Preventative maintenance optimisation in a capital-constrained environment

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Abstract

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Due to the recognition of the importance of maintenance from an organisational perspective, a number of different maintenance-related approaches have been developed. These approaches include reliability centred maintenance, business-centred maintenance, total productive maintenance and life cycle costing. They consider maintenance from specific different viewpoints and no single approach can be applied to all circumstances. Common to all these approaches are techniques to optimise the maintenance strategies using mathematical models. A variety of mathematical approaches are described in the literature, all of which involve the minimisation of the total costs incurred in relation to the required maintenance activities. This study focuses on data-driven optimisation models that consider costs and the reliability performance of equipment. The practical implementation of these optimising maintenance models presents two main challenges. First, the decision on when to use which model would depend on the type of system/equipment under consideration, as well as on available data. Different models based on analysing the historical failure data of the system or component are considered in order to optimise the maintenance strategies to be applied to these two types of individual systems. In the case of having a number of identical components or systems in series, where a shutdown of one of the systems results in the shutdown of the entire series, models are considered to allow for analysis with the correct maintenance technique of components or systems showing these trends. A major limitation of these maintenance optimisation models is that they all require failure data for their implementation, which is not always obtainable. Historical maintenance cost data, however, is mostly available, therefore forecasting techniques and life cycle cost modelling are also considered. Second, the successful implementation of optimised maintenance strategies will be dependent on informed budgetary decisions being made. Therefore, the challenge of integrating the outputs from the variety of optimisation models utilised into a cohesive compilation and sensible presentation of an overall maintenance budget for a complex plant needs to be addressed. This study presents an integrated maintenance optimisation model that uses the appropriate sub-models described individually in the literature to enable the integrated compilation and sound presentation of an overall maintenance budget for a complex plant for appropriate decision-making.

The use of the case study validates this methodology. It illustrates that a concise, integrated overall budgetary maintenance decision model is highly beneficial in communicating the budgetary requirements for an organisation. It was found that the outcome resulted in an effective decision-making tool with significant potential for implementation in a variety of organisations in search of optimal maintenance planning and budgetary requirements.

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Table of contents

Nomenclature

b_i	State @ point in time
C_0	Fixed set-up cost
C_f	Cost of system replacement
C_f	Cost of failure for non-repairable analysis
C_g	Group replacement cost of individual component
C_i	Expected number of failures
C_mr	Minimal repair cost
C_ov	Overhaul cost
C_p	Average cost of repair of failure
C_p	Cost of preventive maintenance for non-repairable analysis
C_pr	Partial renewal cost
C_i^c	Failure cost
C_i^p	Preventive cost
$\mathrm{C(t)}$	Cost curve
CV	Coefficient of variance
c_n	KS test critical value
D_n	KS test statistic
D_n^-	KS test statistic lower limit
D_n^+	KS test statistic upper limit
$\mathrm{E[N(t)]}$	Expected number of failures in (0, T)
F_0	Probabilistic distribution function
F_i	Forecasted value
F_n	Empirical distribution function
$\mathrm{f(t)}$	Weibull probability density function
$\mathrm{F(t)}$	Weibull cumulative probability function
$\mathrm{H(t)}$	Expected number of times component fails in interval
H_0	Null hypothesis
H_a	Alternative hypothesis
K	Total number of cycles before overhaul
k_i	Interval for replacement

L	Laplace test
m	Iteration factor for NHPP model 1
MTBF	Average time between system failures
n	Number of observed failures for component/system
n^*	Optimum number of minimal repairs for repairable systems
N	Number of components
N(T)	Number of failures in (0, T)
$R(T_1, T_2)$	Probability of system survival
S(t)	Weibull survivor function
T	Cumulative time
t	Discrete local time
t_i	Discrete local time at a certain instance
T^*	Optimum replacement time for repairable systems
T_i	Cumulative time of system/component life at certain instant
T_n	Cumulative time of system/component life
T_p	Preventive maintenance time
U_{LR}	Lewis-Robinson test
$Var\|\overline{X}\|$	Variance
$\overline{X}$	Mean
y	Actual value
z(t)	Weibull hazard function
α_0	Parameter of NHPP model 1
α_1	Parameter of NHPP model 1
λ_i	Intensity function
ρ_1	NHPP model 1
ρ_2	NHPP model 2
β	Parameter of NHPP model 2
β	Shape parameter for the Weibull distribution
λ	Parameter of NHPP model 2
η	Scale parameter for the Weibull distribution

1 Introduction

1.1 Background

Historically, preventive maintenance was regarded as a secondary business process that adds additional, albeit necessary, costs to production activities. Recently this perception has changed, and more time and effort have been directed into attempts to optimise maintenance strategies within the context of sustainably achieving the business goals of organisations.

In support of this view, Marowa and Muyengwa (2015) state that the role of maintenance is to enable organisations to reach their goals in terms of profitability and productivity. They also affirm that the perception of maintenance within an organisation has changed, placing a lot more emphasis on maintenance in the overall business context. Studies have found that the total cost of maintenance can account for between 15–70% of the total cost of production within an organisation (Bevilaqua & Bragila, 2000). In addition, it has been established that 30% of maintenance-related costs are due to unnecessary expenditure as a result of the poor implementation of maintenance strategies (Salonen & Deleryd, 2011). Therefore, it is evident that following an accurate and correct maintenance plan is essential. Vilarinho et al. (2017) state that performance, risk and cost must all be considered when developing a maintenance plan.

To indicate the importance of maintenance within companies, Waeyenbergh and Pintelon (2002) found that up to 30% of the workforce involved in a chemical plant comprise maintenance personnel. Dekker (1996) also states that the maintenance and operations departments within companies are usually the most sizeable due to the significance of maintenance. In addition, Bevilacqua and Braglia (2000) determined that the total cost of maintenance in a final product can range from 15–70% of the value. This is a huge portion of the value of the product, which again highlights the core role of maintenance.

Due to the recognition of the importance of maintenance from an organisational perspective, a number of different maintenance-related approaches have been developed, including reliability centred maintenance, business-centred maintenance, total productive maintenance and life cycle costing. These approaches consider maintenance from specific different viewpoints and no single approach can be applied to all circumstances. Common to all these approaches are techniques to optimise the maintenance strategies using mathematical models. Coetzee (1997) and Jardine and Tsang (2013) have outlined several different mathematical approaches, all of which involve minimising the total costs incurred in relation to the required maintenance activities. It is recognised that various other factors apart from economics, such as issues related to safety, the environment and legislation, can affect preventive maintenance strategies and planning. However, this paper focuses on data-driven optimisation models that consider the costs and reliability performance of equipment.

1.2 Problem statement

The practical implementation of these maintenance optimisation models presents two main challenges. First, the decision on when to use which model depends on the type of system/equipment under scrutiny and on available data. Coetzee (1997) differentiates between two different types of systems, namely repairable systems (which can be restored to a working condition by implementing appropriate maintenance techniques) and non-repairable systems (which require replacement when defective). Different models, based on analysing the historical failure data of the system or component, are considered in order to optimise the maintenance strategies to be applied for these two types of individual systems. In the case of having a number of identical components or systems in series, where a shutdown of one of the systems results in the shutdown of the entire series, models developed by Jardine and Tsang (2013) and Laggoune et al. (2008)

are considered to allow for analysis with the correct maintenance technique of components or systems showing these trends.

A major limitation of these maintenance optimisation models is that they all require failure data for their implementation, which is not always obtainable. However, historical maintenance cost data is mostly available and, therefore, forecasting techniques and life cycle cost modelling are also considered.

Second, the successful implementation of optimised maintenance strategies will be dependent on informed budgetary decisions being made. Thus, the challenge of combining the outputs from all the various optimisation models utilised into an integrated compilation and sensible presentation of an overall maintenance budget for a complex plant needs to be addressed.

1.2.1 Research objectives/ questions

The main objective of this research was to develop an overall preventative maintenance optimisation methodology that:

- considers the wide range of current maintenance optimisation models available through an integrated methodology that addresses when to use each method
- examines how to present the results in a combined budgetary manner for an entire plant
- integrates ways to address the uncertainty around the models through confidence levels
- presents ways to make budgetary decisions where the effect of not doing so is evident.

1.2.2 Methodology

A model will be built using numerical analysis and simulation where field data will be implemented into this model as the main input. In order to validate the proposed model and to show its fundamental workings, a comprehensive case study is presented. It is necessary for the case study in question to incorporate real-world field data with varying conditions and data requirements in order to show the variability in the model. The outcome of the case study needs to result in the development of one overall maintenance budget for a specific plant that can be used in a decision process for an organisation. The validity of the output of such a model will then be proven through the use of industry surveys where the benefit of the model can be proven.

1.3 Dissertation layout

A literature study is presented in Section 2 of this dissertation. It starts with a broad overview of the physical asset management process, with an emphasis on asset care, to give the reader a clear understanding of the importance of maintenance in an organisation. The literature study then proceeds to the topic of maintenance. It considers the various types of maintenance practices that are currently in use in industry and the different approaches used by organisations to optimise their businesses. Finally, it examines different maintenance modelling techniques, including hard and soft approaches.

Section 3 outlines the modelling and optimisation techniques that will be used to build the overall maintenance models. All the models briefly outlined in Section 3 are thoroughly examined with their functioning and mathematics presented. An illustrative example is given for each model discussed to show its exact workings and how it can be used practically in a real-world problem.

Section 4 of the dissertation presents an in-depth case study using the developed methodology in Section 3. The case study makes use of data collected from the operating platform of a major mining company. A contrived plant, made up of different systems and components, is developed for the case study to show the underlying working and functioning of the developed model. The methodology outlined in Figure 3.1 in Section 3 is validated using the case study, resulting in the development of an overall budgetary requirement with confidence around it for a plant.

The research in this dissertation is concluded in Section 5 where recommendations about future work and developments are presented. Appendices follow, containing additional information and validations, which should be consulted throughout the dissertation as necessary.

2 Literature study

2.1 Introduction

This section of the dissertation introduces relevant literature that is directly based on the problem statement as described in Section 1. The aim of this literature study is to contextualise the topic of maintenance optimisation in a capital-constrained environment and to determine what other work has been undertaken related to this topic.

The literature study tackles the topic from an initially broad view by discussing subjects such as physical asset management and asset care, which comprise the grounding for the problem statement. It then moves directly towards the topic in its review of various elements, including diverse maintenance techniques, models and approaches. The knowledge acquired here will be applied in Section 3 in which a detailed mathematical background to the overall problem is outlined.

2.2 Physical asset management

According to the *Oxford English Dictionary* (OED, 2018), an asset can be defined as follows:

> An item of property owned by a person or company, regarded as having value and available to meet debts, commitments, or legacies.

The *Oxford English Dictionary* (OED, 2018) defines management as:

> The process of dealing with or controlling things or people.

From these two definitions, it is evident that the term ‘asset management’ encompasses a large range and needs to be whittled down for application to engineering asset management (EAM) and physical asset management. Amadi-Echendu et al. (2010) define engineering asset management as the total management of physical assets, as opposed to financial assets. Physical assets include items such as buildings, land and equipment, while examples of financial assets include stocks and patent rights. However, engineering assets have a financial side which plays an important role in overall engineering asset management (Amadi-Echendu et al., 2010).

In the context of maintenance management, Tsang (2002) addresses the human dimension of engineering asset management and explains how it is a key area in the successful management of engineering assets. A central point to be drawn from Amadi-Echendu (2006) is that asset management is not straightforward; it has various additional elements to normal maintenance management. Amadi-Echendu (2006) gives a holistic view of an entire system rather than just one process within a system. This view is directly related to the value chain of asset management, which encompasses ownership, management and utilisation of the asset. Bearing this in mind, engineering assets are positioned at the base of the pyramid in Figure 2.1 (Amadi-Echendu et al., 2010), while every other type of asset sits above this base layer. All the assets above the base layer are financial assets, which do not form part of the engineering asset management process (Amadi-Echendu et al., 2010).

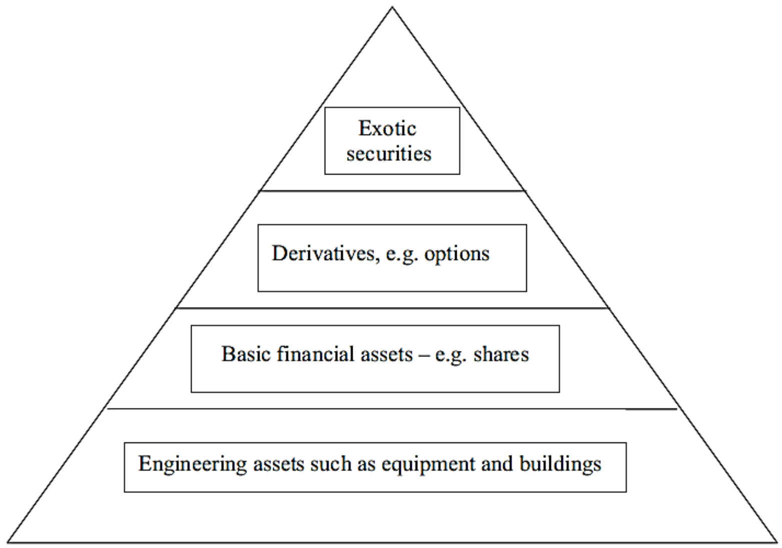

Figure 2.1: Where EAM fits into the picture of total asset management (Amadi-Echendu et al., 2010)

Amadi-Echendu et al. (2010) detail five requirements and challenges that are faced in the broader terms of engineering asset management. These are listed in Table 2.1, along with an explanation.

Table 2.1: Requirements and challenges faced in the broad spectrum of EAM (Amadi-Echendu et al., 2010)

Generality	**Context**
Spatial generality	EAM has a broad scope across physical assets, including human resources.
Time generality	EAM includes short-term and long-term aspects of physical assets.
Measurement generality	Measurement data includes the economic and social value of the physical asset, as well as its physical attributes.
Statistical generality	Risk measurements and normal performance measurements are important in EAM.
Organisational generality	EAM is multi-organisational – it takes place across all organisations.

From Table 2.1 it is evident that engineering asset management is a broad topic. It requires a significant amount of knowledge to fully understand it, which suggests that a competent engineering asset manager needs a diverse skill set in various disciplines.

2.3 Asset care

Asset care is the process that is used to ensure an asset is performing at its full potential. It encompasses all the elements which enable this to occur. Wheelhouse (2009) states that a plant asset care programme allows all types of businesses to plan, repair and replace all their equipment and the plant, if necessary, in order to meet the real needs of the business. According to Jones (2018), asset care can be regarded as the performance of a control strategy in the most cost-effective way; it directly addresses all the failure modes associated with a certain asset. Jones (2018) also states that the main objective of asset care plans is to ensure that an asset is being utilised correctly, in the most cost-effective manner, allowing the greatest probability that the asset will survive until its life end. By contrast, Wheelhouse (2009) states that the optimum goal a plant asset care plan needs to achieve is a balance between safety, cost, performance and availability. Von Petersdorff and Vlok (2014) assert that physical asset management is the process of maximising the value that can be gained from an asset throughout its life cycle via the mix of cost, risk and performance. It is evident that their approach to physical asset management closely correlates to that of Wheelhouse (2009) on asset care. This strongly suggests that asset care is a vital process in physical asset management. Woodhouse (2007) connects asset care to maintenance and risk management. He also links asset management to asset care by stating that it is the best mix of asset care and asset exploitation, a process that needs to be optimised throughout the life cycle of the asset.

The prerequisite of an asset care plan is to create value. Wheelhouse (2009) affirms that there are five ways to create shareholder value. These include a reduction in capital cost, reduced tax burdens, investments for growth, improved asset performance, and an influence on the perception of the stock market. The last two of these listed factors can be affected by asset care. The reason why these last two factors create value is that greater uptime accompanies increased performance. This directly affects sales, thereby boosting the likelihood of increased profit. In addition, an increase in sales means there is a demand for the product. If the company meets that demand, it demonstrates a reliable functioning system. This will strengthen people’s positive perception of the company, thus affecting the stock market.

Lastly, Wheelhouse (2009) states that the following items must always be included in an asset care plan:

- Servicing and maintenance
- Inspections
- Shutdowns
- Spares management
- Asset strategy
- Performance monitoring.

