "A DSS generator for multiobjective optimisation of spreadsheet-based models", *Environmental Modelling & Software,* vol. 26, no. 5, pp. 551-561.

Selvik, J.T. & Aven, T. 2011, "A framework for reliability and risk centered maintenance", *Reliability Engineering & System Safety,* vol. 96, no. 2, pp. 324-331.

Sevaux, M. & Le Quéré, Y. 2003, *Solving a robust maintenance scheduling problem at the French railways company,* Technical report, University of Valenciennes.

Sharma, A., Yadava, G. & Deshmukh, S. 2011, "A literature review and future perspectives on maintenance optimization", *Journal of Quality in Maintenance Engineering,* vol. 17, no. 1, pp. 5-25.

Sherwin, D. 2000, "A review of overall models for maintenance management", *Journal of Quality in Maintenance Engineering,* vol. 6, no. 3, pp. 138-164.

Shum, Y. & Gong, D. 2007, "The application of genetic algorithm in the development of preventive maintenance analytic model", *The International Journal of Advanced Manufacturing Technology,* vol. 32, no. 1-2, pp. 169-183.

Smith, R. & Hawkins, B. 2004, "Lean Maintenance", .

Smith, A.M. 1993, *Reliability-centered maintenance,* McGraw-Hill.

Smith, R. & Hawkins, B. 2004, *Lean Maintenance: Reduce Costs, Improve Quality, and Increase Market Share,* Elsevier Science.

Soh, S.S., Radzi, N. & Haron, H. 2012, "Review on Scheduling Techniques of Preventive Maintenance Activities of Railway", *Computational Intelligence, Modelling and Simulation (CIMSiM), 2012 Fourth International Conference on*IEEE, , pp. 310.

Southgate, C. 2013, *FMMS,* Salt River.

Sriskandarajah, C., Jardine, A. & Chan, C. 1998, "Maintenance scheduling of rolling stock using a genetic algorithm", *Journal of the Operational Research Society,* vol. 49, no. 11, pp. 1130-1145.

Swanson, L. 2003, "An information-processing model of maintenance management", *International Journal of Production Economics,* vol. 83, no. 1, pp. 45-64.

Swanson, L. 2001, "Linking maintenance strategies to performance", *International Journal of Production Economics,* vol. 70, no. 3, pp. 237-244.

Thembinkosi, D. 2013, *Components Store*, Metrorail Salt River.

Tokos, H. & Pintarič, Z.N. 2012, "Development of a MINLP model for the optimization of a large industrial water system", *Optimization and Engineering,* vol. 13, no. 4, pp. 625-662.

Tsang, A.H. 2002, "Strategic dimensions of maintenance management", *Journal of Quality in Maintenance Engineering,* vol. 8, no. 1, pp. 7-39.

Umiliacchi, P., Lane, D., Romano, F. & SpA, A. 2011, "Predictive maintenance of railway subsystems using an Ontology based modelling approach", *Proceedings of 9th world Conference on Railway Research, May*, pp. 22.

Vasili, M., Hong, T.S. & Ismail, N. 2011, "Maintenance optimization models: a review and analysis", *optimization,* vol. 1, pp. 2.

Vassiliadis, C. & Pistikopoulos, E. 2001, "Maintenance scheduling and process optimization under uncertainty", *Computers & Chemical Engineering,* vol. 25, no. 2, pp. 217-236.

Vatn, J., Hokstad, P. & Bodsberg, L. 1996, "An overall model for maintenance optimization", *Reliability Engineering & System Safety,* vol. 51, no. 3, pp. 241-257.

Venter, D. 2013, *Reliability Shop*, Metrorail Salt River.

Verma, A. & Ramesh, P. 2007, "Multi-objective initial preventive maintenance scheduling for large engineering plants", *International Journal of Reliability, Quality and Safety Engineering,* vol. 14, no. 03, pp. 241-250.

Vlok, P.J. 2013, *Introduction to Elementary Statistical Analysis of Failure Time Dat: Lomg Term Cost Optimization and Residual Life Estimation*, Class Note edn, Stelenbosch.

Wireman, T. 2005, *Developing Performance Indicators For Managing Maintenance*, Industrial Press.

Wyman, O. 2009, *, Lean Rolling Stock Maintenance: How to improve efficiency of rolling stock maintenance operations*. Available: www.oliverwyman.com [November 2011, .

Yang, X. 2010, *Engineering optimization: an introduction with metaheuristic applications*, John Wiley & Sons.

Yare, Y. & Venayagamoorthy, G.K. 2010, "Optimal maintenance scheduling of generators using multiple swarms-MDPSO framework", *Engineering Applications of Artificial Intelligence*, vol. 23, no. 6, pp. 895-910.

Yun, W.Y., Han, Y.J. & Park, G. 2012, "Optimal preventive maintenance interval and spare parts number in a rolling stock system", *Quality, Reliability, Risk, Maintenance, and Safety Engineering (ICQR2MSE), 2012 International Conference on*IEEE, , pp. 380.

Zhou, X., Xi, L. & Lee, J. 2009, "Opportunistic preventive maintenance scheduling for a multi-unit series system based on dynamic programming", *International Journal of Production Economics*, vol. 118, no. 2, pp. 361-366.

APPENDIX 1

Literature survey showing applications of optimization models

S/N	Year	Author	Publication	Objective	Solution Technique	Description	Case Study
1	2011	(Peng *et al.*, 2011)	A Heuristic Approach to the Railroad Track Maintenance Scheduling Problem	To minimize the total travel costs of the maintenance teams as well as the impact of maintenance projects on railroad operation which are formulated by three types of side constraints: mutually exclusive, time window, and precedence constraints.	Local Search Heuristic Project Swapping Method	Scheduling has to be designed smartly as the available time for maintenance is very limited due to the various factors such as railroad operations, climate and interrelations among different maintenance projects.	Railway
2	2009	(Min *et al.*, 2009)	Multi-objective Optimization of Preventive Maintenance Schedule on Traction Power System in High- Speed Railway	To optimize the maintenance actions to achieve the maximum reliability and minimum maintenance cost.	Evolutionary Algorithm Chaos Self- Adaptive Evolutionary Algorithm	There will be a 5000kM high speed railway with 350km/h speed constructed in China. The maintenance actions can be categorize into three types which are mechanical service, repair and replacement.	Railway
3	1998	(Sriskandarajah, Jardine & Chan 1998)	Maintenance Scheduling of Rolling Stock Using A Genetic Algorithm	To optimize the overhaul maintenance scheduling of rolling stock. To meet a due date as close as possible and avoid the maintenance tasks from being 'too late' or 'too early'	Genetic Algorithm	Hong Kong Mass Transit Railway Corporation had changed their maintenance policy to train-based maintenance. It is difficult to schedule the preventive maintenance scheduling where a various units of a train may require different maintenance requirement at different due dates.	Rolling Stock
4	2003	(García Márquez, Schmid & Conde Collado 2003)	A reliability centred approach to remote condition monitoring. A railway points case study	To detect gradual failure in railway that will allow a move to an RCM approach of maintenance management.	Algorithm Reliability Centred Maintenance	RCM provides powerful rules to decide a technically appropriate failure management policy. It leads to reliability and it's self-sustainable regarding cost.	Railway

5	2011	(Park *et al.*, 2011)	Optimal preventive maintenance intervals of a rolling stock system	To determine the interval of PM for components in rolling stock system.	Simulation	The use of interval optimization function through the means of AvSim found more efficient PM intervals of rolling stock system	Rolling Stock
6	2011	(Umiliacchi *et al.*, 2011)	(Umiliacchi *et al.*, 2011)Predictive Maintenance of Railway subsystems using an Ontology based modelling approach		Ontology- Based RCM		Railway
7	2000	(Bevilacqua, Braglia 2000)	The analytic hierarchy process applied to maintenance strategy selection	To select the optimal maintenance strategy.	Analytic hierarchy process	This paper described an application of the Analytic Hierarchy Process (AHP) for selecting the best maintenance strategy for an important Italian oil refinery (an Integrated Gasification and Combined Cycle plant)	Oil Refinery
8	2010	(Cheng, Tsao 2010)	Rolling stock maintenance strategy selection, spares parts' estimation, and replacements' interval calculation	To select maintenance strategy for rolling stock and obtain possible spare parts' quantities and replacement intervals.	Analytical Network Process	Preventive maintenance should be more valued than corrective maintenance where safety is the most important factor for rolling stock maintenance strategy	Rolling Stock
9	2009	(Jin, Li & Ni 2009)	Option model for joint production and preventive maintenance	To optimize preventive maintenance under uncertain environment	Analytical model	This paper presents an analytical, option-based cost model for scheduling joint production and preventive maintenance when demand is uncertain	Production System
10	2003	(Apeland, Scarf 2003)	A fully subjective approach to modelling inspection maintenance	To determine how the fully Bayesian approach can be used to identify optimal maintenance inspection strategies	Bayesian approach	This paper introduced a fully subjective approach to delay-time modelling. It demonstrates how the fully subjective approach can be applied to the maintenance optimisation problem for a simple system.	Extrusion press of a production plant
11	2003	(Mechefske, Wang 2003)	Using fuzzy linguistics to select optimum maintenance and condition monitoring strategies	To reduce maintenance cost and improve customer satisfaction by selecting the optimum maintenance and condition monitoring strategy	Fuzzy linguistic using multiple criteria decision making	This paper illustrates the use of fuzzy linguistic variables in a heuristic algorithm to assist decision makers in their evaluation and choice of maintenance strategies and condition-monitoring techniques.	Chemical oil Production

12	2003	(Swanson 2003)	An information processing model of maintenance management	To understand the relationship between the complexity of the production environment and the use of maintenance practices that assist in managing the information processing requirements brought on by such complexity	Galbraith information processing model	In this paper, Galbraith's information-processing model is applied to study how the maintenance function applies different strategies to cope with the environmental complexity of allocating maintenance resources in maintenance scheduling.	Production plants
13	2011	(Saraiva *et al.*, 2011)	A Simulated Annealing based approach to solve the generator maintenance scheduling problem	To minimize the operation cost along the scheduling period plus a penalty on energy not supplied	Mixed integer programming Simulated Annealing	Simulated Anealing was used to solve the combinatorial problems. The solution minimized the generation costs along the maintenance planning horizon and it included a reliability measure when penalizing non zero values of energy not supplied	Power Generator
14	2012	(Borraz-Sánchez, Klabjan 2012)	Strategic Gang Scheduling for Railroad Maintenance	To minimize the overall cost incurred by all maintenance job within the given planning horizon.	Strategic Gang Scheduling Integer programming	The design of solution approach based on very large-scale neighbourhood search idea combine with mathematical programming to solve the railway maintenance scheduling problem.	Railway
15	2004	(Mathew 2004)	Optimal inspection frequency A tool for maintenance planning forecasting	To determine an optimal inspection frequency to forecast and plan the future maintenance requirements of spares, man-hours and total costs	Optimal inspection frequency	This paper develops an optimal model, ensuring that the inspection frequency is capable of matching the varying failure rates throughout the life of the equipment. It also demonstrates how this optimal inspection frequency can then be used to plan and forecast maintenance costs.	General
16	1998	(Dekker, Scarf 1998)	On the impact of optimization models in maintenance decision making	To determine an appropriate application of maintenance models	Operational and strategic decision support system	In this paper applications of maintenance optimisation models where discussed and several ways in which operational and strategic decision support systems models may be used to optimise maintenance where discussed.	Civil and Aircraft
17	2010	(Roux *et al.*, 2010)	Optimization of preventive maintenance through a combined maintenance-production simulation model	To simultaneously ensure a low frequency of failures by an efficient periodic preventive maintenance and to minimize the unavailability of	Petri nets	This paper combined several tools to optimize multi-component preventive maintenance problems by applying a combination of timed Petri-nets and PDEVs models	VLE Simulator

				the system due to preventive maintenance			
18	2005	(Kianfar 2005)	A numerical method to approximate optimal production and maintenance plan in a flexible manufacturing system	To maximize the expected discounted total profit of the firm over an infinite time horizon. In the process of finding a solution to the maintenance problem,	Riccati equation	This paper assumes that the demand of the manufacturing product is time dependent and its rate depends on the level of advertisement on that product. A numerical method was used to solve the Riccati equations derived from the optimal control problem	Manufacturing System
19	2009	(Altuger, Chassapis 2009)	Multi criteria preventive maintenance scheduling through Arena based simulation modelling	To implement a multi criteria decision making approach to select the preventive maintenance schedule that gives the best utility and performance values.	Simulation Arena-Based	The paper provided an overall roadmap on how simulation tools can be incorporated and the outcomes can be used in multi criteria decision making problem.	Food industry
20	2000	(Sherwin 2000)	A review of overall models for maintenance management	To review models for maintenance management	Maintenance organization modelling	This Paper gives a review of maintenance organization models, e.g. advanced tero-technological model (ATM), Eindhoven University of Technology model (EUT), total quality management (TQM) model etc. it suggests that maintenance could be a contributor to profits by use of information technology (IT) and showed that integrated IT permits co-planning of production with maintenance.	General
21	2010	(Chien, Chen 2010)	Optimal spare ordering policy for preventive replacement under cost effectiveness criterion	To present a spare ordering policy for preventive replacement with age-dependent minimal repair and salvage value consideration	Poisson process	A spare ordering policy for preventive maintenance with age dependent minimal repair and savage value was presented by analysing the ordering policy, by modelling the failure process, as non-homogeneous Poisson process.	General
22	2008	(Nahas *et al.*, 2008)	Extended great deluge algorithm for the imperfect preventive maintenance optimization of multi-state systems	To find an optimal sequence of maintenance actions which minimizes maintenance cost while providing the desired system reliability level.	Universal generating function technique	The paper used universal generating function technique, to evaluate reliability and propose an optimization method on the basis of extended great deluge algorithm.	Multi-state systems
23	2010	(Yare, Venayagamoorthy 2010)	Optimal maintenance scheduling of generators using multiple swarms-	To improve the quality of the maintenance schedules generated during generator	Particle Swarm Optimization	The results presented in this paper shows great potential for utility application in their area control centres for effective	Power System

			MDPSO framework	maintenance scheduling in terms of reliability and energy cost.		energy management, short and long term generation scheduling, system planning and operation.	
24	2008	(Rezvanizaniani *et al.,* 2008)	Reliability centred Maintenance for rolling stock A case study in coaches‟ wheel sets	To implement RCM as a tool to reduce the maintenance cost.	Reliability Centred Maintenance	RCM is applied to the most substantial section of rolling stock which is the wheel set. This process was able to reduce the downtimes of coaches during service.	Railway
25	2011	(Selvik, Aven 2011)	A framework for reliability and risk centred maintenance	This paper aims to suggest an extension of the RCM to reliability and risk centred maintenance by also considering risk as the reference for the analysis in addition to reliability	Reliability Centred Maintenance	A framework based on existing RCM, which improves the risk and uncertainty assessments by adding some additional features to the existing RCM methodology is presented, the essential feature of the presented framework is the managerial review and judgement, which places the decision process into a broader management context.	Oil and Gas

APPENDIX 2

A

GENETIC ALGORITHM (Moghaddam, Usher 2011)

Begin Generational Genetic Algorithm

g=0

Produce initial population P(g)

Determine the fitness values of members in P(g)

While GA termination condition is not satisfied, do

g=g+1

Select solutions from P(g-1) for P(g) based on their fitness value with the Probability $P_{selection}$ *of as the selected parents*