2.4 Maintenance techniques

According to Dekker (1996) and the British Standards Institution (1984), maintenance can be defined as “the combination of all technical and associated administrative actions intended to retain an item or system in, or restore it to, a state in which it can perform its required function”. Waeyenbergh and Pintelon (2002) state that companies have several different systems which all interact with one another to achieve one goal. They assert that maintenance makes a significant contribution to meeting that goal. It assists in reaching all the company objectives, in keeping all life cycle costs to a minimum, and in increasing the overall performance of a company in terms of its systems (Waeyenbergh & Pintelon, 2002). De Jonge et al. (2017) argue that the importance of maintenance has increased significantly in terms of its performance by employees and its escalating costs due to the rapid increase in technological development and the complexity of systems because people demand more from them. Like De Jonge et al. (2017), Vilarinho et al. (2017) affirm that the main driving force behind the importance of maintenance is technology. This has resulted in improved maintenance techniques, better decisions and a striving towards maintenance excellence. To reach this state of excellence and achieve the best possible solution in terms of maintenance, it is essential to consider performance, risk and cost (Vilarinho et al., 2017).

To demonstrate the importance of maintenance within companies, Waeyenbergh and Pintelon (2002) found that up to 30% of the workforce involved in a chemical plant comprise maintenance personnel. Dekker (1996) also states that the maintenance and operations department within companies are usually the most sizeable due to the significance of maintenance. In addition, Bevilacqua and Braglia (2000) determined that the total cost of maintenance in the final product can range from 15–70% of the value. This is a huge portion of the product value, which again highlights the core role of maintenance.

Maletic et al. (2012) state that a main function of maintenance is to contribute towards the company's profit, not to reduce it. The work of Alsyouf (2007) shows how effective maintenance policies can influence the productivity and profitability of a manufacturing process. He found that the implementation of proper maintenance policies led to the avoidance of unplanned stoppages and lost production due to maintenance-related issues. As a result, the plant could experience an increase of nearly US$0.975 million per year, which equated to almost 12.5% of the plant's annual maintenance budget (Alsyouf, 2007). Maletic et al. (2012) also determined that profit could increase by up to 3.22% if there was a reduction in unplanned stoppages and lost production. Al-Najjar and Alsyouf (2004) found that the introduction of an appropriate vibrations-based monitoring technique in a Swedish paper mill could result in a maintenance cost reduction of US$0.385 million and an average potential savings of up to US$3 million. Thus, from the examples given above, it is evident that organisations with proper maintenance practice derive significant benefit in terms of profit, and further development of maintenance in different organisations is essential.

According to Ghosh and Roy (2009), over the last few decades there has been a complete paradigm shift in how maintenance is performed and what techniques are used. The shift has evolved mainly from a corrective type of approach that allows a system to fail first before any action is implemented, to a preventive type of approach that allows for a system to be fixed *before* failure occurs (Ghosh & Roy, 2009).

Figure 2.2 shows a breakdown of the different types of maintenance techniques.

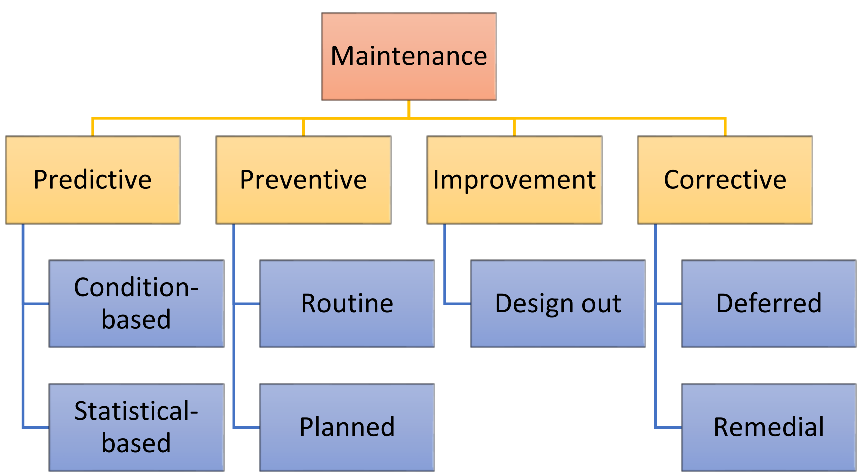

Figure 2.2: Structural hierarchy of maintenance activities, adapted from Shaalane (2012)

From Figure 2.2 it can be noted that there are four types of maintenance techniques: predictive, preventive, improvement and corrective. The most common two types of maintenance techniques are preventive maintenance and corrective maintenance from which the other two types (predictive and improvement) have developed. Dekker (1996) states that a maintenance strategy is a mix of all the different types of techniques and policies needed in a certain facility. According to Alsyouf (2007), a maintenance approach is an integration of all the maintenance concepts and strategies to build the best model possible for an organisation. It is evident from these findings that all the maintenance techniques, strategies and concepts need to be considered in a systematic way to ensure their best implementation into different organisations. This necessitates a comprehensive understanding of the available knowledge.

2.4.1 Corrective maintenance

Corrective maintenance is the actions that are put into place when a system or component fails. These actions need to restore the system to a functioning state, which can involve different processes. Wang et al. (2014) define corrective maintenance as a maintenance task that is performed to identify and rectify the cause of failure in a failed system or component. Adolfsson and Dahlstrom (2011) state that corrective maintenance is implemented to return a system or component back to its working condition after a breakdown has occurred. Corrective maintenance is not schedulable and only occurs once failure has happened, which contrasts to preventive and proactive maintenance techniques (Adolfsson & Dahlstrom, 2011).

Swanson (2001) states that a disadvantage of corrective maintenance is higher levels of out-of-tolerance and scrap output. This results from the disposal of equipment and unpredictable and fluctuating production capacity because corrective maintenance cannot be scheduled and incurs higher costs due to the need to repair catastrophic failures (Swanson, 2001).

According to Manganye et al. (2008), corrective maintenance can be grouped into two categories, that is, immediate or remedial maintenance and deferred maintenance, which can be seen in Figure 2.3. Depending on the severity of the failure that occurs, one of the following tasks will be performed:

- *Immediate maintenance:* This maintenance activity is performed immediately after failure has occurred since the failure can cause more imminent damage or extended lost production.

- *Deferred maintenance:* This maintenance activity does not have to be performed immediately and can be delayed. The result can be the scheduling of the maintenance activity for another period, based on the priority of activities (Manganye et al., 2008).

Once it has been determined what type of corrective maintenance needs to take place in terms of the prioritisation of all activities, the corrective maintenance activity required for a specific situation can then be implemented. The different types of activities, with an explanation, can be seen in Table 2.2.

Table 2.2: Corrective maintenance activities with an explanation (Shaalane, 2012)

Corrective maintenance activity	Explanation
Fail-repair	The item that has failed is restored to its operating state so that a specific process can continue.
Overhaul	Only repair and fix the parts in an item that are necessary to enable the item to function to its required standards.
Servicing	This action entails all the servicing that is currently required due to the corrective maintenance.
Salvage	An item that has failed is completely removed from the system and disposed of.
Rebuild	An item is completely restored to a functioning state using new or reconditioned parts. The performance of the new item must be on a par with the performance of the original item.

2.4.2 Preventive maintenance

Manganye et al. (2008) state that preventive maintenance can be defined as the maintenance performed before any type of failure occurs in a system or a component. Preventive maintenance preserves the condition of the system or component in a satisfactory manner. According to Theron (2016), time-based maintenance is the most common type of preventive maintenance strategy to be implemented. It requires maintenance tasks to be performed on a fixed-time basis that is determined through a variety of different mathematical techniques, as stated by Schneider et al. (2006). Time-based maintenance is the most appropriate technique to use for failure mechanisms such as abrasion, erosion, corrosive wear and fatigue (Schneider et al., 2006). This type of technique is prominent in rotary machinery applications.

Lee and Scott (2009) describe preventive maintenance as one of the most effective maintenance strategies to reduce the frequency of breakdown. However, they also state that incorrect implementation of preventive maintenance is an ineffective solution because it can cause too early and unnecessary replacement of components. It is evident, therefore, that an extensive understanding of the preventive maintenance technique is essential before it is implemented into a system.

According to Corman et al. (2017), preventive maintenance actions can be placed into three main categories:

1. ***Perfect preventive maintenance:*** This maintenance activity restores the system or component to an 'as good as new' condition, which means that the system or component has returned to its optimum condition.

2. ***Minimal preventive maintenance:*** This maintenance activity restores the system or component to a condition that is comparable to just before the maintenance activity was performed. This is called 'as bad as old' restoration.

3. ***Imperfect preventive maintenance:*** In most real-life cases, neither perfect nor minimal preventive maintenance is reached, but rather some sort of activity in between the two. This is referred to as imperfect preventive maintenance.

Corman et al. (2017) also categorise three main maintenance activities that can take place when performing preventive maintenance. These activities are described in Table 2.3.

Table 2.3: Preventive maintenance activities

Activity	Description	Outcome
Service	This includes all preventive maintenance activities, such as cleaning, adjusting, refilling and tightening components.	It reduces the rate of deterioration without improving the reliability of the system.
Low-level repair	This includes small part replacement in addition to all the service-related activities.	It improves the reliability of the system to a state that is in between 'as good as new condition' and 'as bad as old condition'.
High-level repair	This includes systems overhaul as well as replacement.	It improves the reliability of the system to an 'as good as new' condition.

2.4.3 Predictive maintenance

Predictive maintenance is a maintenance technique that uses various activities, such as condition monitoring, to measure the condition of a component or system to determine its state. Once this is achieved, an appropriate maintenance approach can be employed to extend the service life of the component or system at hand. TextileToday (2012) states that the main difference between predictive maintenance and preventive maintenance is that predictive maintenance uses monitoring techniques to determine the actual mean time to failure of a certain piece of equipment, while preventive maintenance uses life statistics that are found in the industry. Some engineers consider predictive maintenance to be a type of preventive maintenance (TextileToday, 2012).

According to Barabady and Kumar (2007), condition-based monitoring is a method used in predictive maintenance to detect faults with the use of equipment; preventive maintenance methods are then used to fix the fault. Theron (2016) states that condition-based monitoring can include two types of decision-making process: the first involves locating the source of the fault, known as diagnostic decision making, and the second involves predicting when the failure may occur, which is known as prognostic decision making. Block and Geitner (1983) assert that 99% of all machine failures are preceded by certain signs, conditions or indications that something is not right. This indicates that the implementation of a system such as condition monitoring could be hugely beneficial to the performance of an organisation.

2.4.4 Design out maintenance

Design out maintenance is a technique associated with improvement maintenance. According to Theron (2016), design out maintenance can be defined as a maintenance action that takes place in order to remove the cause of a systems or components failure. This allows other maintenance tactics to be more effective in managing the root cause of failure. Jain (2013) states that design out maintenance is applicable to the following: systems with high downtime periods, resulting in a high maintenance cost; equipment that requires a high level of maintenance effort or a number of spare parts; and systems with unacceptably high failure rates. A choice needs to be made between the cost of redesign, which is directly related to design out maintenance, and the cost of recurring maintenance, which is a result of the other types of maintenance techniques (Jain, 2013).

There are three main reasons why systems and components can result in high maintenance costs, which can then lead to design out maintenance (Jain, 2013):

1. Poor maintenance implementations and actions
2. The equipment in an organisation operates outside its original design specifications, leading to more frequent failures
3. The original piece of equipment designed for a certain application is poor and below standard.

Markeset and Kumar (2003) state that a major factor which must be considered in terms of design out maintenance is whether the reliability of the system increases by using a newly designed system. It is also essential to look at all the costs involved and ascertain if it will be feasible to implement such a technique. One way to determine this is to perform a trade-off analysis between the alternatives and to choose the best option from the analysis.

Figure 2.3 shows the approach taken by Markeset and Kumar (2003) in the trade-off analysis, using life cycle costing (LCC) as the analysis tool.

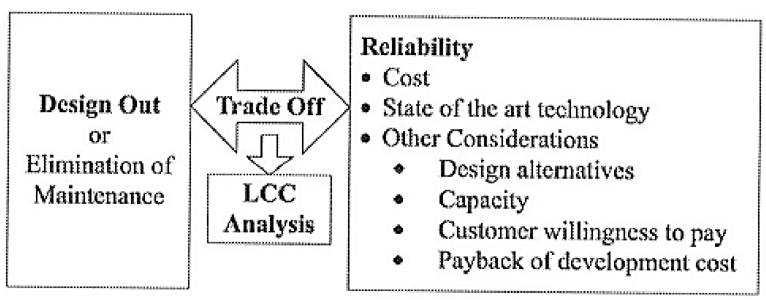

Figure 2.3: Design out maintenance trade-off analysis (Markeset & Kumar, 2003)

2.5 Maintenance optimisation

Moore and Starr (2006) state that, at present, one of the most vital factors to consider in an organisation is the complete optimisation of its costs. The cost of maintenance is one of the greatest contributors to operational costs. If maintenance is inadequate and not up to standard, it can lead to lost production, spare parts, fines for late orders, unsatisfied customers due to late production, and the need to rework and scrap

(Moore & Starr, 2006). These factors will directly increase the costs incurred by the organisation, resulting in a sub-optimal system.

Dekker and Scarf (1998) and Von Petersdorff (2013) found that the most common practice in maintenance optimisation was the development of a mathematical model that aimed at either determining the best balance between cost and benefits related to maintenance, or establishing the best interval in which to perform maintenance. Von Petersdorff (2013) states that the literature focused more on the latter.

Maintenance optimisation is a task that begins in the design phases and carries on throughout the life cycle of a system, again emphasising the importance of maintenance optimisation in an organisation (Von Petersdorff, 2013). Figure 2.4 shows the process that needs to be applied to the data in an organisation in order to reach maintenance optimisation.

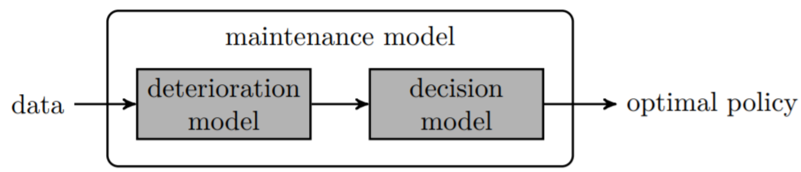

Figure 2.4: Maintenance optimisation process (Kallen, 2007)

From Figure 2.4 it is evident that there is neither one generic failure modelling technique that can be applied to all organisations, nor one technique that can be used in final decision making. This means that several different factors and techniques need to be taken into consideration when it comes to implementing the optimal maintenance strategy.

2.6 Maintenance approaches

This section of the literature study gives an overview of all the different maintenance approaches that are currently in use. Lee and Scott (2009) state that a maintenance approach is a policy that integrates all the different maintenance strategies (corrective, preventive, proactive and design out) to result in the best solution for an organisation. One of the deciding factors in which strategy or approach to use is directly related to the resources available to the organisation. The main resource is linked to the cost involved in the process. According to Coetzee (1999), maintenance strategies and approaches should be directly connected to the detailed design of the maintenance cycle for different organisations. Tse (2002) states that the majority of maintenance activities over the years have been failure-driven, time-based, condition-based and reliability-centred.

2.6.1 Reliability-centred maintenance (RCM)

Reliability-centred maintenance (RCM) developed from the aviation industry when a comprehensive study was performed in the sixties to determine a preventive maintenance programme for the new Boeing 747 (Ben-Daya et al., 2009). It was found that this programme would not be economically viable and that something needed to be changed. At this point, different textbooks were written, including the MSG-1. Development in the field led to the MSG-3, which then resulted in the creation of RCM (Ben-Daya et al., 2009).

A major downfall of preventive maintenance is the misconception of people in industry that the more maintenance performed on a certain item or system, the more reliable the system will be, which is not the case. According to Shaalane (2012), RCM reaches the inherent reliability of a system or item by implementing effective maintenance programmes. However, the central focus of these maintenance programmes is the balance between the cost and the benefits. In the aviation industry, Ben-Daya et al. (2009) found that only 11% of components exhibited failure modes that would benefit from scheduled repair or replacement maintenance. This type of maintenance would be ineffective on the other 89% and would simply not work. This led to the new way of thinking in which maintenance now focuses on an entire system rather than just one function within the system.

As a result of this complete change in thinking, the Society of Automotive Engineers developed a document named SAE JA-1011 which outlines seven basic processes that need to occur when an RCM analysis is performed. These seven processes are defined as follows (Leverette, 2004):

1. What are the functions and the associated desired standards of performance of the asset in its present operating context?
2. In what ways can it fail to fulfil its functions?
3. What causes each functional failure?
4. What happens when each failure occurs?
5. In what ways does each failure matter?
6. What should be done to predict or prevent each functional failure?
7. What should be done if a suitable proactive task cannot be found?

If these seven questions are answered correctly, a document can be drawn up that looks at the most efficient and cost-effective way to implement maintenance in an organisation, which can be regarded as RCM. Ben-Daya et al. (2009) state that RCM can be used to create the most cost-effective maintenance strategy that considers and addresses all the main causes of failure found in an organisation. At the same time, it provides the required availability and reliability at the lowest cost possible (Ben-Daya et al., 2009).