Make an offspring from selected parents from P(g-1) with the probability of $P_{crosspver}$

Mutate solutions from P(g-1) with the probability of $P_{mutation}$

Determine the fitness values of the new generated solutions in P(g)

End while

End Generational Genetic Algorithm

B

Simulated Annealing Algorithm(Moghaddam, Usher 2011)

Begin SA

k=0

Select $T_{initial}$ *and* T_{final} *if the termination criterion involves* T_{final}

Randomly produce an initial solution x_0 *from S*

Determine the fitness value of the initial solution $f_0 = Cx_0$

While a sufficient number of times to ensure a near-equilibrium condition, do

Randomly select a transition $x_k = y$ *and compute* $\Delta C = C(y) - C(x_k)$*. If* $\Delta C \leq 0$*,*

accept the transition. If $\Delta C > 0$*, accept the transition with probability* $Pr_k(\Delta C) = e^{(\frac{-\Delta C}{T_k})}$

and

reject it with probability $1 - Pr_k(\Delta C)$

If the transition is accepted, update $x_k = y$ *and* $f_k = C(y)$. *(To accept or reject the transition with* $\Delta C > 0$, *First generate a random number p from (0,1). If* $p \leq Pr_k(\Delta C)$, *accept the transition; otherwise, reject it)*

k = k + 1. Find T_k *from* T_{k-1}, *based on the rule for decreasing the control parameter T*

$x_k = x_{k-1}, \quad f_k = f_{k-1}$

End while

End SA

APPENDIX 3

ROLLING STOCK MAINTENANCE PROGRAM

INDEX

1. **PREVENTITIVE MAINTENANCE**
   - 1.1 PASSENGER SAFETY AND COMFORT
   - 1.2 FULL SHEDDING
   - 1.3 CARRIAGE AND WAGON LIFTING

2. **CORRECTIVE MAINTENANCE**
   - **2.1** FAULTS, DEFECTS AND VEHICLE BUILDING REPAIR
   - **2.2** COACH BODY REPAIR AND COMPONENT CHANGE OUT
   - **2.3** COMPONENT REPAIR

3. **HEAVY MAINTENANCE**

4. **WRECKS AND BURNOUT REPAIR**

5. **DEPOT FACILITIES MAINTENANCE**

6. **MAINTENANCE TO VANDALISED ASSETS**

7. **BREAKDOWN AND SITE CLEARING**

Maintenance Program:

1 Preventive Maintenance

1.1 Passenger safety & comfort (PS&C or Intermediate Shed)

In service inspection ***(2 weekly cycle for the Cape Region, Pretoria Region, Wits Region and Durban Region)*** which entails measurement, cleaning, change out, repair and testing of all safety critical aspects such as wheels, doors, hooters, brakes, lights and control instrument gauges. Check passengers comfort requirements e.g. heating. Check oil levels and brush wear on all rotating machines. Do non-critical in-service repairs. The required work is done by suitably qualified personnel on an inspection pit in the allocated maintenance sheds. Sequence-, power- and brake tests are done after completion of work where after the Rolling Stock is certified as ready for service. In service Inspection & Repair of all passenger and driver safety & comfort related equipment must be done by suitably qualified personnel.

	System name or Work done	**Description of repairs done on system, component or sub-assembly**	**Maintenance standards**
1.1.1	High Tension Traction System	-Check & Repair worn components on pantograph, test for correct functioning. -Examine Traction Motor commutator, suspension bearing and brush gear. Clean where necessary and lubricate. -Inspect and repair all High Tension (HT) & low Tension (LT) -equipment. -Examine all High Tension (HT) cables and Low Tension (LT) Wiring	-Refer to shedding checklists. -Maintenance- and repair manuals.
1.1.2	Electric Control System	-Check and repair worn components or defective components. -Check and change-out all defective Auto Notching Equipment. -Inspect, clean or repair all defective electrical components.	-As Above

1.1.3	Body	-Examine vacuum pipes for leaks. -Do vacuum tests after all repairs are done -Examine all air pipes. -Examine inner and outer stem guides on vestibule couplers. -Inspect & Repair all doors for free movement. Check correct speed. Perform electrical test for correct functioning. -Examine & repair defective lights. -Inspect and repair heating system -Examine & repair Hooters and Wipers	-As Above -C&W Handbook Volume 2
1.1.4	Body (Vehicle Building)	-Examine all windows, seats, wall-panels, the ceiling, partitions and end doors. -Examine & Repair all damaged & vandalised interior- and exterior equipment applicable to Vehicle Building. -Remove graffiti	-Maintenance and component overhaul manuals.
1.1.5	Auxiliary Equipment	-Inspect and repair all defective and worn components on auxiliary equipment. -Examine and check commutator, bearing and brush wear. -Lubrication and inspect Compressor and Exhauster	Refer to 1.1.1.
1.1.6	Coach Compressed Air System	-Examine & repair air system for leaks or damage. Change defective components	-As Above
1.1.7	Coach Steering and Support	-Examine bogies and wheels for cracks and any wear & tear. -Examine coil springs and snubbers for cracks and wear & tear. -Examine wheels for the following defects: High, sharp, or thin flanges, skidded wheels, grooved and loose tyres. -Examine bogies and repair where necessary. -Visually examine axle boxes.	-As Above -C&W Handbook Volume 2 -Code of Practice no 2 -C&W checklist
1.1.8	Brake system	-Examine all Brake Blocks, measure and renew or replace where necessary. -Examine all Brake Gear components and repair where necessary. -Renew defective slack adjusters. -Vacuum test brake system.	-C&W Handbook Volume 2

1.2 Full Shedding

The Regional schedules are as follows:
Wits: 18,000km in-service preventative maintenance program carried out on a 4,6,8 or 12 week cycle. Capetown: 18,000km in-service preventative maintenance program carried out on an 8week cycle. Pretoria: 18,000km in-service preventative maintenance program.

Durban: 18,000km in-service preventative maintenance program.

The program entails the Inspection, condition monitoring, lubricating, cleaning and/or replacing of all High Tension (HT) and low Tension (LT) electrical- and mechanical-, roof equipment, body and undercarriage. Suitably qualified personnel must do the required work in the inspection pits in the allocated maintenance sheds. Program work and smaller modifications are done.Sequence-, power- and brake tests are done after completion of work and the train set is then certified as road worthy and ready for service.

All Passenger safety & Comfort maintenance is also done.

	System name or Work done	Description of repairs done on system, component or sub-assembly
1.2.1	High Tension (HT) Traction system	-Check & Repair worn and defective components on Pantograph. Test for correct functioning, grease and lubricate. -Examine Traction Motors Commutators, Suspension Bearings and brush wear. Clean, repair, lubricate & replace where necessary. -Inspect & Repair all defective High Tension (HT) & LT Equipment. Clean and lubricate. Test for correct functioning of Switch Gear. -Clean & Vacuum High Tension (HT) Compartment. -Examine & Repair all High Tension (HT) Cables and LT Wiring -Inspect Gears & Gear cases for leaks and lubricate
1.2.2	Electric Control System	-Inspect, Clean & Repair defective mechanical- and electrical components. -Test & change detective or worn components on Master Controller
1.2.3	Body	-Examine coupler for wear & tear. -Examine inner- and outer stem guides and Vestibule couplers. -Inspect & repair all doors for free movement and correct speed. Electrically test for correct operation. -Examine & repair defective lights and clean lights fittings. -Inspect and repair heating system -Inspect & repair hooter and wipers

1.2.4	Body (Vehicle Building)	-Examine & repair Windows, Floors, Seats, Wall Panels, Ceiling, Partitions, Doors, Roof ventilation and Catwalks, Step Boards & Trimming. -Examine & Repair all interior and exterior equipment for damage and vandalism -Repair Toilets -Remove graffiti
1.2.5	Auxiliary Equipment	-Inspect, clean and change of defective and worn components. -Examine & check Commutator condition, Bearing and Brush wear. -Condition monitoring on Compressor & Exhauster
1.2.6	Coach Compressed Air Supply System	-Examine air system for damage or leaks. Repair where defective. -Change out Valves on Program Work schedules.
1.2.7	Steering and coach body support	-Examine Bogie for cracks, wear and missing split pins and replace where necessary. -Examine Coil springs and Snubbers for cracks, wear, brakeages and perished rubbers. -Examine and measure Wheel wear and profile of all Wheels.
1.2.8	Program work	-Program Work done on components as per applicable schedule.
1.2.9	Brake system	-Examine carefully all brake blocks. Replace brake blocks where needed. -Examine carefully all the brake gear. Replace or repair where needed. -Replace defective slack-adjusters. -Vacuum-test the braking system.

1.3 Carriage and Wagon Lifting

Scheduled 18month preventative maintenance of undercarriage, frame, body and brake system on Plain Trailers, ***and on Motor Coaches as- and-when they undergo Corrective Maintenance***. Coaches are withdrawn from service for the inspection, measurement, replacement or renewal of all defective or worn components or parts. Before being placed back into service, all systems and components are tested and the coach is then declared roadworthy. Work performed by suitably qualified personnel.

	System name or Work done	Description of repairs done on system, component or sub-assembly
1.3.1	Body. (Draw gear)	-Examine and repair all Draw gears. Measure bushes and replace or renew where necessary. -Inner and Outer Stem Guides, Vestibule Couplers and Stem Guide Rods are examined and repaired where necessary.
1.3.2	Brake system	-All Vacuum Cylinders are overhauled every 36 months on Motor coaches & Plain trailers. They are stripped, cleaned, examined, assemble and tested. -Slack Adjusters are tested, overhauled and/or replaced -Brake Gear components are examined for wear and tear and replaced or renewed. -Brake Blocks must be measured against the required standards and renewed or replaced where necessary. -All Vacuum pipes are examined and repaired, cleaned or replaced. -Brake system is adjusted and tested
1.3.3	Coach steering and support (Wheel and Bogie)	-Examine wheels for visible defects. -Link, Brake-, split pins are examined, measured and replaced where necessary.

APPENDIX 4

Critical Failure Analysis for 5M2A MOTOR COACH

Summary	No of faults
Compressed Air System (A)	150
Brake Equipment (B)	58
Cab and Body and doors (C)	48
Electrical and Electronic Equipment (E)	262
Auxiliary Machines (M)	296
High Voltage and switch Equipment (P)	257
Wheel/Axle/Bogie(X)	68
FIRE EXTINGUISHER(Z)	1

Fault Group	Number of in service failures																													
	MC1	MC2	MC3	MC4	MC5	MC6	MC7	MC8	MC9	MC10	MC11	MC12	MC13	MC14	MC15	MC16	MC17	MC18	MC19	MC20	MC21	MC22	MC23	MC24	MC25	MC26	MC27	MC28	MC29	MC30
Compressed Air System (A)	0	1	0	1	9	0	1	3	10	7	10	4	11	5	18	5	10	1	6	2	0	0	1	1	12	14	2	11	0	5
Brake Equipments (B)	3	4	0	0	3	2	0	0	0	1	0	1	4	7	1	3	5	1	1	1	0	0	1	1	6	0	2	4	1	6
Cab,Body and Doors (C)	0	2	1	0	1	0	0	3	3	0	2	4	1	1	2	0	11	0	0	0	0	2	1	0	5	3	2	3	0	1
Electrical and Electronic Equipment (E)	0	2	1	3	12	4	0	10	25	9	43	8	12	15	18	12	20	7	2	5	2	0	3	6	9	14	1	4	7	8
Auxiliary Machines (M)	10	7	6	1	26	7	9	12	7	22	3	27	12	12	2	19	16	4	0	14	13	3	2	1	11	3	4	18	9	16
High Voltage and switch Equipment	0	2	0	0	20	0	1	14	4	7	16	16	21	18	8	14	21	10	1	0	2	1	0	8	21	9	0	13	1	29
Wheel/Axle/Bogie(X)	0	0	0	0	4	6	3	6	10	3	0	1	1	0	2	0	4	0	0	0	0	4	0	2	5	4	4	3	0	6
FIRE EXTINGUISHER(Z)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0

Fault Grouping and Codes

Fault Group	Code	Description	Fault Group	Code	Description
Compressed Air System (A)			**Auxiliary Machines (M)**		
AC	ACTA	Test / Examination	MK	MKAM	Armature Defective
AC	ACOA	Oil Level Low	MM	MMBS	Brush Box Worn / Burnt
AP	APAC	Air Hose Perished / Missing	MM	MMBT	Brushes Worn / Chipped / Sticky
AP	APDT	Drain Valve Def / Missing	MM	MMTA	Test / Examination
AP	APHC	Hose Coupling Seal Perished / Missing	MS	MSSJ	Siren Defective
AP	APRE	Reducing Valve Defective	MT	MTAM	Armature Defective/ Earthed
AP	APVF	Valve Sticky / Dirty	MT	MTBB	Bearing Failure
AW	AWIA	Idler / Wiper Arm Bent / Loose / Broken	MT	MTBS	Brush Box Worn / Burnt / Loose
AW	AWTA	Test / Examination	MT	MTCL	Commutator Worn
AW	AWWF	Wiper Motor Defective	MT	MTCV	Cover Missing
AW	AWWG	Blade Worn / Damaged	MT	MTED	Ext. Cables /Connections / Boxes Def
Brake Equipment (B)			MT	MTGA	Fields Earthed
BJ	BJTA	Test / Examination	MT	MTID	Int. Cables / Fields / Interpoles Flash
BK	BKLB	Leaking Through	MT	MTLG	Low Megger Reading
BV	BVVD	Valve / Pipe Blocked	MT	MTTA	Test / Examination
BW	BQLB	Pulling Through	**High Voltage and switch Equipment (P)**		
BQ	BQPW	Program Work	GP	GPBA	Balancing Gear Defective
BQ	BWOA	Oil Level Low	GP	GPIC	Insulators Flashed / Dirty / Broken
Cab,Body and Doors (C)			GP	GPPB	Panto Skate Strips Worn
CI	CIGC	Globes Blown / Missing	HL	HLSY	Switch Burnt / Defective
CM	CMWC	Window Broken / Stuck / Missing	PCA	PCABF	Blow Out Coil O/C / Flashed / Sb