2.6.1.1 Main RCM principles and benefits

One of the fundamental concepts on which RCM is based is the task of assigning different levels of criticality to different failure modes, based on the consequences of their failure to the organisation (Ben-Daya et al., 2009). This is done in order to create the most cost-effective and efficient system.

Four main principles outline an entire RCM process (Ben-Daya et al., 2009):

1. *Preserving the system function:* This involves determining the current systems level of output and ensuring that the availability of the same output can be met.

2. *Identification of the specific failure modes that could potentially cause functional failure:* This is critical at the times when a maintenance plan needs to be developed or design changes might occur.

3. *Prioritising key functional failures:* This is a core principle in terms of achieving cost effectiveness and efficiency within the organisation. It is implemented to ensure that resources are allocated to the correct area in order to minimise unavailability.

4. *Selection of applicable and effective maintenance tasks for high priority items*: This is done to achieve cost effectiveness and efficiency within the organisation.

Shaalane (2012) states that, in order to categorise an RCM strategy as a true RCM strategy, all the maintenance components in Figure 2.5 need to be examined. This is directly related to the fourth principle – *Selection of applicable and effective maintenance tasks for high priority items*, at which stage it becomes necessary to perform the RCM process.

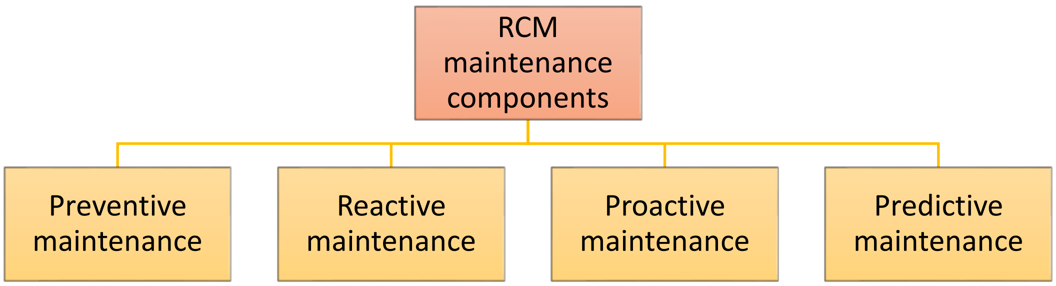

Figure 2.5: RCM maintenance components, adapted from Shaalane (2012)

From Figure 2.5 it is evident that an in-depth understanding of all the different types of maintenance techniques is required before any attempt at an RCM analysis can be performed in a maintenance organisation. Ben-Daya et al. (2009) give a complete overview of all the benefits RCM can produce, which are summarised in Table 2.4.

Table 2.4: Benefits that can arise from conducting RCM (Ben-Daya et al., 2009)

RCM benefits	
1. Determine optimum maintenance plan	2. An increase in technical knowledge related to maintenance
3. Optimise maintenance efforts in terms of operational efficiency and cost efficiency	4. Cost savings from the implementation of the correct maintenance action
5. Retain most crucial functions as the main focus, thereby neglecting inessential actions	6. Improved safety and environmental effects
7. Correct distribution of resources	8. Workload reduction and an increase in operational performance

2.6.2 Total productive maintenance (TPM)

Total productive maintenance is a maintenance approach that was developed in the seventies by the Japanese with the aim of extending preventive maintenance to become more like a productive maintenance strategy. Ben-Daya et al. (2009) state that TPM has become a widely recognised tool, which has been used to increase the overall effectiveness of different production facilities around the world. In Ben-Daya et al. (2009), Ahuja (2009) states that the three words in TPM can be split up as follows:

Total: All aspects in an organisation are covered, following a top-to-bottom approach.

Productive: Activities are performed while production takes place in order to minimise production difficulties.

Maintenance: Equipment upkeep is performed autonomously by operators in order to keep it in good condition.

The division of TPM into three different parts makes it clear that it is not simply regarded as a maintenance function that needs to be performed, but rather a function that is recognised as one of the main focuses of an organisation (Ben-Daya et al., 2009). According to McCarthy (2004), the core focus of TPM is to help to identify and fix defects in manufacturing, to increase the elimination of waste, and to assist in improving inefficient operations cycles.

One of the breakthrough moments in TPM was the concept of lean thinking and the integration of all working personnel in organisations in order to create a more effective system. According to McCarthy (2004), this move hugely reduced defects since operations staff could now check the buffers through which defects used to pass, which previously could only be inspected by specialised personnel. There was also a significant push away from the system of forecasting about what needs to be produced in a manufacturing plant. A greater emphasis was put on a pull system that did not use forecasting, but rather put forward operations in response to actual customer needs. This move away from the push system towards the pull system allowed some internal disruptions to occur, which did not take place in the push system. It also enabled immediate customer satisfaction and a smoother process.

McCarthy (2004) found that the emphasis in this lean thinking approach on the redesign of the production system led to the elimination of all the poor processes in this system, the bulk of which resulted from mass production. The largest poor feature eliminated from the system was waste. Seven forms of waste were improved on in plant production (McCarthy, 2004):

1. Over-production
2. Unnecessary inventory
3. Inappropriate processing
4. Unnecessary transportation
5. Unnecessary delays
6. Unnecessary defects
7. Unnecessary motion.

From this improvement in waste management in organisations, McCarthy (2004) details a study that was performed in plants in the UK and Japan. The UK plants still followed the old method of mass production and the Japanese plants followed a lean TPM process. Figure 2.6 shows the results of the study performed.

Indicator	Japanese in Japan	All Europe
Performance		
Productivity (hours/car)	16.8	36.2
Quality (Defects/100 cars)	60	97
Layout		
Space (sq.ft/car/year)	5.7	7.8
Inventory (sample 8 parts)	0.2	2.0
Size of Repair Area (% Assembly Hall)	4.1	14.4
Workforce		
% in Teams	69.3%	0.6%
Suggestions/Employee	61.6	0.4
Absenteeism	5%	12.1%
Training of New Production Workers (hrs)	380.3	173.3

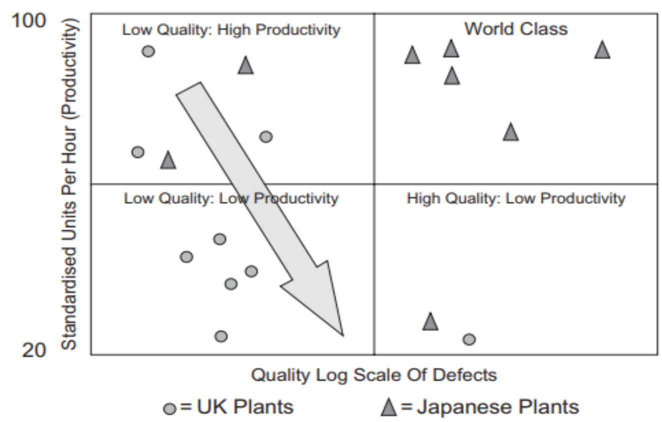

Figure 2.6: Lean TPM comparison between UK and Japanese plants (McCarthy, 2004)

The enormous benefit associated with the transition from normal mass production to a leaner TPM process is evident in Figure 2.6. Nakajima (1988) outlines the five main focus areas and aims of TPM:

1. Maximise the efficiency of the production system.
2. Establish a system that helps to prevent the occurrence of failures – the main goal is the final product.
3. Apply TPM to all the departments in an organisation.
4. Full participation is required, from management to operators.
5. Achieve minimal loss through small group activities.

The direct effect of these five focuses of TPM can be seen in the results of the study performed in Figure 2.6. McCarthy (2004) also emphasises that the full participation of the employees in the production system should result in the improved reliability, availability, safety, quality and performance of the equipment. In addition, Nakajima (1988) states that the benefits of TPM – which include productivity (P), quality (Q), cost (C), delivery (D), safety (S) and morale (M) – have a direct impact on the overall equipment effectiveness (OEE) found within an organisation. This results in an organisation that can output its goods in the most effective manner possible. OEE can also be considered as one of the most important performance measures of TPM.

2.6.3 Business-centred maintenance (BCM)

Business-centred maintenance was developed in the eighties by Anthony Kelly. He saw an opening in the market with the need for a more cost-effective maintenance model in which safety was one of the main priorities (Mungani & Visser, 2013). BCM is an approach that can be used in various applications, such as power stations, mines and even communications and transport networks. Thomas (2015) found that up to 40% of a company's cost can be controlled by a maintenance manager who can also have a significant impact on the production output of a company. Despite this, however, there has still not been a substantial shift in trying to integrate business objectives with maintenance outputs.

Mungani and Visser (2013) state that a core focus and emphasis of BCM is to align the maintenance function with the organisational objectives of a company to enable the two functions to work together to create an optimal organisation. According to Waeyenbergh and Pintelon (2002), the framework of BCM works by first identifying all the business-related objectives and then translating them into maintenance-orientated objectives. A large amount of data is needed to determine these objectives, which includes all the different production processes, failure data, availability data, life plans and the forecasted workload of the plant. From all this data, the drive of BCM is to maximise the overall contribution of maintenance within an organisation to enhance the total profitability of the organisation (Waeyenbergh & Pintelon, 2002).

Figure 2.7 shows the overall BCM maintenance approach and how it aims to maximise the total profit of an organisation.

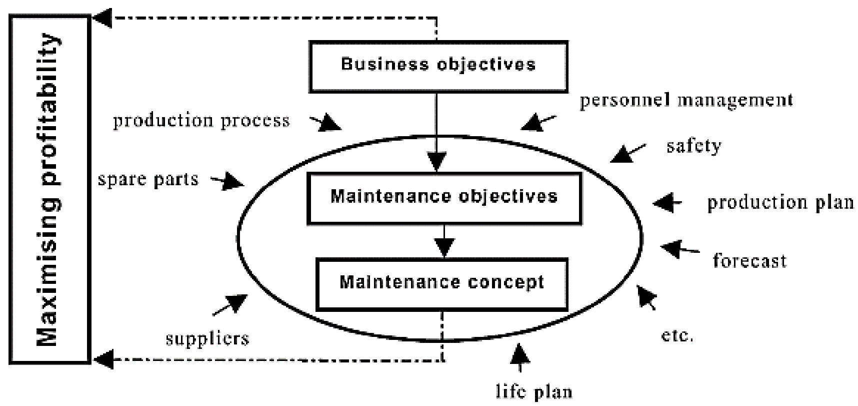

Figure 2.7: The BCM approach to maximise profit (Waeyenbergh & Pintelon, 2002)

Waeyenbergh and Pintelon (2002) found that the main difference between BCM and RCM is that BCM is more focused on increasing the profitability of a company, while RCM is more focused on the technical performance of an organisation. However, both maintenance approaches look at all the different units in an organisation and how they interact with one another in order to determine the optimal maintenance solution for the organisation.

2.6.4 Life cycle costing (LCC)

According to Kirstein and Visser (2017), life cycle costing is the process of determining the cost of something from the acquisition phase, to the operation and maintenance phase, to the final disposal phase.

White and Ostwald (1976) state that "The life cycle cost of an item is the sum of all funds expended in support of the item from its conception and fabrication through its operation to the end of its useful life". This process of life cycle costing is done by prediction. The results obtained from such an analysis can be used to make future decisions about the element on which life cycle costing is being performed. It is evident from Kirstein and Visser (2017) and White and Ostwald (1976) that the life cycle costing analysis examines all the costs associated with an element. Only thereafter can a decision about the element be made.

According to Ellram (1995), the main focus of LCC is on capital assets. Asiedu and Gu (1998), however, state that LCC can be performed on a variety of different products by gearing the nature of the analysis towards the different products. This suggests that there is not one generic LCC method that can be performed on all the different capital assets and products. Korpi and Ala-Risku (2008) assert that the main purpose for developing LCC was to look at the viability of the procurement of certain assets, which focused predominantly on the client's perspective and tended to neglect the manufacturer's perspective.

In order to integrate the perspective of both the client and the manufacturer, Korpi and Ala-Risku (2008) outlined a methodology developed by Barringer and Weber (1996) which shows the overall purpose of performing an LCC analysis:

- **Affordability studies:** These use the LCC to measure the long-term impact of costing on the company's budget and operating results.
- **Source selection studies:** These compare different alternative systems or elements using LCC estimates to ensure that optimum goods/services are implemented.
- **Design trade-offs:** These look at various factors in the LCC and optimise those that most influence the system.
- **Repair level analysis:** The LCC outlines actual maintenance costs and demands using maintenance cost modelling. This ensures that correct decisions are made in terms of the capital equipment that is vital to the sustainability of a company.
- **Warranty and repair costs:** This uses maintenance modelling to allow the organisation to understand the effect of equipment or system failure in terms of overall cost.
- **Sales strategies of suppliers:** This process merges the LCC analysis and the maintenance failure rate analysis to allow for the optimum replacement age of a system or an asset.

From the above overview of the purpose of performing an LCC analysis, it is evident that maintenance optimisation plays a vital role in this analysis in terms of cost and optimum decision making. Both elements work together to ensure that the best decisions are made.

2.6.4.1 Life cycle costing estimation methods

Since LCC is an analysis process in which the costs of a system are forecast into the future, the costs that make up the total cost of a system are required. These costs are unknown since they are forecast into the future, which means that a cost-estimating method is needed in order to determine them.

Fabrycky and Blanchard (1991) state that the life cycle costs of a system can be broken down into different phases, as shown in Figure 2.8.

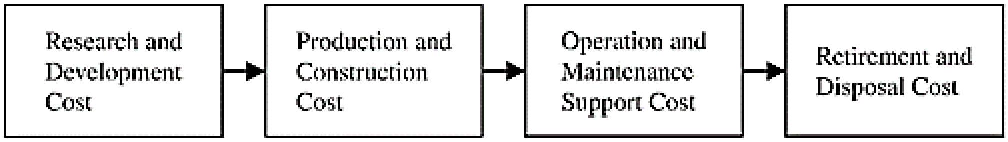

Figure 2.8: Cost phases of a life cycle cost analysis (Fabrycky & Blanchard, 1991)

For each distinct phase in Figure 2.8, a different cost estimation method could be applied. Korpi and Ala-Risku (2008) outline three different cost estimation methods that can be used in an LCC analysis:

1. **Estimation by engineering procedures**

   This cost estimation method makes uses of labour time and rates as well as material quantity and prices in order to gain an overall cost estimate of a product or system (Asiedu & Gu, 1998). It is regarded as the costliest method to implement since a large quantity of data is needed which requires a large portion of time to gather. Asiedu and Gu (1998) state that, despite the expense, this method can result in the best output if carried out correctly with all the required data inputted into the model.

2. **Estimation by analogy**

   According to Asiedu and Gu (1998), the estimation by analogy method identifies a product or system with similar attributes and adjusts the costs for the differences between this system and the wanted system or product. Korpi and Ala-Risku (2008) state that the main problem with this type of estimation method is the high degree of judgement it requires since a target product is being compared to another product with similar attributes. The comparison needs to be accurate to result in useful outputs. This is the most inaccurate but cheapest method to implement since it does not require a lot of data (Korpi and Ala-Risku, 2008). Nevertheless, this approach has been found to give good estimates for new products, as determined by Korpi and Ala-Risku (2008) and Asiedu and Gu (1998).

3. **Estimation by parametric methods**

   This estimation method uses different statistical techniques and methods. It employs both costs and measurable attributes of the system at hand in order to gain the cost estimates. According to Asiedu and Gu (1998), this method makes use of historical data and information and implements different mathematical models to reach the required outputs. They state that the parametric estimation method can be used throughout the design process and through all the different cost phases, as seen in Figure 2.9. In addition, Asiedu and Gu (1998) affirm that although this method requires a large amount of information, time and money to set up, once it is in operation its output of results is reasonably quick.

On assessing these three estimation methods, Korpi and Ala-Risku (2008) assert that the best method to use in most situations is the parametric estimation method. The reason is that, although it is not the most cost-effective method initially, once it has been set up for a system or product, only small changes need to be made to the model when modifications occur. This makes it highly appealing to most designers. For all the estimation methods, one of the main factors that needs to be considered is the time value of money – because all the cost estimates are forecasts into the future, the value of money also changes. Therefore, interest rates and future discounted values need to be considered to ensure that an accurate model is represented by the LCC analysis.

Finally, it must be noted that to ensure the development of an accurate model, all costs need to be appraised. This includes general operations costs, which can be regarded as standard non-varying costs, and maintenance costs, which can be regarded as volatile. A significant amount of time needs to be spent on gaining these costs to ensure the development of the best possible LCC model. A detailed methodology for an LCC analysis, as outlined by Barringer and Weber (1996), can be seen in Appendix B.