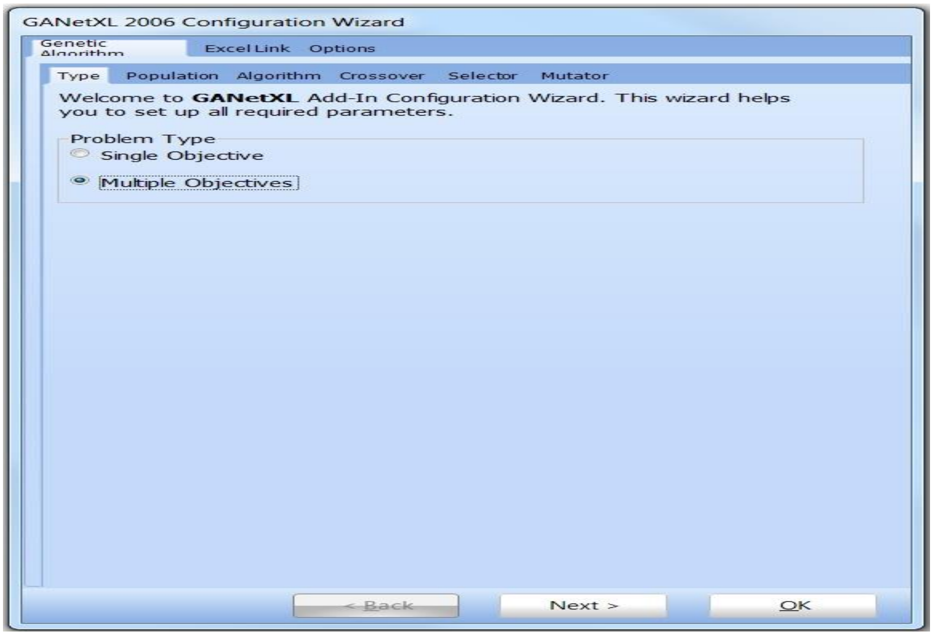
CM	CMWE	Window Glass Scratched	PCA	PCACC	Cables / Wiring Burnt / Oc / Loose
IF	IFFO	Floor Structure Damaged	PCA	PCATA	Test / Examination
OE	OEDL	Door Lock Missing / Damaged	PCB	PCBPF	Piston Leaking / Sluggish
OE	OEWC	Window Broken / Stuck / Missing	PCB	PCBMA	Magnet Valve Sticky
UB	UBGD	Guides Worn	PCB	PCBSX	Support Bars Flashed / Earthed
Electrical and Electronic Equipment (E)			PCC	PCCBF	Blow Out Coil O/C / Flashed / Sbt
EA	EADC	Defective	PCC	PCCCC	Cables / Wiring Burnt / Oc / Loose
EG	EGEA	Electronics Def (Cards, Timers etc)	PC	PCCO	Contact Gaps Incorrect
EC	ECCC	Cables / Wiring Burnt / Oc / Loose	PCC	PCCPG	Poppit Valve Worn / Sticky / Leaking
EC	ECCQ	Contacts Glazed / Burnt / Worn / Broken	PC	PCCQ	Contacts Glazed / Burnt / Worn / Broken
EG	EGCD	Calibration	PCD	PCDCM	Connection Loose / Burnt
EG	EGET	Transducer Defective	PC	PCIE	Interlocks Defective
EG	EGIE	Interlocks Defective	PC	PCSS	Inlet Valve Worn / Sticky / Leaking
EG	EGTA	Test / Examination	PC	PCSX	Shunt Strap Frayed / Burnt / Flashed
EI	EIDC	Defective	PC	PCTA	Test / Examination
EI	EIGC	Globes Blown / Missing	PV	PVRJ	Resistor O/C
EI	EIOD	Gauges Out Dated	**Wheel/Axle/Bogie(X)**		
EJ	EJCC	Cables / Wiring Burnt / Oc / Loose	XF	XFTA	Test / Examination
EJ	EJDB	Damaged / Missing	XW	XWEH	Excessive Hollow Wear
ELA	ELASC	Sealed Beam Blown / Broken	XW	XWTA	Test/Examination
ELA	ELAGC	Globes Blown / Missing	XW	XWTB	Thin Flange / Tyre Down To Gauge
EL	ELGC	Globes Blown / Missing	**FIRE EXTINGUISHER(Z)**		
EMB	EMBCI	Circuit Breaker Burnt / O/C	ZF	ZFTA	Securing Belt Damaged
EMB	EMBSY	Switch Burnt / Defective			
EO	EOEF	Encoder Shaft Defective / Broken			
EO	EOSP	Speedo Cable O/C			
EO	EOSR	Speedo Probe Defective			

EO	EOTA	Test / Examination			
ERB	ERBCD	Calibration			
EU	EUCQ	Contacts Glazed / Burnt / Worn / Broken			
EQ	EQCU	Cover / Clip Missing / Broken			
EQ	EQSV	Spring Weak / Missing			
EY	EYBD	Bell Plunger Sticky / Adjustment			