2.6.5 Maintenance approach overview

Table 2.5 gives an overview of all the different maintenance approaches that have been discussed in this literature study by outlining the advantages and disadvantages associated with each approach.

Table 2.5: Maintenance approach overview, adapted from Waeyenbergh and Pintelon (2002)

Concept			
RCM	**TPM**	**BCM**	**LLC**
Advantages			
Cost savings Looks at a plant in its entirety Involves maintenance education Involves both operators and maintainers Optimisation and cost efficiency Only focuses on most important functions	Involves both operators and managers Increased productivity Decrease in unnecessary operations Increase in quality Increase in productivity	Focuses on maximising the profit of organisations Integrates organisational objectives with maintenance objectives Accurate approach	Looks at costs over the entire life of the system with the future in mind Considers all costs involved in a system Can make capital decisions from the model outcome
Disadvantages			
Highly complex Needs excessive data Fails to recognise the problem of economics	Economics not considered (costs + profits) Not a definite maintenance concept	Highly complex Needs excessive data	Needs a large quantity of data Meticulous and time-consuming process

2.7 Modelling techniques

This section of the literature study outlines a variety of maintenance optimisation and decision-making modelling techniques that are currently in use, as stated by Von Petersdorff (2013). Several different techniques have been compared. These include hard approaches to the problem of optimisation and soft approaches that take a more philosophical stance. The techniques discussed include Markov chains, Weibull analysis, NHPP models, block replacement models, optimum grouping models, simulation, FMEA/ FMECA and forecasting models.

2.7.1 Markov chains

According to Von Petersdorff (2013), Markov chains are an analytical technique that can be used as a modelling technique for the stochastic production/failure process. Dawid et al. (2015) state that Markov chain models are a powerful tool that can be used for diagnostics, prognostics and maintenance optimisation in a variety of different organisations. According to Dawid et al. (2015), Markov chains are a random process in which the probability between the transition of the states only depends on the current state. The previous state has no influence, thus making it a 'memoryless' process, as found by Von Petersdorff (2013). Welte et al. (2006) have developed a model that is used for the scheduling and optimisation of maintenance renewal in which the deterioration process found in equipment is modelled by the Markov chain method. The model developed was able to compute different types of performance measures and operational costs over a finite length of time, which could be used for future analysis. Van der Laan (2016) states that, for any given system, a Markov model supplies a list of all the possible states of that system, all the different paths that can occur between the different states, and the rate parameters for the different transitions between the different paths.

When modelling Markov models graphically for maintenance-related systems, Van der Laan (2016) notes that two states can occur, namely healthy or failed. This is depicted in Figure 2.9.

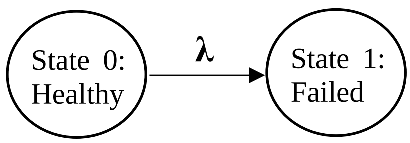

Figure 2.9: Markov states, adapted from Van der Laan (2016)

According to Van der Laan (2016), **λ** denotes the rate parameter of the transition between the two states. A probability can also be assigned to each state. If state 0 is initially healthy, then its probability is seen to be P0(0) = 1 and the probability of state 1 is seen to be P1(0) = 0. As time progresses, the probability of state 0 decreases and the probability of state 1 increases, which is due to operational wear of the component being modelled. Von Petersdorff (2013) has found various instances in literature where Markov models are used in a maintenance-related manner. These include modelling a physical system, coupled with failure data and life expectancies; determining the optimum maintenance policy for a certain set of components/systems; modelling identical manufacturing systems in terms of breakdowns, repairs and preventive maintenance actions; modelling the planning and maintenance plan for a particular organisation; determining the optimum preventive maintenance installation plan for a production line; and optimising production inventory plans for a production system. It is evident from the above that Markov models have a wide scope and can be adjusted and modified for use in different situations, depending on the system being modelled.

2.7.2 Weibull analysis

The Weibull distribution was developed in 1951, mainly for its use in failure work (Coetzee, 1997). An empirical formula was developed that can model most types of failure data through its manipulation. The formula makes use of historical failure data in order to understand the failure characteristics and behaviour of a certain set of components or a system. Abernethy et al. (1983) state that the Weibull distribution is the best distribution to use when analysing failure data as it has been found to best fit the different types of data. The Weibull distribution can also model systems and components when there are inadequacies in the data, such as small sample sizes, as determined by Abernethy et al. (1983). Due to the versatility of the Weibull distribution, Coetzee (1997) found that it can be used to model most maintenance renewal problems. A core advantage of the Weibull distribution, according to Abernethy et al. (1983), is that it can be used in a risk and forecast analysis. The results of this analysis can be utilised to determine the condition of the components within a system, thus allowing for decisions to be made that ensure an optimally running organisation.

According to Coetzee (1997) and Abernethy et al. (1983), the Weibull analysis entails the following five steps:

1. Plotting and interpreting data
2. Predicting and forecasting failures
3. Developing maintenance strategies with cost-effective replacements
4. Forecasting when spares parts will be needed
5. Developing a corrective action plan.

If these five steps are followed correctly, the Weibull analysis can be hugely beneficial to an organisation in terms of cost savings and optimum performance, as found by Coetzee (2015). Von Petersdorff (2013) states that, even though the Weibull analysis is highly beneficial in terms of its ability to model different failure distributions, a major downfall is that it can only model components and is not system-based. For this reason, it does not consider the interactions that take place within a system. This is a disadvantage since these interactions can vastly affect the failures that can occur. Nonetheless, the Weibull analysis still results in the output of accurate and reliable results that can be used for further analysis.

2.7.3 NHPP model

According to Lai and Garg (2012), the non-homogenous Poisson process (NHPP) model is a well-developed stochastic process that is used in reliability engineering. The NHPP model generates an infinite series of failure events for which the inter-arrival times between the events are neither independent nor identically distributed (Coetzee, 2015). The main difference between the NHPP model and the homogenous Poisson (HPP) model is that the expected number of failures can vary with time in the NHPP model, which is not the case in the HPP model (Lai & Garg, 2012).

Asekun and Fourie (2015) state that the NHPP model has proved to be suitable to model failure data that shows a trend. It is a straightforward model for which a lot of theoretical knowledge has been developed. Coetzee (1997) states that the NHPP model works particularly well for systems with reliability degradation in their failure data. He also asserts that the NHPP model has only been developed for repairable systems; other models should be used if the system being analysed is not repairable. The reason is that many models have been developed for components with renewal properties. This means that, once a failure occurs, the entire component can be replaced. However, in many cases when a system fails, the entire system is not replaced and only minimal repairs occur. Therefore, the same models that model renewal systems cannot be applied to repairable systems, hence the development of the NHPP model.

Asekun and Fourie (2015) have outlined the basic conditions that the NHPP model needs to satisfy:

1. $N(t) > 0$
2. $N(t)$ is an integer
3. $N(t)$, $T \geq 0$ has independent increments
4. If $T_1 < T_2$ then $N(T_1) < N(T_2)$

5. The number of events in interval (T_1, T_2) have a Poisson distribution with a mean of $\int_{T1}^{T2} u(t)dt$.

The NHPP model has been applied to various maintenance-related systems on which numerous tests have been performed to verify the model (Coetzee, 1997). The model can also be used and manipulated into a cost-optimisation analysis, as determined by Coetzee (1997). The benefits of the model are significant in terms of the implementation of preventive maintenance actions on a specific system within an organisation.

2.7.4 Block replacement models

The Weibull analysis described in Section 2.7.2 is an effective analysis tool to use when modelling historical failure data which allows for its use in maintenance renewal problems, as outlined by Coetzee (1997). There is a major downfall to the sole use of the Weibull distribution in the development of an optimum maintenance plan, as described by Von Petersdorff (2013). In terms of its use in renewal-based problems, it is limited to single component replacement, as stated by Jardine and Tsang (2013). Single component replacement policies can be highly beneficial when varying components within a system have completely different failure statistics and the components being analysed are vastly different. One area where an improvement in this single-based replacement strategy can be implemented is in a system in which various similar or identical components are present and an optimum plan needs to be developed for the preventive maintenance of all the system elements. Jardine and Tsang (2013), as well as Coetzee (1997), have all outlined maintenance models that can be used to analyse a system when such a scenario occurs. The model developed by these authors is the block replacement model.

The block replacement models were all developed based on economic viability. Jardine and Tsang (2013) and Coetzee (1997) argue that it would be economically more viable to replace a group of similar elements within a system at a certain point in time, than to replace each similar element individually. The reason behind this is the assumption that, in total, a group replacement of similar components costs less than individual replacement. This assumption is verified though the calculation that setup costs and downtime costs due to lost production on an individual component replacement policy will be a lot greater than in a block replacement policy because they are incurred several more times. The results of implementing a model like the block replacement model will be highly advantageous in a system with various similar components and in need of the development of an optimum maintenance policy. It must be noted, however, that this model can only be used when similar components are present. The individual maintenance policy briefly described in Section 2.7.2 should always be compared to the block replacement policy to ensure that the optimal maintenance plan is implemented.

2.7.5 Optimum grouping models

The Weibull analysis described in Section 2.7.2 is an extremely effective tool to use in conjunction with renewal-related problems, where components are analysed on an individual basis. The block replacement model outlined in Section 2.7.4 is an addition to the Weibull distribution, enabling similar components within a system to be modelled, resulting in an optimum maintenance plan for various similar system elements. One area which neither of these two models covers is a common scenario in industry – the development of a maintenance plan for one system comprised of varying components with similar failure characteristics. Laggoune et al. (2008) have developed a model which fulfils this exact purpose. The model developed is based on the rationale that it is more cost effective to group maintenance activities for components with similar failure statistics, than to optimally replace each component separately, as done using the Weibull analysis in Section 2.7.2. The reason is that it can cost a company a substantial amount more to shut down a system for each individual preventive action than to not replace a component at its optimum age. This results from the huge costs associated with downtime and the large setup costs for the implementation of the various preventive actions.

The optimum grouping model developed by Laggoune et al. (2008) makes use of an intensity function in conjunction with a Weibull distribution. The outcome of the model is the minimisation of a cost function. To implement the grouping policy and ensure that it is the optimal policy to incorporate into a maintenance plan, three different scenarios need to be considered: a single replacement approach, a mono-replacement approach and a multi-replacement approach. The single replacement approach is similar to the Weibull analysis described in Section 2.7.2 in which all the components within a dependant system are looked at individually, resulting in the development of multiple maintenance plans for each individual element. The mono-replacement approach determines the optimum age to replace all the elements within a system at one set interval. This approach results in large reductions in the downtime and setup costs. The disadvantage is that various elements are not replaced close to their optimum values. The multi-replacement approach model determines the optimum intervals to replace certain elements within a system with the intention of minimising the downtime and setup costs that can be endured. It has been determined that the optimum grouping model is highly beneficial in terms of cost reduction within maintenance plans on implementation. It must be noted that all three scenarios need to be considered before a decision can be made about the optimum maintenance plan. The reason is that varying systems have varying failure characteristics. A single replacement approach could sometimes result in a more optimum answer than the optimum grouping strategy presented here.

2.7.6 Simulation

Simulation can be defined as the process of building a model that is based on a real-life system in which all the inputs, constraints and outputs need to be investigated. This results in a model that mimics the behaviour of the real-life system, allowing for certain system outputs to be observed. According to Von Petersdorff (2013), one of the greatest benefits of simulation is to model systems that cannot be solved analytically due to the complexity of the system being analysed. Simulation can be used in a wide variety of applications, including cost models, physical asset modelling, inventory modelling and maintenance tactics selection, as well as in different decision-making processes.

Von Petersdorff (2013) states that one of the most important applications of simulation is in the process of evaluating the capital investment of physical assets in an organisation. In this case, simulation is used to investigate all the alternative methods and scenarios that can be played out. Barringer and Weber (1996) used Monte Carlo simulation in life cycle cost modelling to create variability and to verify the LCC model they had developed. Murthi (2003) used simulation to develop a model that outputs the best maintenance strategy for a specific organisation. He found that one maintenance method does not suit all companies and, in order to gain the competitive edge over other competitors, it is essential to implement the best method. It is evident, therefore, that simulation can be used in a wide range of activities and can be modified for use in most systems.

2.7.6.1 Monte Carlo simulation

Monte Carlo simulation is one of the leading simulation techniques used in maintenance optimisation, as determined by Barringer and Weber (1996), due to its ease of understanding and the vast variability and validation it can create in a systems model. Yeh and Sun (2011) state that Monte Carlo simulation first originated from its use in statistical sampling. The simulation makes use of random numbers and probabilities to solve different problems, depending on the system being analysed. A Monte Carlo simulation can also be employed to evaluate deterministic models by using random numbers (Yeh & Sun, 2011).

Yeh and Sun (2011) outline seven elements that make up a successful Monte Carlo simulation:

1. Development of a probability density function for use in all the mathematics
2. Random number generator
3. Sampling prescription
4. Computing methods to result in decisions
5. Miscalculation methods to determine all statistical errors present
6. Different change reduction techniques to reduce computation time
7. Parallel and vertical integration techniques to allow for effective computer architecture.

It is evident that, if all seven elements are present within a simulation, the outputted results of the simulation can be highly beneficial in terms of the system validation. In addition, Monte Carlo simulation can be used for event-based systems. If something happens in a system that results in a large and meaningful change, which then becomes classified as an event, it can be used in time-based simulation. Different time intervals are simulated in order to gain the required outputs for a system. It can also be used in agent-based simulation, which appraises all the factors that can affect a system to achieve an optimal result. Therefore, Monte Carlo simulation can be regarded as a highly useful tool for use in maintenance optimisation or to develop the best possible model for different types of systems.

2.7.7 FMEA/FMECA

According to Von Petersdorff (2013), failure modes and effects analysis (FMEA) can be defined as a highly effective tool that can be applied to determine and examine possible failure modes. The outcome of this process can be used to eliminate the potential failures in a systems design. The main aim of this tool is to provide an organisation with quantitative and qualitative measures that can be utilised to draw up a ranking system based on the consequences and risks of different failure modes that might arise in a certain system. From this, various corrective actions can be implemented in a system that will allow for its overall optimisation in terms of cost as well as operation.

FMEA has also been defined as a systematic analysis that aims to determine all the potential failure modes with the intention of preventing future failure in a system (Ben-Daya et al., 2009). To understand all the steps that take place in an FMEA analysis, Ben-Daya et al. (2009) have developed a logic process, as seen in Figure 2.10.

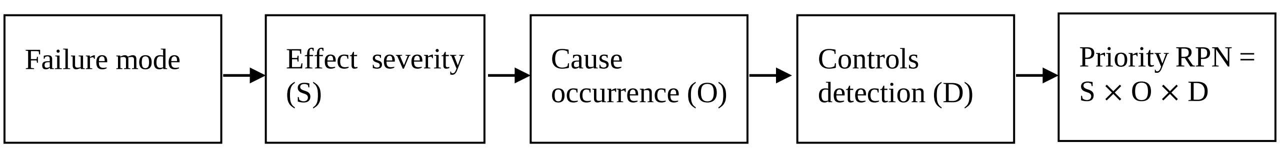

Figure 2.10: FMEA logic process, adapted from Ben-Daya et al. (2009)

As is evident in Figure 2.10, the last step that needs to take place is to determine the risk priority number (RPN). This number is based on all the previous steps that have occurred. It allows for the different failure modes to be ranked and prioritised according to their importance in the overall system. Once this process has taken place, decisions about the system can be made. Von Petersdorff (2013) states that this method falls short in terms of assessing the potential economic effects of failures. The reason is the difficulty of assigning quantitative economic values to the effect of failure in a system. Nevertheless, the FMEA methodology can be applied to a system in need of an economic analysis in order to make better decisions on the system once economic values have been found using other models.

A FMEA with the inclusion of a criticality analysis is called a FMECA. The main aim of this analysis is to determine the assets that would have the greatest effect on an organisation if they were to fail. The main components to make up this analysis are the *frequency of failure* and the *consequence of failure*. These two components can be comparatively plotted in order to show the risk of a certain asset to an organisation in graphic form. According to Von Petersdorff (2013), the outcome of the analysis should allow one to see the assets with the largest potential impact on the overall business goals of an organisation. Decisions can then be made to reduce the potential impacts.

In terms of maintenance optimisation, the FMECA logic and tools can be adapted and used to rank different assets based on their cost consequences to a company. The main outcome of understanding FMECA in terms of maintenance optimisation would be to comprehend the different ranking systems that are available, and to modify these to assist in making capital decisions in an organisation.

2.7.8 Forecasting

All the modelling techniques described in this section rely heavily on the acquisition of historical failure data for their implementation in a real-world scenario. In a number of engineering industries, the acquisition of such failure data is not always available since it is either not recorded or the systems are not in place to record it. One set of data that is almost always available is historical cost data associated with maintenance-related activities because this data must be accounted for in the yearly financial records of an organisation. It must be noted that the models outlined in the previous sections cannot be used to develop a maintenance plan for the system/components under scrutiny as they require failure data for their implementation.

One way to develop a maintenance plan based on budget is by using forecasting techniques. Hyndman et al. (1998) indicate that a vast variety of different forecasting techniques are available in literature, ranging from quantitative techniques to qualitative techniques to unpredictable techniques. Some of the most common forecasting techniques used in the engineering industry are quantitative, as outlined by Chase and Jacobs (2018). Three conditions need to be meet before these forecasting techniques can be used: first, information about the past needs to be available; second, this information on the past can be quantified into numerical data; and, third, the assumption can be made that aspects of the past pattern of historical data can be continued into the future (Hyndman et al., 1998). These three elements can usually be assumed in the engineering industry, hence the use of such a forecasting technique. As in the use of any forecasting technique, the result of the forecast is an estimate of what could occur rather than a conclusive answer. In terms of a budgetary requirement for a certain organisation, however, an estimate of the predicted budget for a specific year is better than relying on heuristics alone.

2.8 Decision making

Within the maintenance environment, a variety of decisions are constantly being made on both a strategic level and an operational level. These decisions vary from large managerial outcomes to more technical issues. Von Petersdorff (2013) states that different factors and concerns are relevant to managers in the engineering industry. These include system availability; expected failures; probability of failure at a certain point in time; the effect of downtime on overall production; and the optimum age and cost of a replacement/overhaul to a system/component. Von Petersdorff (2013) emphasises the importance of one area: when making maintenance-related decisions, the criticality of the decisions cannot be based on discussions and experience alone. Fixed modelling techniques and methods need to be employed to ensure more certainly around specific decisions. However, it is essential that the decision-making tools utilised are clearly understood and documented to ensure their ease of use and validity.

To develop a powerful decision-making tool, Von Petersdorff (2013) states that it should incorporate some sort of risk association element in which the implementation of confidence intervals is recognised as highly beneficial. In addition, system boundaries and limitations of the decision-making tool should always be stated clearly to ensure the correct application of the methodology. This allows a vastly improved understanding of the functioning of an engineering system in terms of its maintenance. As the result of such a tool, the optimal maintenance decision can be chosen for a system. It must also be noted that the human element can never be eliminated from a decision-making tool as this would result in the acceptance of a solution without any careful thought and evaluation. Thus, in the application of a technical decision-making tool, it is vital to maintain a balance between the technical aspects of the tool and the human interactions and understanding of the tool. From this, integrated maintenance decisions can be made that will directly affect the success and output of an organisation by reducing downtime and implementing an integrated maintenance plan.

2.8.1 Integration of multiple modelling techniques

As noted above, one of the largest contributors to any decision-making process is the use of some sort of tool that will enable a decision maker to determine the best decision for a certain scenario. Various different models and methods are available to ensure these decisions can be made. The methods range from the implementation of simple linguistic models to complex mathematical models that use a variety of techniques to ensure the best decisions are reached. It is evident, therefore, that modelling plays a vital role in the overall decision-making process. The outcome of a model can completely change a decision choice.

Von Petersdorff (2013) states that a model can be defined as a simplified description of a system within a certain environment. The model describes the relationships between the system itself and all its components. For a model to be developed, three elements are needed: system boundaries, input parameters and output parameters. The first two elements allow the output parameters to be determined, which directly results in the information a decision maker utilises for computation (Von Petersdorff, 2013).

In Section 2.7, a variety of maintenance modelling techniques were briefly discussed. These techniques all placed optimisation at the forefront of their implementation, related to profitability in an organisation. The implementation of these maintenance techniques has proved to be hugely beneficial in terms of the development of an optimised maintenance plan. However, one element that all these techniques require is accessibility to maintenance data to enable their implementation. A central flaw in the use of these modelling techniques is that each one is used for a different scenario, dependent on the available data, and resulting in a segmented approach. No generic maintenance model has been developed. Limited literature was found on the integration of all these maintenance optimisation techniques into one overall maintenance model. Although approaches such as RCM, BCM and TPM (discussed in Section 2.6) have been developed to look at maintenance from an overall point of view, these maintenance techniques lack quantitative measurements that allow cost benefit relations to be computed. The development of any maintenance model should always be based on models that can quantify their benefits and contribute significantly to the decision-making process in maintenance (Von Petersdorff, 2013).

2.9 Conclusion

The literature study presented in Section 2 outlines a substantial number of the different issues and elements involved in maintenance optimisation. It began by looking at the broad spectrum of physical asset management and asset care. This plays an integral role in the understanding of how maintenance can affect an organisation, and how crucial the optimisation of this process is to the success of many organisations.

The literature study then moved on to the topic of maintenance and considered all the different maintenance techniques in depth. It was found that preventive maintenance can be hugely beneficial to an organisation. The implementation of this maintenance technique needs to be carefully examined in all maintenance departments as it can result in significant cost savings. It was also determined that the practice of only using corrective maintenance can be detrimental to an organisation in terms of loss of income. However, it was recognised as imperative to consider all the different maintenance techniques for the varied systems within an organisation. This is essential because one maintenance technique cannot fit all systems. Different systems require different techniques, which all need to be examined in order to attain an optimal maintenance department.

The literature study then continued to explain the different maintenance approaches currently in use. Soft approaches such as TPM and BCM were discussed in order to understand the managerial side of maintenance. It was determined that correctly implementing and managing the different maintenance strategies is just as important as developing the right strategy for a system. Hard approaches such as RCM and LCC were also considered to gain insight into their benefits and an awareness of the diverse elements needed to ensure the success of the maintenance approach. It was found that LCC plays a vital role in the overall optimisation of a capital-constrained environment since it considers and extrapolates into the future all the lifetime costs of a specific system to enable important decisions to be made.

Finally, different maintenance modelling techniques were examined. It was determined that techniques such as the Weibull analysis, the NHPP model, the block replacement model and the optimum grouping strategy are excellent to implement when historical data is accessible. Simulation can also be applied to these techniques in order to create variability in the models and to validate them. From the literature study presented, it was found that the Weibull analysis, the NHPP model, the block replacement model and the optimum grouping strategy are all valid methods for the analysis of failure data; however, their implementation is dependent on the type of failure data being analysed. The outcomes of these different analysis techniques can be incorporated into an overall maintenance model to gain a better understanding of maintenance in terms of overall physical asset management and asset care. From this, capital budgetary decisions can be made based on actual relevant systems data and by examining a specific system over its entire lifetime. In addition, an overview of the decision-making process within the maintenance environment was presented. It was found that limited literature is available on the integration of the quantitative maintenance techniques into one overall maintenance model that can be used in the process of making decisions on capital.

The following section presents the theory and conceptual application of a comprehensive set of different models found in the literature. These are aimed at either optimising preventive maintenance strategies for different types of equipment or systems in different operational scenarios where sufficient data is available or estimating future costs where sufficient data for optimisation is unavailable.

3 Preventive maintenance budgetary decision model

This section introduces all the different modelling techniques that will be used to make verified decisions about their budgetary benefits and whether to implement preventive maintenance tactics within an organisation. The aim of Section 3 is to give a basic overview of different types of failure data that can be found throughout the different systems within an organisation. Different modelling and optimisation techniques will be used to analyse this failure data, resulting in calculated decision making in terms of budgetary requirements.

The methodology process in this section first explains the mathematics associated with the different techniques. Second, an illustrative example is presented for each technique where the previously explained mathematics is implemented and verified. Different failure statistics methods are explained, namely repairable and non-repairable systems modelling, block replacement modelling and opportunistic/grouping replacement modelling. Forecasting models and life cycle cost models are also presented. An overview of the application of each budgetary decision model is given in Figure 3.1. The decision outcome of all these models is one optimal capital budget that identifies the effects of implementing these preventive maintenance techniques.

3.1 Budgetary decision model overview

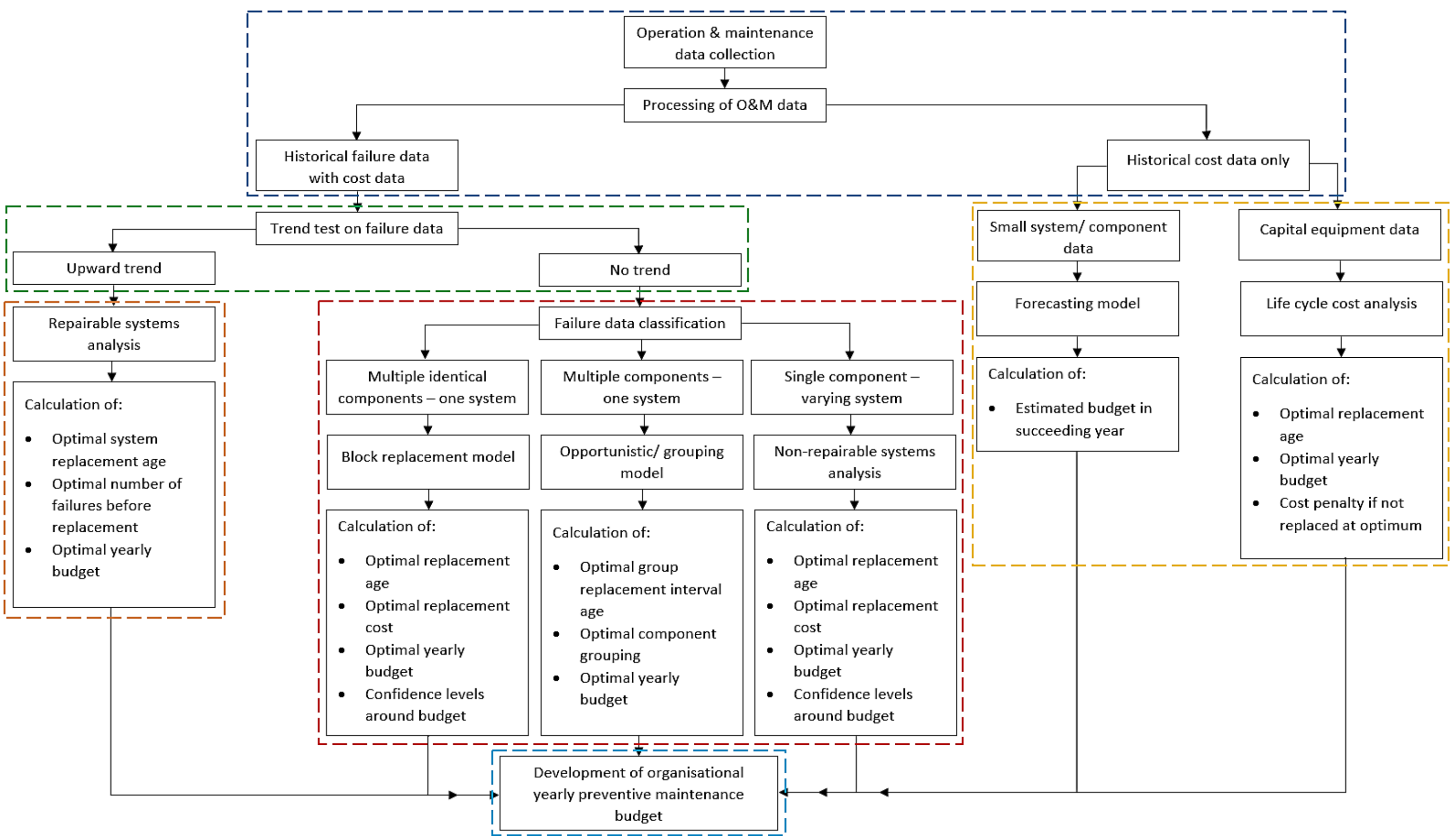

Figure 3.1: Complete budgetary decision model overview

In order to develop a complete budgetary decision model, it is important to first understand how all the sub-budgetary decision models interlink, depending on the type of data available and the system being analysed. The overall methodology behind this model is given in Figure 3.1.

It is evident from Figure 3.1 that a vast number of steps and sub-models need to be developed before a complete budgetary decision can be made for a certain organisation about the implementation of preventive maintenance and its allied cost. As stated in Section 1, the main outcome of this research is to create an overall budgetary preventive maintenance decision model for an organisation. This means that not only one part of an organisation will be considered, but rather the organisation in its entirety. This results in a large variety of data being drawn from the different systems within an organisation. Each set of data will not lead to the application of the same model due to variability in the datasets. Before the development of any budgetary decision model takes place, the first step that needs to occur is the acquisition of data from which certain models can be developed. A substantial amount of historical data is needed for this development to occur (Shaalane, 2012). The data can be in two forms: either historical failure data or historical operation and maintenance cost data for a certain piece of machinery. Shaalane (2012) states that the greater the amount of data available, the more reliable the prediction of a model will be.

Once the data has been drawn from all the different systems within an organisation, it needs to be separated into two different categories, namely historical failure data with failure/maintenance costs and historical cost data only. This process is outlined by the dark blue section in Figure 3.1. The reason for this separation within the dataset is that the same modelling logic cannot be used to analyse these two types of datasets. Different techniques need to be applied to the datasets.

3.2 System/components life cycle stages

Once the data has been collected and all the relevant boundaries have been applied, it can be separated into two categories, namely failure data with costs, and cost data only. If failure data is collected, it is first important to understand the stages that a typical system undergoes during its lifespan before failure data models can be developed. Figure 3.2 shows the bathtub curve, which is typical of most components. The failure rate is plotted as a function of time.

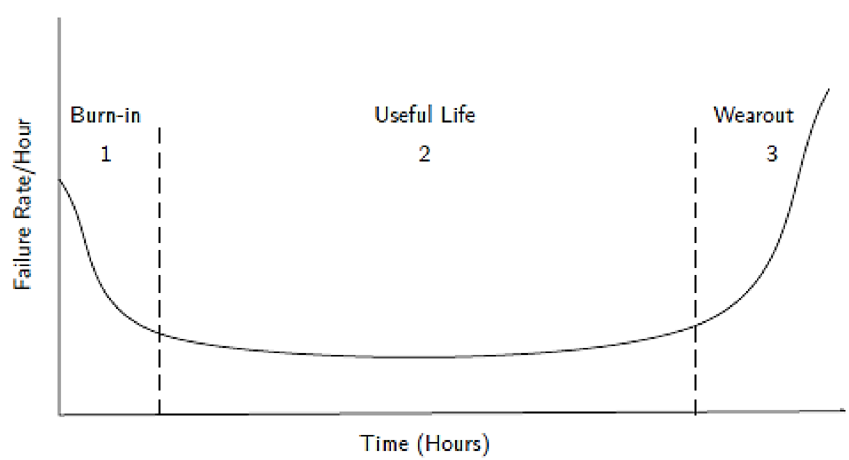

Figure 3.2: Bathtub curve (Shaalane, 2012)

Figure 3.2 shows that a system can go through three phases during its lifetime, namely burn-in, useful life and wear-out.

1. **Burn-in:** This is the phase when a component is new; it shows reliability improvement as time progresses. The failure rate is initially high, but it decreases fast. Failures in this phase can be attributed to manufacturing faults or design flaws.

2. **Useful life:** In this phase the failure rate of a component is reasonably constant over time, and there is a lower risk of failure. The duration of this phase demonstrates the durability of the system/component. Wear does occur during this phase, but the system/component can still perform its task.

3. **Wear-out:** This is the phase in which the component increasingly wears out until failure occurs. It is imperative to try to avoid failure in this phase as it can cause knock-on damage for the rest of the system, resulting in exponentially larger cost implications.

From the above analysis, it is evident that a system/component goes through various phases in its lifetime. Different techniques and models will be needed to analyse the failure data, depending on the life phase of the system/component and the trends found in the data. Nevertheless, the modelling process for failure data can now begin. The first step in this process determines the trends that lie in the data.

3.3 Trend test methods

In deciding on the correct analysis technique to use on a set of failure data, it is imperative to determine the correct trend in the data. This will enable one to ascertain whether an upward trend technique or a no-trend technique should be used, as shown by the green outline in Figure 3.1. Asekun and Fourie (2015) state that statistical hypothesis tests such as the graphical method, the Laplace trend method, and the Lewis-Robinson method are effective ways to establish if a trend is present in the inter-arrival failure times for different sets of data.

Figure 3.3 outlines the process that will be used to determine what type of analysis technique will be utilised to analyse the failure data.