APPENDIX 5

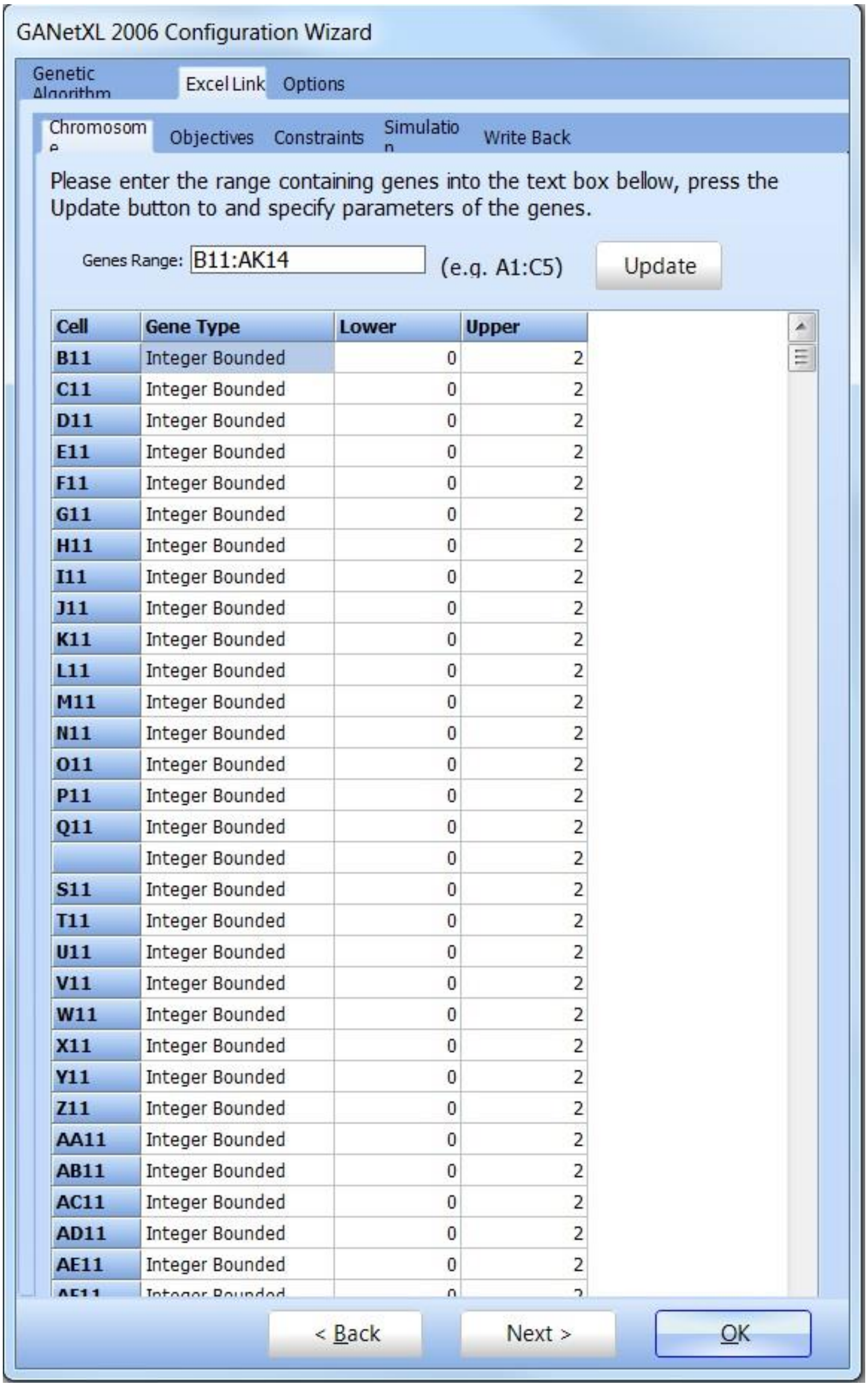
GENeXL optimization window

MODEL TYPE SELECTION

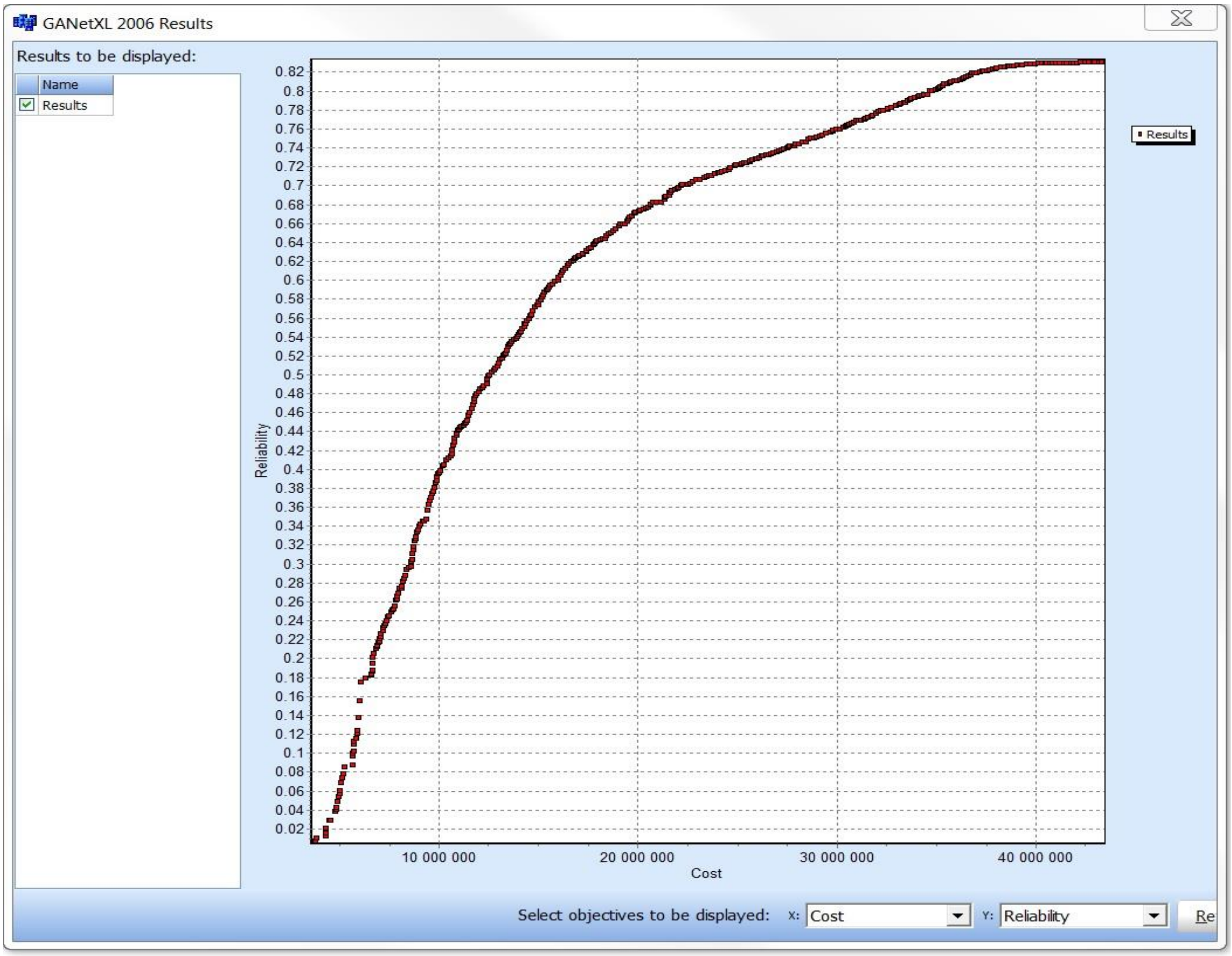


DEFINING OBJECTIVE FUNCTIONS

SPECIFY DECISION VARIABLES AND BOUNDERIES


GANetXL 2006 Configuration Wizard
Genetic Algorithm
Excel Link
Options
Chromosome
Objectives
Constraints
Simulation
Write Back
Please enter the range containing genes into the text box bellow, press the Update button to and specify parameters of the genes.
Genes Range: B11:AK14
(e.g. A1:C5)
Update
Cell | Gene Type | Lower | Upper
B11 | Integer Bounded | 0 | 2
C11 | Integer Bounded | 0 | 2
D11 | Integer Bounded | 0 | 2
E11 | Integer Bounded | 0 | 2
F11 | Integer Bounded | 0 | 2
G11 | Integer Bounded | 0 | 2
H11 | Integer Bounded | 0 | 2
I11 | Integer Bounded | 0 | 2
J11 | Integer Bounded | 0 | 2
K11 | Integer Bounded | 0 | 2
L11 | Integer Bounded | 0 | 2
M11 | Integer Bounded | 0 | 2
N11 | Integer Bounded | 0 | 2
O11 | Integer Bounded | 0 | 2
P11 | Integer Bounded | 0 | 2
Q11 | Integer Bounded | 0 | 2
Integer Bounded | 0 | 2
S11 | Integer Bounded | 0 | 2
T11 | Integer Bounded | 0 | 2
U11 | Integer Bounded | 0 | 2
V11 | Integer Bounded | 0 | 2
W11 | Integer Bounded | 0 | 2
X11 | Integer Bounded | 0 | 2
Y11 | Integer Bounded | 0 | 2
Z11 | Integer Bounded | 0 | 2
AA11 | Integer Bounded | 0 | 2
AB11 | Integer Bounded | 0 | 2
AC11 | Integer Bounded | 0 | 2
AD11 | Integer Bounded | 0 | 2
AE11 | Integer Bounded | 0 | 2
< Back
Next >
OK

RESULTS


GANetXL 2006 Results
Results to be displayed:
Name
Results
Reliability
Cost
10 000 000
20 000 000
30 000 000
40 000 000
Results
Select objectives to be displayed:
X: Cost
Y: Reliability

APPENDIX 6

GENETIC ALGORITHM MATLAB CODES

GENETIC ALGORITHM

```
%*************************************************************
% Number of components and periods
N = 4;
T = 36;
%*************************************************************
% Genetic Algorithm
% Genetic algorithm parameters
% Number of generations: 500
% Population size: 2000
% Probability of selection: 0.20
% Probability of crossover: 0.40
% Probability of mutation: 0.30
generation_number = 100;
population_size = 2000;
p_selection = 0.20;
p_crossover = 0.50;
p_mutation = 0.50;
min = 0;
max = 2;
% Initial population
a = zeros(1,T*N);
initial_population = zeros(population_size,T*N+3);
for i = 1:1:population_size
for j = 1:1:T*N
a(j) = fix((max-min+1)*rand+min);
end
[Tcost,Reliability,fit1,reliability_schd,A,Aver_Rel] =
Fitness(a);
initial_population(i,1:N*T) = a ;
initial_population(i,N*T+1:N*T+3) =[Tcost,Reliability,fit1];
end
population = initial_population;
for g = 1:1:generation_number
% Selection procedure
population_sorted = sortrows(population,N*T+3);
population_selected
=population_sorted(1:fix(p_selection*population_size),:);
% Crossover procedures
for i = 1:1:p_crossover*population_size
parent1 = population(fix((population_size)*rand+1),:);
parent2 = population(fix((population_size)*rand+1),:);
if parent1(:,N*T+3) ~= parent2(:,N*T+3)
%NT point crossover
offspring = NTpointcrossover(parent1,parent2);
elseif parent1(:,N*T+3) == parent2(:,N*T+3)
% Two point inverse crossover
```

```
offspring = Tpointcrossover(parent1,parent2);
end
[Tcost,Reliability,fit1] = Fitness(offspring);
population_crossover(i,1:N*T) = offspring;
population_crossover(i,N*T+1:N*T+3) =[Tcost,Reliability,fit1];
end
% Mutation procedure
for i = 1:1:p_mutation*population_size
individual = population(fix((population_size)*rand+1),:);
individual_mutated = Mutation(individual);
[Tcost,Reliability,fit1] =Fitness(individual_mutated);
population_mutation(i,1:N*T) = individual_mutated(:,1:N*T);
population_mutation(i,N*T+1:N*T+3) =[Tcost,Reliability,fit1];
end
% This section generates a new population based on
selection,crossover and mutation procedures
population
=[population_selected;population_crossover;population_mutation
];
% This section sorts the solutions in the current population
based on their fitness value and selects the best one in each
generation
ss = sortrows(population,N*T+3);
solution_improvement(g,:) = ss(1:1,:);
end
% This section sorts the last population based on its fitness
values and then changes the final solution(1,N*T) to
PMR_Schedule(N,T)
last_population = sortrows(population,N*T+3);
final_solution = last_population(1:1,:);
PMR_Schedule = zeros(N,T);
for i = 1:1:N
for j = 1:1:T
PMR_Schedule(i,j) = final_solution(1,(i-1)*T+j);
end
end
```

FITNESS FUNCTIONS

```
function [Tcost,Reliability,fit1,reliability_schd,A,Aver_Rel]
= Fitness(a)
%**************************************************************
%Data of the Multi-Objective Optimization Model
% Number of components and periods
N = 4;
T = 36;
J = 36;
L = T/J;
% Specification of the components
% Parameters of the Failure function
Gamma = [0.002376738 0.000119814 0.002626395 0.000022679];
Delta = [1.620982079 2.212852684 1.529811075 2.551833431];
```

```
% Improvement factor (Age reduction coefficient)
Alpha = [0.7 0.7 0.7 0.7];
% Failure cost
Failure_Cost = [400720 210720 222720 340720];
% Maintenance cost
M_Cost = [20000 65000 40000 70000];
% Replacement cost
R_Cost = [320000 85000 120000 210000];
% Opportunity cost
Opportunity_Cost = 500000;
% Parameters of the multi-objective optimization model
% Weights of the objective functions in weighted method, W1+W2
= 1
%W1 = 0.0; W2 = 1.0;
%W1 = 0.1; W2 = 0.9;
%W1 = 0.2; W2 = 0.8;
%W1 = 0.3; W2 = 0.7;
%W1 = 0.4; W2 = 0.6;
W1 = 0.5; W2 = 0.5;
%W1 = 0.6; W2 = 0.4;
%W1 = 0.7; W2 = 0.3;
%W1 = 0.8; W2 = 0.2;
%W1 = 0.9; W2 = 0.1;
%W1 = 1.0; W2 = 0.0;
% Design goals for the objective functions in goal attainment method
RR = 0.5;
%*************************************************************
% This section changes a(1,N*T) to A(N,T)
A = zeros(N,T);
 for i = 1:1:N
     for  j = 1:1:T
          A(i,j) = a(1,(i-1)*T+j);
     end
end

% This section calculates the x(starting effective age) and
xp(ending effective age)
x = zeros(N,T);
 for i = 1:1:N
     for j = 1:1:T-1
          if A(i,j) == 0
             x(i,j+1) = x(i,j)+L;
          elseif A(i,j) == 1
             x(i,j+1) = Alpha(i)*(x(i,j)+L);
          elseif A(i,j) == 2
             x(i,j+1) = 0;
          end
     end
end
xp = x+L;
```

```
%This section calculates the Expected number of failures of
components
E = zeros(N,T);
 for i = 1:1:N
     for j = 1:1:T
         E(i,j) = Gamma(i)*((xp(i,j)^Delta(i))-(0^Delta(i)));
     end
end

%This section calculates the Failure cost of components
Fcost = zeros(N,T);
 for i = 1:1:N
     for j = 1:1:T
         Fcost(i,j) = Failure_Cost(i)*E(i,j);
     end
end
% This section calculates the Cost of maintenance and
replacement and failure
cost = zeros (N,T);
 for i = 1:1:N
     for j = 1:1:T
          if A(i,j)== 0
             cost(i,j) = Fcost(i,j);
          elseif A(i,j) == 1
             cost(i,j) = Fcost(i,j)+M_Cost(i);
          elseif A(i,j) == 2
             cost(i,j) = Fcost(i,j)+R_Cost(i);
          end
     end
end
Tcost = 0;
costm = zeros(1,T);
 for j= 1:T
     costm (j) = sum(cost(:,j));
     if sum(A(:,j))>0
        costm(j)= Fixed_Cost+sum(cost(:,j));
        Tcost = sum(costm);
     end
end
%This section calculates the Maximum Cost
Max_cost = 0;
xx = zeros(N,T);
costma = zeros (N,T);
 for j = 1:1:T
     for i = 1:1:N
        xxp = xx+L;
        costma (i,j) =
(Failure_Cost(i)*(Gamma(i)*((xxp(i,j)^Delta(i))-
(xx(i,j)^Delta(i)))))+R_Cost(i);
     end
end
costmaa = zeros(1,T);
```

```
 for j= 1:T
     costmaa(j)= Fixed_Cost+sum(costma(:,j));
     Max_cost = sum(costmaa);
 End

%This section calculates the reliability of components
reliability_schd=zeros(N,T);
System_Reliability = zeros(1,T);
 for j = 1:1:T
     for i = 1:1:N
         reliability_schd(i,j)= exp(-E(i,j));
     end
         System_Reliability(j) = prod(reliability_schd(:,j));
end
Reliability = prod(System_Reliability);
Aver_Rel = mean(System_Reliability);
% The fitness functions,
fit1 = W1*(Tcost/Max_cost)+W2*(-Reliability);
fit2 =(Tcost/Max_cost)+abs(RR-Reliability);
```

NT CROSSOVER

```
function [offspring] = NTpointcrossover(parent1,parent2)
%*************************************************************
% Number of components and periods
N = 4;
T = 36;
%*************************************************************
 for i = 1:1:(N*T)/2
     offspring(:,2*i-1) = parent1(:,2*i-1);
     offspring(:,2*i) = parent2(:,2*i);
 end
```

TWO POINT INVERSE CROSSOVER

```
function [offspring] = Tpointcrossover(parent1,parent2)
%*************************************************************
% Number of components and periods
N = 4;
T = 36;
%*************************************************************
crossoverpoint1 = fix(N*T*rand+1);
crossoverpoint2 = fix(N*T*rand+1);
crossoverpoint1 = abs((crossoverpoint1+crossoverpoint2)/2)-
abs((crossoverpoint1-crossoverpoint2)/2);
crossoverpoint2
=abs((crossoverpoint1+crossoverpoint2)/2)+abs((crossoverpoint1
-crossoverpoint2)/2);
 for i = 1:1:N*T
     parent1_inv(:,N*T-i+1) = parent1(:,i);
```

```
 end
offspring
=[parent1_inv(:,1:crossoverpoint1),parent2(:,crossoverpoint1+1
:crossoverpoint2),parent1_inv(:,crossoverpoint2+1:N*T)];
```

MUTATION

```
function [individual] = Mutation(individual)
%*************************************************************
*************
% Number of components and periods
N = 4;
T = 36;
%*************************************************************
*************
mutation_point = fix(N*T*rand+1);
 if individual(:,mutation_point) == 0
     if (rand < 0.5)
          for k = 1:1:N
               if mod(mutation_point,T) == 0
                individual(:,(mod(mutation_point,T)+k*T)) = 1;
               else
                individual(:,(mod(mutation_point,T)+(k-1)*T))=
          1;
               end
          end
     elseif (rand >= 0.5)
          for k = 1:1:N
               if mod(mutation_point,T) == 0
                  individual(:,(mod(mutation_point,T)+k*T)) =
          2;
               else
               individual(:,(mod(mutation_point,T)+(k-1)*T)) =
          2;
               end
          end
     end
elseif individual(:,mutation_point) == 1 ||
individual(:,mutation_point) == 2
     for k = 1:1:N
          if mod(mutation_point,T) == 0
             individual(:,(mod(mutation_point,T)+k*T)) = 0;
          else
             individual(:,(mod(mutation_point,T)+(k-1)*T)) =
     0;
          end
     end
end
```