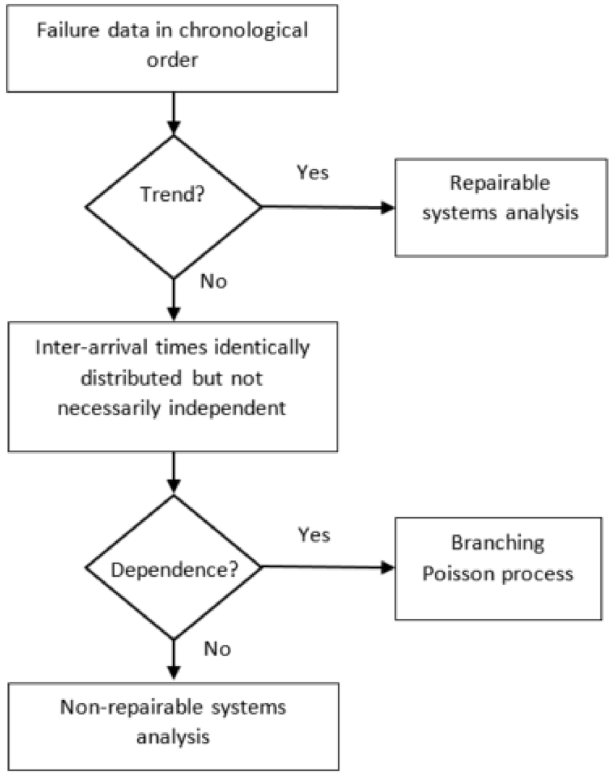

Figure 3.3: Trend test logic, adapted from Coetzee (1997)

It is clear from Figure 3.3 that establishing the type of trend present in the data is at the core of the final decision about the analysis technique that should be used to analyse the failure data. This suggests the need to put a strong emphasis on trend test methods since they play a vital role in the outcome of the analysis.

3.3.1 Graphical trend test

The graphical trend test is the most basic method that can be used to determine whether a trend is present in a given set of data. The test is achieved by plotting the cumulative number of failures against the cumulative operating time. This can be seen in Figure 3.4.

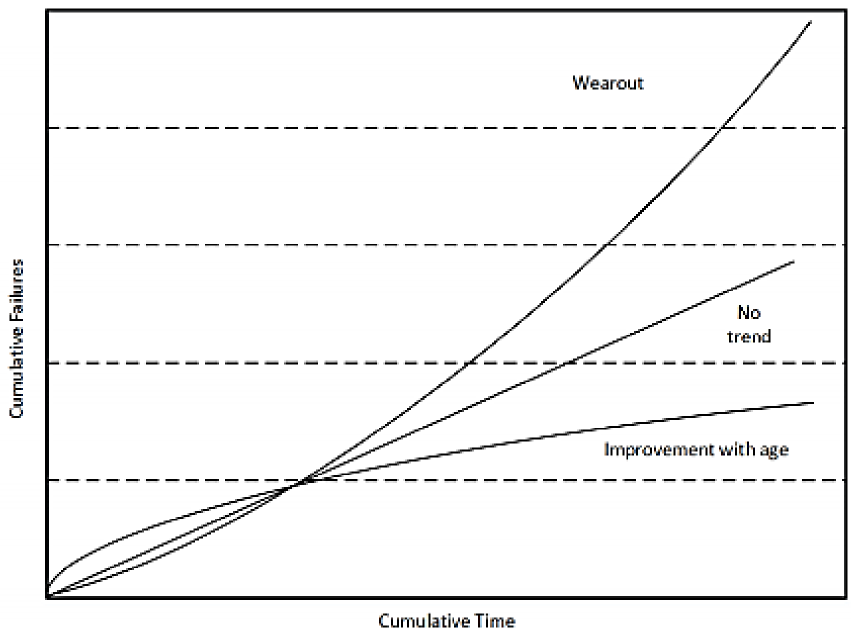

Figure 3.4: Graphical trend test analysis (Asekun & Fourie, 2015)

From Figure 3.4 it is evident that if the plot results in a straight line, no trend is present in the failure data; if the plot results in a convex shape, it indicates an increasing failure trend; and, if the plot results in a concave shape, there is an improvement with age (Asekun and Fourie, 2015). Coetzee (1997) states that the graphical method cannot be used on its own to reach a conclusive answer about the trend in the data. To be effective, it must be used in conjunction with another method.

3.3.2 Laplace test

The Laplace test, also commonly known as the centroid test, is a data trend test that compares the centroid value of an observed set of data to the midpoint of the period of observation. The main purpose of this test is to determine whether a trend exists in the dataset. The appropriate data analysis tool can then be applied to analyse the failure data. The hypothesis test is:

$$H_0\text{: HPP}$$

$$H_a\text{: NHPP}$$

Asekun and Fourie (2015) state that under H_o and conditional Tn, …, Tn–1, the assumption is that the first (n – 1) arrival times are uniformly distributed on (0, Tn). The test statistic for the Laplace trend test can be seen in Equation 3.1:

$$L = \frac{\frac{1}{n-1}\sum_{i=1}^{n-1} T_i - \frac{T_n}{2}}{T_n\left[\frac{1}{12(n-1)}\right]^{1/2}} \qquad [3.1]$$

where n = number of failures and $T_i = i^{th}$ failure arrival time.

Coetzee (1997) states that L has a standard normal distribution at a 5% level of significance with the assumption that the null hypothesis of the data is independent and identically distributed. Figure 3.5 shows the results of the Laplace trend test.

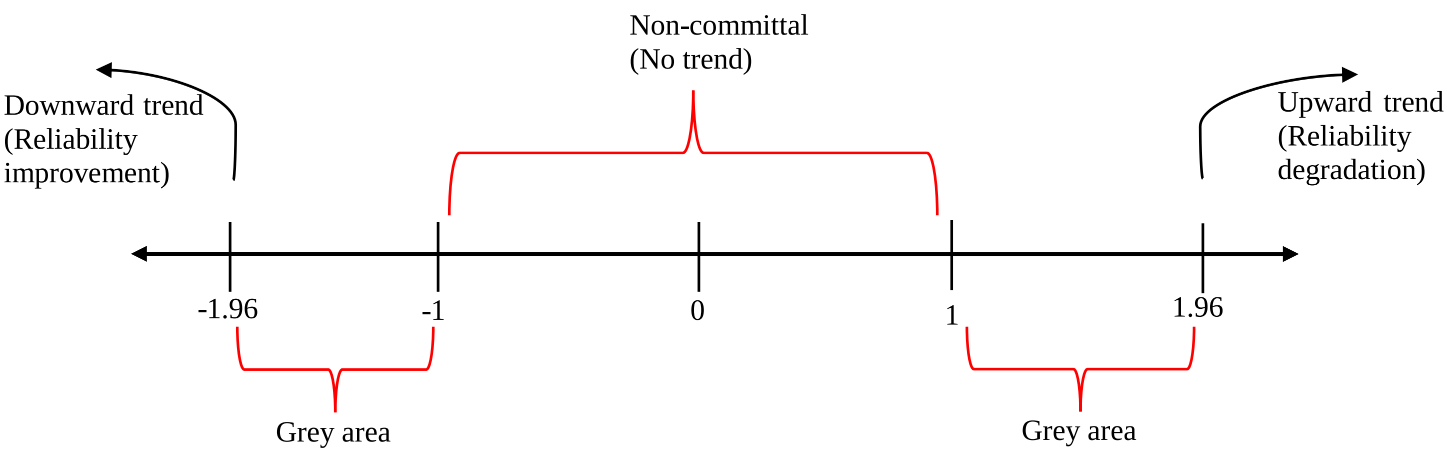

Figure 3.5: The Laplace trend test, adapted from Shaalane (2012)

Using Figure 3.5, the results of the Laplace trend test are as follows: if $L \geq 1.96$, there is a 95% certainty that a significant upwards trend of the data exists, which indicates reliability degradation in the failure data. If $L \leq -1.96$, there is a 95% certainty that a significant downwards trend of the data exists, which indicates reliability improvement in the failure data. If $-1 \leq L \leq 1$, then there is no evidence of a trend in the data, which suggests a noncommittal dataset. In the last two cases, when $1.96 > L > 1$ and $-1 > L > -1.96$, this is called a grey area (Coetzee, 2015) in which the Laplace trend test is unable to give a definite answer about whether there is a trend present in the failure data. As a result, another trend test is needed in order to determine what to do with the failure data when it lies in between that range. Shaalane (2012) states that the Lewis-Robinson test is an alternative test that can be used, which is explained in Section 3.3.3.

3.3.3 The Lewis-Robinson test

As stated in Section 3.2.2, the Laplace trend test cannot give a definite answer about what trend lies in the data when $1.96 > L > 1$ and $-1 > L > -1.96$. To overcome this, the Lewis-Robinson test has been developed. It is a build-on to the Laplace trend test in order to provide a definite answer about what to do when the failure data lies in the grey areas in Figure 3.5.

The hypothesis test is:

$$H_0\text{: Renewal process}$$

$$H_a\text{: Non} - \text{renewal process}$$

The Lewis-Robinson test statistic is derived by dividing the Laplace trend test value by the coefficient of variation for the failure inter-arrival times (Asekun & Fourie, 2015). This can be seen in Equation 3.2.

$$U_{LR} = \frac{L}{CV} \qquad [3.2]$$

CV is derived by using Equation 3.3 (Asekun & Fourie, 2015).

$$CV = \frac{\sqrt{Var|X|}}{\bar{X}} \quad [3.3]$$

Now the rejection criteria of the Lewis-Robinson test are similar to those of the Laplace trend test, which are given by Reject H_0 if $U_{LR} > Z_{\alpha/2}$ or $U_{LR} < -Z_{\alpha/2}$, also at a confidence interval of 95%.

3.3.3.1 Laplace trend test example

An example of how the Laplace trend test works in practice is shown in this section. The reason is to better illustrate the use of the test in practice and to show the outcome of the test results. An example set of data from Coetzee (1997), comprised of 23 failure events, can be seen in Table 3.1 which shows the inter-arrival times and the failure arrival times of the data points.

Table 3.1: Laplace trend example data

Observed example failure point	Failure inter-arrival times (t_i) (hours)	Observed example failure point	Failure inter-arrival times (t_i) (hours)
1	74	***13***	60
2	84	***14***	71
3	62	***15***	43
4	21	***16***	104
5	49	***17***	84
6	52	***18***	94
7	59	***19***	79
8	92	***20***	123
9	44	***21***	95
10	110	***22***	45
11	76	***23***	76
12	92		

Using the information in Table 3.1 as well as Equation 3.1, the following results from a Laplace trend test were found:

where:

$$\sum_{i=1}^{n-1} T_i = 17296$$

$$\therefore L = \frac{\frac{1}{23-1} \times 17296 - \frac{1686}{2}}{1689\left[\frac{1}{12(23-1)}\right]^{1/2}} = -0.561$$

From the result it is evident that the Laplace value is –0.561. This suggests there is no trend in the dataset, according to Figure 3.5, and that an appropriate model can now be used to analyse the failure data.

3.4 Goodness of fit tests

Goodness of fit (GOF) tests are used to determine whether a certain model fits a given dataset with enough certainty. In technical terms, GOF tests determine how well a specific probabilistic distribution fits an actual dataset and whether the probabilistic distribution can be used to emulate the actual dataset. Some of the most common GOF tests available in the literature are analytical tests. These involve specifying a test statistic, which is the distance between the probabilistic distribution and the actual data. From here, the model accuracy can be obtained. GOF tests are imperative to the development of the overall maintenance model as they determine certainty and trust around the application of the different failure models. In the literature, various GOF tests are available to test whether a certain distribution is suited to a dataset. The most common tests include the Chi-squared test, the Anderson-Darling test, the Shapiro-Wilk test and the Kolmogorov-Smirnov test. For the balance of the discussion in this section, the GOF test is limited to the Kolmogorov-Smirnov (K-S) test.

The K-S test is a non-parametric test used to model adequacy tests for continuous distributions. It is used to compare the empirical cumulative distribution function with a fitted or hypothesised parametric cumulative distribution function, as stated by Leemis (2009). Unlike many of the other GOF tests such as the Chi-squared test, the K-S test does not suffer from arbitrary interval limitations or dataset sizes, which suggests it is a dynamic test that can be used in different scenarios (Leemis, 2009).

The basis of the K-S test is two hypotheses, as seen in Equations 3.4 and 3.5.

$$H_0\text{: The data follows a specified distribution } F_n(x) = F_0(x) \quad [3.4]$$

$$H_1\text{: The data does not follow the specified distribution } F_n(x) \neq F_0(x) \quad [3.5]$$

If the null hypothesis, as seen in Equation 3.4, is failed for rejection, it suggests that the fit between the actual data and the probabilistic distribution is a good enough fit. This means that the probabilistic distribution can be used to approximate the actual data. If the null hypothesis is rejected, it means that the probabilistic distribution cannot be used to approximate the actual data as the fit is not good enough. The main outcome of the K-S test is to determine a test statistic, which is the largest vertical distance between the empirical cumulative distribution and the fitted cumulative distribution. This can then be compared to a critical value to determine whether the null hypothesis can be rejected. In order to establish the K-S test statistic, the following methodology can be used.

The empirical distribution function $F_n(x)$ is given in Equation 3.6.

$$F_n(x) = \frac{number\ of\ elements\ in\ sample\ \leq x}{n} = \frac{1}{n}\sum_{i=1}^{n} X_i \leq x \quad [3.6]$$

The K-S test statistic determines the largest vertical difference between the empirical function and the hypothesised function at each X_i and can be calculated using Equation 3.7.

$$D_n = sup_x \, |F_n(x) - F_0(x)| \quad [3.7]$$

Leemis (2009) states that one of the best methods to compute D_n is to follow Equations 3.8 – 3.10:

$$D_n^+ = \max_{i=1,2,\ldots n} \left(\frac{i}{n} - F_0(x_i) \right) \quad [3.8]$$

$$D_n^- = \max_{i=1,2,\ldots n} \left(F_0(x_i) - \frac{i-1}{n} \right) \quad [3.9]$$

$$D_n = \{D_n^+, D_n^- \} \quad [3.10]$$

Once D_n has been computed, it can be compared to some critical value. If D_n exceeds this critical value, the null hypothesis is rejected. The test condition for this is given in Equation 3.11.

$$D_n > c_n \quad [3.11]$$

The critical value for the K-S test can be obtained from the K-S one-sample statistical table.

3.5 Repairable systems analysis

Once a trend test has been applied to a certain dataset that results in an upward trend, then the following budgetary modelling technique should be applied to that set of data, as seen by the orange outline in Figure 3.1. A repairable system can be defined as a system that undergoes some form of repair that restores it to a functioning operation using any possible method, other than replacement of the entire system. Coetzee (1997) states that renewal theory is common practice in many instances, especially when only a component is being examined and not an entire system. However, when there is reliability degradation and an increase in the failure rate, repairable systems analysis is the correct choice.

Coetzee (2015) states that by using repairable systems, a system can be returned to one of the following states of repair (see Section 2.4.2), depending on the type of system and the disrepair of the current system: 'as good as new', 'as bad as old', 'better than old but worse than new', 'better than new' and 'worse than old' (Coetzee, 2015). When conducting the analysis for non-repairable systems, it can be assumed that the failure data is identically distributed and independent. This same assumption cannot be made for repairable systems, which means that a different technique is needed to analyse the failure data.

Coetzee (1997) affirms that there are generally two models accepted in literature related to the analysis of repairable systems. Both models analyse the non-homogenous data using the non-homogenous Poisson Process (NHPP). The first NHPP model was introduced by Cox and Lewis (1966), and the rate of change of frequency (ROCOF) for this model can be seen in Equation 3.12.

$$\rho_1(T) = e^{\alpha_0 + \alpha_1 T} \quad [3.12]$$

with: $-\infty < \alpha_0, \alpha_1 < \infty$ and $T \geq 0$

Coetzee (1997) states that the first model represents repairable systems best when $\alpha_1 > 0$. The second proposed NHPP model is the 'Power Law Process', and the ROCOF for the model can be seen in Equation 3.13, as stated by Crow (1974).

$$\rho_2(T) = \lambda \beta T^{\beta - 1} \qquad [3.13]$$

with: $\lambda, \beta > 0$ and $T \geq 0$

Coetzee (1997) states that the second NHPP model represents repairable systems best when $\beta > 1$. If $\beta = 2$, it results in a linearly increasing failure rate.

3.5.1 Standard functions

The regression model that describes the failure rate of a certain system over a long-term period or time (T) is described in this section for both the first and second NHPP models. This model will be used to optimise the maintenance strategy by employing the cost-optimisation techniques explained in Section 3.5.3.

First model:

From the definition of a non-homogenous Poisson process (see Section 2.7.3), the expected number of failures (N) in a certain interval (T_1, T_2) can be computed using Equation 3.14.

$$E\{N(T_2) - N(T_1)\} = \frac{e^{\alpha_0}}{\alpha_1}\left(e^{\alpha_1 T_2} - e^{\alpha_1 T_1}\right) \qquad [3.14]$$

with: $-\infty < \alpha_0, \alpha_1 < \infty$ and $T_1, T_2 \geq 0$

Next, the survival function for the first NHPP model in an interval (T_1, T_2) can be computed using Equation 3.15. This function gives the probability that a system will survive up to a certain point in time.

$$R(T_1, T_2) = e^{-\frac{e^{\alpha_0}}{\alpha_1}\left(e^{\alpha_1 T_2} - e^{\alpha_1 T_1}\right)} \qquad [3.15]$$

with: $-\infty < \alpha_0, \alpha_1 < \infty$ and $T_1, T_2 \geq 0$

Finally, the mean time between failures (MTBF) in an interval (T_1, T_2) can be calculated using Equation 3.16. This function is important in terms of optimising the maintenance strategy as it gives a finite answer to the MTBF. This allows for the prevention of failure if the correct strategy is implemented using the MTBF.

$$MTBF(T_1, T_2) = \frac{\alpha_1 (T_2 - T_1)}{e^{\alpha_0}\left(e^{\alpha_1 T_2} - e^{\alpha_1 T_1}\right)} \qquad [3.16]$$

with: $-\infty < \alpha_0, \alpha_1 < \infty$ and $T_1, T_2 \geq 0$

Second model:

As in the first NHPP model, all the NHPP functions of the second model can be seen in Equations 3.17 – 3.19. Equation 3.17 shows the expected number of failures.

$$E\{N(T_2) - N(T_1)\} = \lambda\left(T_2{}^{\beta} - T_1{}^{\beta}\right) \qquad [3.17]$$

with: $\lambda, \beta > 0$ and $T_1, T_2 \geq 0$

Equation 3.18 shows the survival function for the second NHPP model.

$$R(T_1, T_2) = e^{\lambda\left(T_2{}^{\beta} - T_1{}^{\beta}\right)} \qquad [3.18]$$

with: $\lambda, \beta > 0$ and $T_1, T_2 \geq 0$

Equation 3.19 shows the MTBF of the second NHPP model.

$$MTBF(T_1, T_2) = \frac{(T_2 - T_1)}{\lambda\left(T_2{}^{\beta} - T_1{}^{\beta}\right)} \qquad [3.19]$$

with: $\lambda, \beta > 0$ and $T_1, T_2 \geq 0$

3.5.2 Parameter estimation

To solve all the standard function equations as seen in Section 3.5.1 for the first and second NHPP models, a number of variables need to be resolved first. Coetzee (1997) proposes a method in which this can be done.

First model:

Using the maximum likelihood theory, the parameters for the first NHPP model can be computed. These parameters include α_1 and α_0 which can be seen in Equation 3.12. The first parameter α_1 can be computed through an iterative process using Equation 3.20. The iterative process can be performed using mathematical tools such as Microsoft Excel.

$$\sum_{i=1}^{n-1} T_i + n\alpha_1^{-1} - nT_n\{1 - e^{-\alpha_1 T_n}\}^{-1} = 0 \qquad [3.20]$$

Once α_1 has been computed, α_0 can be found by substituting α_1 into Equation 3.21.

$$\alpha_0 = \ln\left\{\frac{n\alpha_1}{e^{\alpha_1 T_n} - 1}\right\} \qquad [3.21]$$

Second model:

As in the first NHPP model, the parameters of the second model can be estimated using the maximum likelihood theory which results in the computation of Equations 3.22 – 3.23. β *and* λ from Equation 3.5 are the two variables that need to be calculated in order to compute the standard function.

$$\beta = \frac{n}{\sum_{i=1}^{n} Ln\frac{T_n}{T_i}} \quad [3.22]$$

$$\lambda = \frac{n}{T_n^{\beta}} \quad [3.23]$$

Unlike the first NHPP model, no iteration is needed to calculate the parameters; thus, the failure data can be substituted straight into Equation 3.14 to calculate β. Once β has been calculated, it can be substituted into Equation 3.23 and λ can be computed.

3.5.3 Cost modelling

Using all the parameters and estimates found in Sections 3.5.1 and 3.5.2, an optimum cost model for both the first and second NHPP models can be obtained, as found by Coetzee (1997). The output of this cost model results in an optimum cost per unit time in maintaining a certain system, as well as an optimum replacement age for the system. These two factors can be used to determine the budgetary requirements of the system in a specific year. Coetzee (1997) states that two different types of cost policies can be implemented to find the optimum replacement interval. The first policy involves determining the optimum replacement age based on minimal repairs at breakdown at a certain age. The second policy involves replacement of the system after the optimum number of failures of the system have been minimally repaired. Coetzee (1997) asserts that the second policy is superior to the first policy since the system is only replaced at the end of the last minimal repair, meaning that the entire life of the final repair is utilised and not cut short, as in the first policy.

First model:

Equation 3.24 shows the optimum replacement time for the first NHPP model, using the first policy. An iterative process is used to calculate the optimum replacement time T^*.

$$Policy\ 1: e^{\alpha_1 T^*}\left(T^* - \frac{1}{\alpha_0}\right) = \frac{C_p}{C_f e^{\alpha_0}} - \frac{1}{\alpha_1} \quad [3.24]$$

Equation 3.25 shows the optimum number of failures that need to occur before replacement takes place, using the second policy. The variable m is needed to find the solution. An iterative process in Equation 3.26 is used to calculate this variable, as seen in Coetzee (1997).

$$Policy\ 2: n^* = \frac{(m-1)e^{\alpha_0}}{\alpha_1} \quad [3.25]$$

$$\frac{m}{\alpha_1}(\ln(m-1)) = \frac{C_p}{C_f e^{\alpha_0}} - \frac{1}{\alpha_1} \quad [3.26]$$

Once both T^* *and* n^* have been computed, an optimum decision can be reached.

Second model:

For the second model, Equations 3.27 and 3.28 show the optimum replacement age based on time and the number of failures respectively. The second NHPP cost model does not require any iterations and values can be substituted directly into Equations 3.27 and 3.28.

$$Policy\ 1:\ T^* = \left[\frac{C_p}{\lambda(\beta-1)C_f}\right]^{\frac{1}{\beta}} \quad [3.27]$$

$$Policy\ 2:\ n^* = \frac{C_p}{C_f(\beta-1)} \quad [3.28]$$

The final step in the cost-optimisation analysis is to give a graphic representation of the replacement cost versus time to illustrate the importance of cost optimisation. This is done using Equation 3.29.

$$C(t) = \frac{C_f E[N(t)] + C_p}{T} \quad [3.29]$$

The optimum cost determined from the minimum point in the graphic developed from the use of Equation 3.29 can be transformed into a yearly cost. This will be the annual budgetary cost in the preventive maintenance of a certain system.

3.5.4 Illustrative example

To illustrate the repairable systems model, an example is given. The failure data used in the example is for a Caterpillar 789 180 ton haul truck, as published by Coetzee (1996). The failure data can be seen in Appendix C. The cost figures for replacement of the system are \$1 300 000 and the cost of minimal repair is \$7 165 (Coetzee, 1997). Using this information, the analysis can begin.

The first step in the analysis is to determine whether there is a trend in the dataset. This is done through the Laplace test, using Equation 3.1. The outcome of the Laplace test using the data seen in Appendix C is 6.94, which shows there is a significant trend in reliability degradation. This means that repairable systems analysis can be used for the analysis.

The first NHPP model was used for the rest of the analysis. Using an iterative process, α_1 *and* α_0 were found, as seen in Table 3.2.

Table 3.2: Repairable systems parameters

Parameter	Value
α_1	0.000107
α_0	–6.545

From Table 3.2 it can be seen that $\alpha_1 > 0$, which means that the original assumption to use the first NHPP model was correct. Using α_1 and α_0, Figure 3.6 was produced to show the results of all the standard functions in Section 3.5.1.

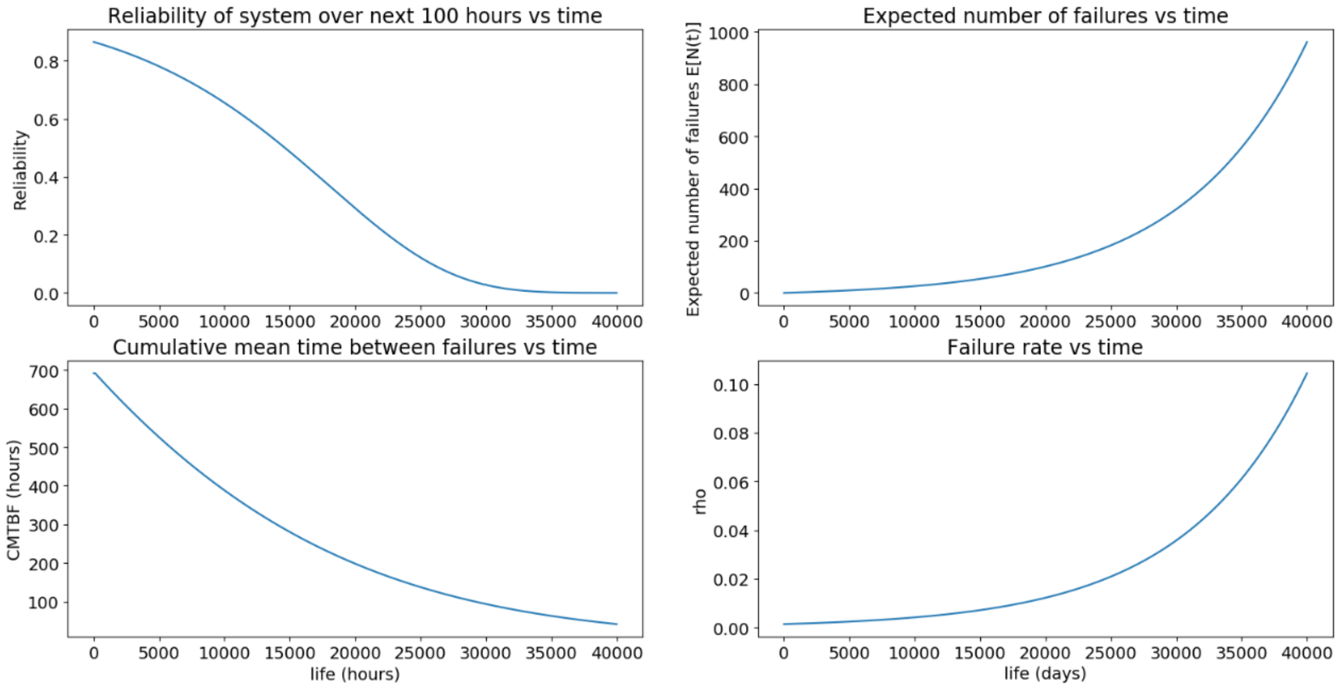

Figure 3.6: Repairable systems standard function graphs

It is clear in Figure 3.6 that the failure data results in an increasing failure rate and an increasing expected number of failures versus time. Again, this shows the presence of reliability degradation and the benefit of using maintenance optimisation to reduce overall system costs. By applying the failure data and Equations 3.27 and 3.28, the optimum replacement time based on age and the number of failures can be found using an iterative process in Microsoft Excel.

$$T^* = 21\ 284 \text{ hours and } n^* = 118 \text{ failures}$$

Thus, according to the repairable systems model, it would be most economical to replace the system after 21 284 hours or after 118 failures have occurred with minimal repair actions taken. Using Equation 3.29, the optimum cost graph was computed as seen in Figure 3.7.

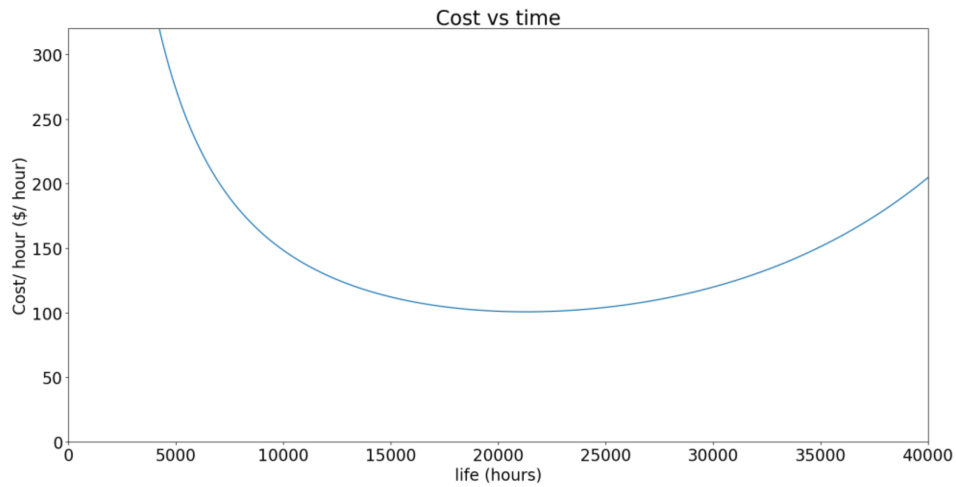

Figure 3.7: Repairable systems cost graph, recreated from Coetzee (1997)

Figure 3.7 shows that the optimum replacement cost is $100.74/hour, which correlates to the optimum replacement time T^*. It also demonstrates that the system is sensitive to this optimum replacement time, which means that system replacement too early or too late will result in a large additional cost. This indicates the importance of maintenance optimisation for repairable systems analysis. The optimum replacement cost can be transformed into a budgetary cost of $882 482 per year, which is the annual cost that an organisation needs to budget to ensure the system keeps up and running with the implementation of preventive maintenance.

3.6 Non-repairable systems analysis

Non-repairable systems analysis deals with components and, in rare cases, systems in which replacement and/or reconditioning occurs. It is assumed that the component or system is left in as 'good as new condition'. The most common process used in this analysis is the renewal theory, as stated by Coetzee (1997), which applies a statistical approach to solve the problem. The renewal theory makes use of the Weibull distribution, which has proved to be the most versatile distribution in terms of its ability to emulate other distributions. Further discussions can be found in Section 3.6.5.

For non-repairable systems analysis to take place, no trend in the failure data can be present, as found by using the Laplace test. It is also assumed that the data being analysed is independent and identically distributed.

3.6.1 Standard functions

This section explains the renewal theory standard functions that will be used throughout the analysis, in which the two-parameter Weibull distribution is used.

The failure density of a component is given in Equation 3.30, which shows the probability of failure of a component over its own life, as stated by Coetzee (1999). At any specified point in the life of the component, the probability of failure is given at that exact moment in time.

$$f(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^{\beta}} \quad [3.30]$$

The cumulative failure distribution of a component is given in Equation 3.31. It states the probability that a component would have failed before or at that point in time during its life, as stated by Coetzee (1999). The cumulative failure distribution always starts at zero since the probability of failure is assumed zero for a new component. It will always end at one since it is a given that components will eventually fail.

$$F(t) = 1 - e^{-\left(\frac{t}{\eta}\right)^{\beta}} \quad [3.31]$$

The survival function of a component is given in Equation 3.32, which states the percent probability that a component will survive up to a certain point in time. This is a useful function as it indicates the exact percentage of the number of components that have survived up to a specific point in time.

$$S(t) = e^{-\left(\frac{t}{\eta}\right)^{\beta}} \quad [3.32]$$

Equation 3.33 shows the hazard function of a component, which Coetzee (1999) states is the most useful function. It presents the probability that a component will fail at a certain age, given that it has survived up to that age. It can also be regarded as a measure of the risk of failure of a component at a certain age (Coetzee, 1999).

$$z(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \quad [3.33]$$

The hazard function can tell a lot about the type of maintenance strategy that should be employed in a system to result in the most economical decision. If the hazard function decreases with time, meaning that $\beta < 1$, then it is not viable to apply preventive-based maintenance since the risk of failure will not be lower than before the maintenance took place. If the hazard function increases, meaning that $\beta > 1$, preventive maintenance actions can be employed since these will result in a decrease in the hazard of the component. However, before any maintenance task can be applied to a system or component, it is essential to consider the economics to ensure the implementation of the most economical option.