APPENDIX 7

SIMULATED ANNEALING MATLAB CODES

SIMULATED ANNEALING ALGORITHM

```
%*************************************************************
************
% Data of the Multi-Objective Optimization Model
% Number of components and periods
N = 4;
T = 36;
J = 36;
L = T/J;
%*************************************************************
************
% Simulated Annealing Algorithm
% Simulated annealing algorithm parameters
% Initial temperature: 1000000
% Final temperature: 0.01
% Decreasing rate: 0.98
t_initial = 1000000;
t_final = 0.01;
t_rate = 0.99;
min = 0;
max = 2;
% Initial solution
a = zeros(1,T*N);
 for j = 1:1:T*N
     a(j) = fix((max-min+1)*rand+min);
 end
[Tcost,Reliability,fit1,reliability_schd,A] = Fitness(a);
initial_solution(1,1:N*T) = a ;
initial_solution(1,N*T+1:N*T+3) = [Tcost,Reliability,fit1];
x = initial_solution;
t_current = t_initial;
i = 1;
 while t_final <= t_current

% Transition procedure
y = Transition(x);
[Tcost,Reliability,fit1] = Fitness(y);
y(1,N*T+1:N*T+3) = [Tcost,Reliability,fit1];

% Acceptation procedure
 if y(1,N*T+3) < x(1,N*T+3)
     x = y;
 elseif y(1,N*T+3) >= x(1,N*T+3)
          if rand <= exp(-(y(1,N*T+3)-x(1,N*T+3))/t_current)
              x = y;
          end
     end
```

```
solution_improvement(i,1:N*T+3) = x;
t_current = t_rate*t_current;
i = i+1;
 end

% This section changes the final solution (1,N*T) to
PMR_Schedule(N,T)
ss = sortrows(solution_improvement,N*T+3);
final_solution = ss(1:1,:);
PMR_Schedule = zeros(N,T);
 for i = 1:1:N
     for j = 1:1:T
         PMR_Schedule(i,j) = final_solution(1,(i-1)*T+j);
     end
 end
```

FITNESS FUNCTIONS

```
function [Tcost,Reliability,fit1,reliability_schd,A,Aver_Rel]
= Fitness(a)
%***************************************************************
***
%Data of the Multi-Objective Optimization Model
% Number of components and periods
N = 4;
T = 36;
J = 36;
L = T/J;
% Specification of the components
% Parameters of the Failure function
Gamma = [0.002376738 0.000119814 0.002626395 0.000022679];
Delta = [1.620982079 2.212852684 1.529811075 2.551833431];
% Improvement factor (Age reduction coefficient)
Alpha = [0.7 0.7 0.7 0.7];
% Failure cost
Failure_Cost = [400720 210720 222720 340720];
% Maintenance cost
M_Cost = [20000 65000 40000 70000];
% Replacement cost
R_Cost = [320000 85000 120000 210000];
% Opportunity cost
Opportunity_Cost = 500000;
% Parameters of the multi-objective optimization model
% Weights of the objective functions in weighted method, W1+W2
= 1
%W1 = 0.0; W2 = 1.0;
%W1 = 0.1; W2 = 0.9;
%W1 = 0.2; W2 = 0.8;
%W1 = 0.3; W2 = 0.7;
%W1 = 0.4; W2 = 0.6;
W1 = 0.5; W2 = 0.5;
%W1 = 0.6; W2 = 0.4;
```

```
%W1 = 0.7; W2 = 0.3;
%W1 = 0.8; W2 = 0.2;
%W1 = 0.9; W2 = 0.1;
%W1 = 1.0; W2 = 0.0;
% Design goals for the objective functions in goal attainment method
RR = 0.5;
%***************************************************************
************
% This section changes a(1,N*T) to A(N,T)
A = zeros(N,T);
 for i = 1:1:N
     for  j = 1:1:T
          A(i,j) = a(1,(i-1)*T+j);
     end
end

% This section calculates the x(starting effective age) and
xp(ending effective age)
x = zeros(N,T);
 for i = 1:1:N
     for j = 1:1:T-1
          if A(i,j) == 0
             x(i,j+1) = x(i,j)+L;
          elseif A(i,j) == 1
             x(i,j+1) = Alpha(i)*(x(i,j)+L);
          elseif A(i,j) == 2
             x(i,j+1) = 0;
          end
     end
end
xp = x+L;

%This section calculates the Expected number of failures of
components
E = zeros(N,T);
 for i = 1:1:N
     for j = 1:1:T
         E(i,j) = Gamma(i)*((xp(i,j)^Delta(i))-(0^Delta(i)));
     end
end

%This section calculates the Failure cost of components
Fcost = zeros(N,T);
 for i = 1:1:N
     for j = 1:1:T
         Fcost(i,j) = Failure_Cost(i)*E(i,j);
     end
end

% This section calculates the Cost of maintenance and
replacement and failure
cost = zeros (N,T);
```

```
 for i = 1:1:N
     for j = 1:1:T
          if A(i,j)== 0
             cost(i,j) = Fcost(i,j);
          elseif A(i,j) == 1
             cost(i,j) = Fcost(i,j)+M_Cost(i);
          elseif A(i,j) == 2
             cost(i,j) = Fcost(i,j)+R_Cost(i);
          end
     end
end
Tcost = 0;
costm = zeros(1,T);
 for j= 1:T
     costm (j) = sum(cost(:,j));
     if sum(A(:,j))>0
        costm(j)= Fixed_Cost+sum(cost(:,j));
        Tcost = sum(costm);
     end
end

%This section calculates the Maximum Cost
Max_cost = 0;
xx = zeros(N,T);
costma = zeros (N,T);
 for j = 1:1:T
     for i = 1:1:N
        xxp = xx+L;
        costma (i,j) =
(Failure_Cost(i)*(Gamma(i)*((xxp(i,j)^Delta(i))-
(xx(i,j)^Delta(i)))))+R_Cost(i);
     end
end
costmaa = zeros(1,T);
 for j= 1:T
     costmaa(j)= Fixed_Cost+sum(costma(:,j));
     Max_cost = sum(costmaa);
 End

%This section calculates the reliability of components
reliability_schd=zeros(N,T);
System_Reliability = zeros(1,T);
 for j = 1:1:T
     for i = 1:1:N
         reliability_schd(i,j)= exp(-E(i,j));
     end
         System_Reliability(j) = prod(reliability_schd(:,j));
end
Reliability = prod(System_Reliability);
Aver_Rel = mean(System_Reliability);
% The fitness functions,
fit1 = W1*(Tcost/Max_cost)+W2*(-Reliability);
```

```
fit2 =(Tcost/Max_cost)+abs(RR-Reliability);
```

TRANSITION

```
function [x] = Transition(x)
%***************************************************************
************
%Data of the Multi-Objective Optimization Model
% Number of components and periods
N = 4;
T = 36;
%***************************************************************
************
transition_point = fix(N*T*rand+1);
 if x(:,transition_point) == 0
     if (rand < 0.5)
          for k = 1:1:N
               if mod(transition_point,T) == 0
                  x(:,(mod(transition_point,T)+k*T)) = 1;
               else
                  x(:,(mod(transition_point,T)+(k-1)*T)) = 1;
               end
          end
     elseif (rand >= 0.5)
          for k = 1:1:N
               if mod(transition_point,T) == 0
                  x(:,(mod(transition_point,T)+k*T)) = 2;
               else
                  x(:,(mod(transition_point,T)+(k-1)*T)) = 2;
               end
          end
     end
 elseif x(:,transition_point) == 1 || x(:,transition_point) ==
2
     for k = 1:1:N
          if mod(transition_point,T) == 0
             x(:,(mod(transition_point,T)+k*T)) = 0;
          else
             x(:,(mod(transition_point,T)+(k-1)*T)) = 0;
          end
     end
end
```