3.6.2 Parameter estimation

In order to determine the standard functions in Section 3.6.1, two parameters – β and η – need to be established first. While β is the shape parameter – meaning changes in this parameter will directly change the shape of the results of the standard functions, η is the scale parameter – meaning changes to this parameter will alter the scale of the results of the standard functions. To determine the two parameters, the maximum likelihood method is used. This results in a likelihood function as seen in Equation 3.34, stated by Coetzee (1997).

$$lnL(\beta,\eta) = \sum_{i=1}^{n}\left(ln\beta - \beta\ln(\eta) + (\beta-1)\ln(t_i) - \left(\frac{t_i}{\eta}\right)^{\beta}\right) \quad [3.34]$$

Solving for Equation 3.34 results in Equations 3.35 and 3.36.

$$\frac{1}{n_i}\sum_{i=1}^{n}\ln(t_i) = \frac{\sum_{i=1}^{n} t_i{}^{\beta} ln(t_i)}{\sum_{i=1}^{n} t_i{}^{\beta}} - \frac{1}{\beta} \qquad [3.35]$$

$$\eta = \left[\frac{\sum_{i=1}^{n} t_i^{\beta}}{n}\right]^{1/\beta} \qquad [3.36]$$

An iterative approach is used to solve for β in Equation 3.35. Once β has been iteratively computed using a tool such as Microsoft Excel, η can be computed to find the standard functions.

3.6.3 Cost modelling

One of the most important outcomes of the entire renewal analysis is to determine the optimum cost of replacement of the component on which the analysis is being performed. This is a major aspect that must be considered when making a decision about a specific component, and the main factor to incorporate into a yearly budget for an organisation. To calculate this, the standard functions in Section 3.6.1 will be used as well as the expected life of the system, resulting in an optimum cost function as seen in Equation 3.37 (Coetzee, 1997).

$$C(t_p) = \frac{C_p R(t_p) + C_f[1 - R(t_p)]}{(t_p + T_p)R(t_p) + \int_{-\infty}^{t_p} tf(t)dt + T_f[1 - R(t_p)]} \qquad [3.37]$$

Equation 3.37 works by adding up the total cost of prevention and failure and dividing this by the total expected life of the component. $C_p R(t_p)$ is seen as the preventive cost, while $C_f[1 - R(t_p)]$ is regarded as the cost of failure. C_p is the cost of preventive maintenance and C_f is the cost of failure. The resulting equations for these variables can be seen in Equations 3.38 and 3.39 respectively.

$$C_p = \text{Labour costs} + \text{Material costs} + \text{Reconditioning costs} \qquad [3.38]$$

$$C_f = \text{Labour costs} + \text{Material costs} + \text{Downtime } \times \text{Production loss} + \text{Reconditioning costs} \qquad [3.39]$$

The use of Equation 3.37 will result in a cost-optimisation graph that will allow the user to make various decisions leading to the determination of the most economical replacement age of the component. It will also enable the user to ascertain the cost consequences if the optimum replacement age is not followed. This makes this graph one of the most important functions of decision making. The output of this graph will also be incorporated into the annual budget of an organisation for preventive maintenance.

3.6.4 Illustrative example of non-repairable systems analysis

A hypothetical example is given to illustrate the decision-making process related to using the non-repairable systems analysis techniques. The data is the same as that used in the illustrative example in Section 3.3.3.1

from Coetzee (1997). Table 3.1 outlines the life of a bearing given in days; it is assumed that if the bearing fails, the entire assembly fails too. It is also assumed that all maintenance activities take place during planned maintenance periods. The cost of preventive maintenance is R4 808 and the cost of failure is R28 808, as outlined by Coetzee (1997).

In Section 3.3.3.1 it was already found that the Laplace value is –0.561, which means that the data is noncommittal and non-repairable systems analysis can take place. Using Equations 3.35 and 3.36 and an iterative process on Microsoft Excel, β and η can be computed, as seen in Table 3.3.

Table 3.3: Weibull parameters

Weibull parameters	Value
β	3.38
η	81.80

Using the values in Table 3.3 and Equations 3.30 – 3.33, Figure 3.8 can be produced to show the results of all the standard functions given in Section 3.6.1. All the standard function graphs will allow various decisions to be made about the component as they show the probability of survival and the risk of failure as time progresses.

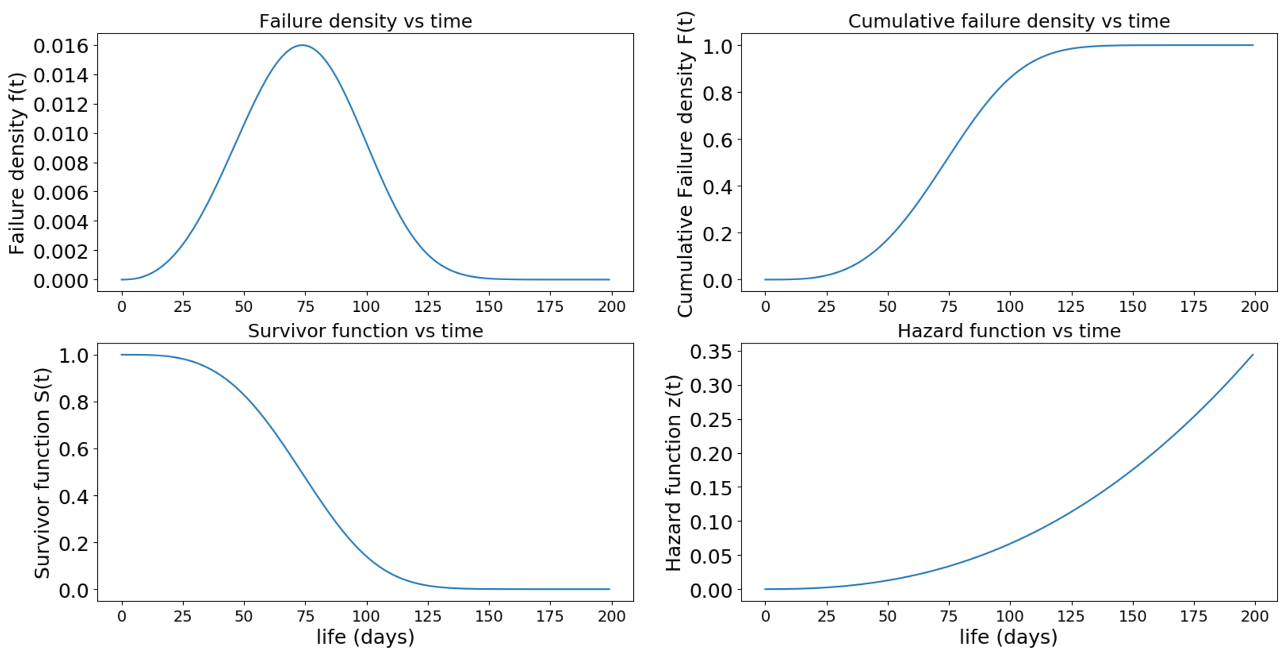

Figure 3.8: Non-repairable systems standard function graphs

Figure 3.8 shows that the example results in an increasing hazard function with time. This means that preventive maintenance tactics can be applied since they will result in a hazard reduction when implemented

(Coetzee, 1999). Using the information given in the standard function graphs, the optimum cost graph can be computed using Equation 3.37, as seen in Figure 3.9.

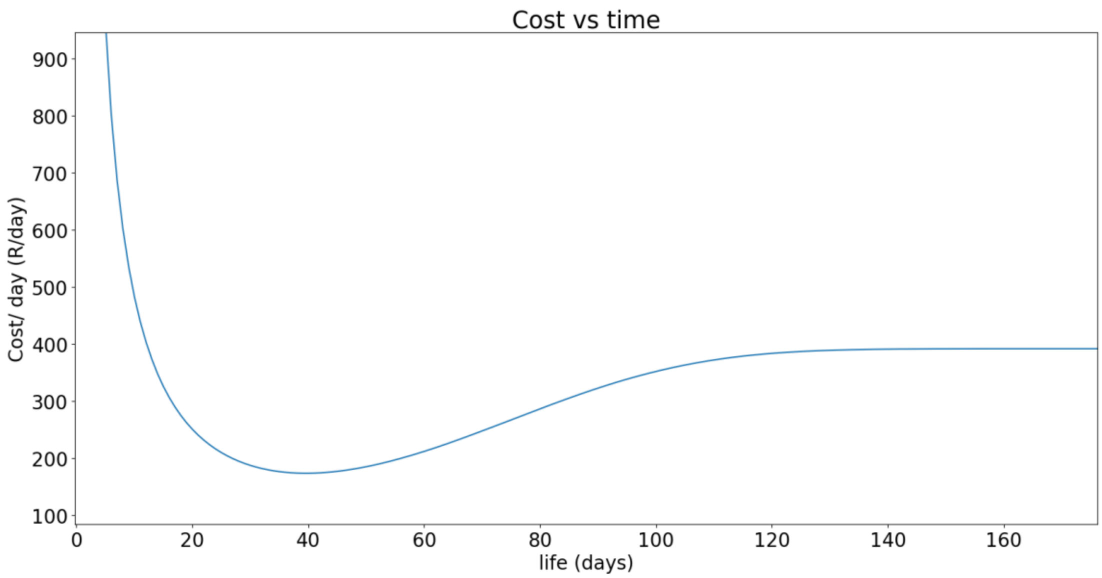

Figure 3.9: Non-repairable systems optimum cost graph, recreated from Coetzee (1997)

Figure 3.9 shows a major dip in the graph, which suggests that preventive maintenance actions will result in a large reduction in cost when compared to leaving the component to fail. The optimum results and run to failure (RTF) results can be seen in Table 3.4.

Table 3.4: Non-repairable systems decision-making data

Decision factor	Value
Optimum replacement age	40 days
Optimum replacement cost	R174.07
Probability of failure @ optimum	8.5%
Run to failure cost	R392.11

Table 3.4 demonstrates that there is a huge difference between the optimum replacement cost and the run to failure cost. The difference between the two costs is 125.3%, which shows that if the component was left to run to failure, the company would experience huge cost detriment. In addition, the probability of failure at the optimum is only 8.5%. This indicates that the optimum replacement cost is a safe option and the replacement age could be extended if needed, although it would result in additional cost. The above example emphasises that it is imperative for non-repairable systems analyses to take place to ensure the correct expenditure within a company and to reduce maintenance costs.

3.6.5 Flexibility of the Weibull distribution

The Weibull distribution is a highly versatile distribution that can take on the shape of a variety of other distributions just by altering the shape parameter β. Figure 3.10 outlines this versatility simply by altering β.

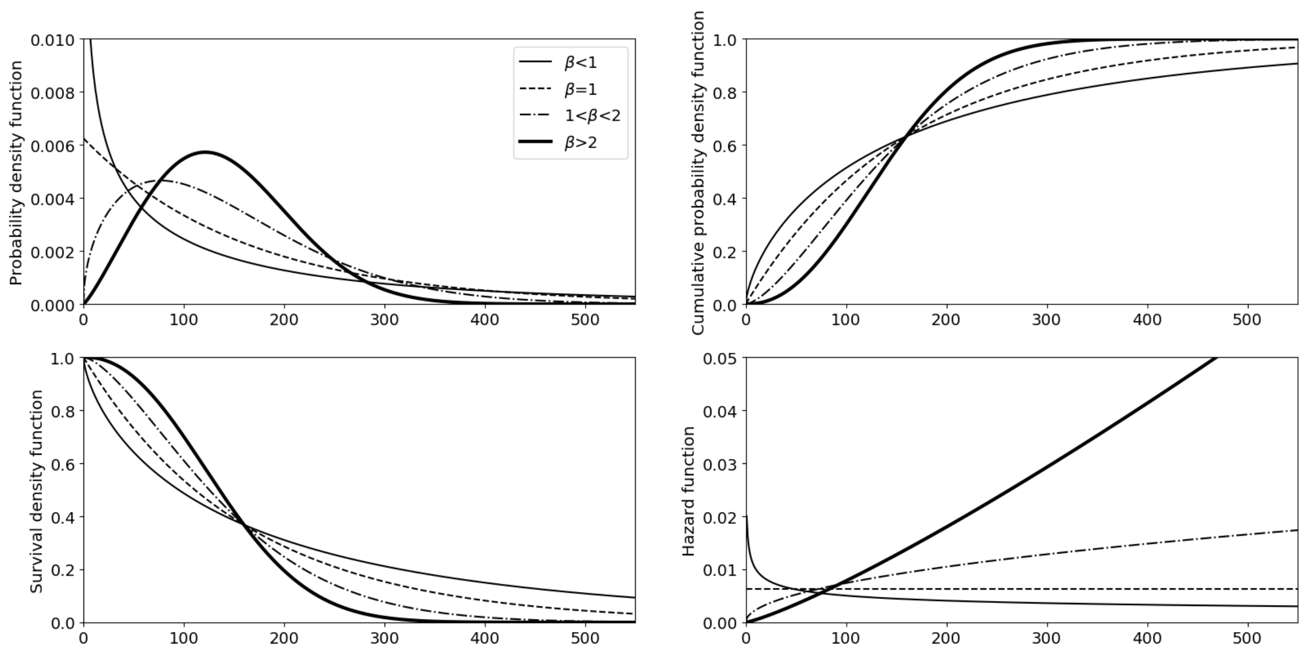

Figure 3.10: Flexibility of Weibull distribution with varying beta values

Von Petersdorff (2013) lists some of the distributions that the Weibull distribution can model by changing the β value:

- β = 1 is equivalent to the exponential distribution
- β = 2 is equivalent to the Rayleigh distribution
- 1 < β < 3.6 approximates the log normal distribution
- 3 < β < 4 approximates the normal distribution
- β = 5 approximates the peaked normal distribution.

Figure 3.10 shows that the Weibull distribution can model different failure distributions just by changing the value of β. This is an important characteristic of the Weibull distribution because it means there is no need to develop different models for various types of failure data. In addition, different factors can be obtained by looking at the β value and the hazard function graph in Figure 3.10. If β is less than 1, the result is a decreasing hazard rate. This suggests that preventive maintenance should not be implemented since it will not decrease that hazard. If β is greater than 1, the result is an increasing hazard rate in which the larger the value of β, the greater the increase. This makes it imperative to implement a preventive maintenance technique.

3.7 Non-repairable systems yearly budgetary validation model

As stated is Section 1, one of the main outcomes of this research is to determine the yearly budget of an organisation through the implementation of all the different preventive maintenance techniques discussed in Section 2. In Section 3.6 the non-repairable systems analysis model was discussed; it found the optimal age to replace a component within a system based on the minimisation of cost. This was done using the renewal theory. A core disadvantage of this model is that it outputs an average cost per unit time as a result of the integral function in Equation 3.37. This means that determining an annual budget for an organisation using the optimal cost outputted by the model would result in an average yearly budget. This suggests that a lot of variability exists around this budget. It also implies that the budget presented is more likely to be an average representation of the cost in a specific year rather than an accurate representation of the probable budget. In terms of the overall budgetary requirements of an organisation, this variability in the budget may not be acceptable. More certainty around the budget is sure to be needed. This section outlines a methodology that can be followed in order to create more certainty around the answers found using the model discussed in Section 3.6. It was achieved through the development of an extensive program using Monte-Carlo simulations.

3.7.1 Development of yearly budget using renewal theory only

This section outlines the process that is used to determine the budgetary requirements of an organisation if the model presented in Section 3.6 is utilised. This model focuses on determining the optimal age to replace a component within a system by finding an optimum balance between the number of failure and preventive actions in a certain time frame, as stated by Coetzee (1997). It is evident from Section 3.6.3 and Equation 3.37 that this optimal age is found by minimising the cost that is given per unit time. However, using the output of Equation 3.37, Equation 3.40 can be applied to determine the cost of maintaining a certain component over a specified time period.

$$C_{budget} = C(optimal\ age) \times T_b \qquad [3.40]$$

where: T_b is the specified budgetary time period considered.

Thus, from Equation 3.40, it is evident that the budgetary cost outputted is an average over the specified time period as a result of the cost per unit time being computed as an average in Section 3.6.3. Since this budget is an average, there is only a 50% chance of it being reached within the specified time period. This uncertainty around the budget is not ideal as there is insufficient confidence around this output. The result is too risky if the answer were to be taken as the final budgetary requirement. Aware of the flaw in this preventive maintenance model, the author developed a novel model that allows for a choice with confidence around the budget.

3.7.2 Development of yearly budget using renewal theory and confidence intervals

In Section 3.6 it was found that using the renewal theory with the relevant cost optimisation model resulted in a budget that represented an average for a specific period with limited confidence surrounding it. This section illustrates a methodology that can be implemented in conjunction with the renewal theory in order to create more confidence around an outputted budget.

In order to aid the simulation methodology to be explained, a general diagrammatic overview of the functioning and processing of the simulation is illustrated in Figure 3.11.

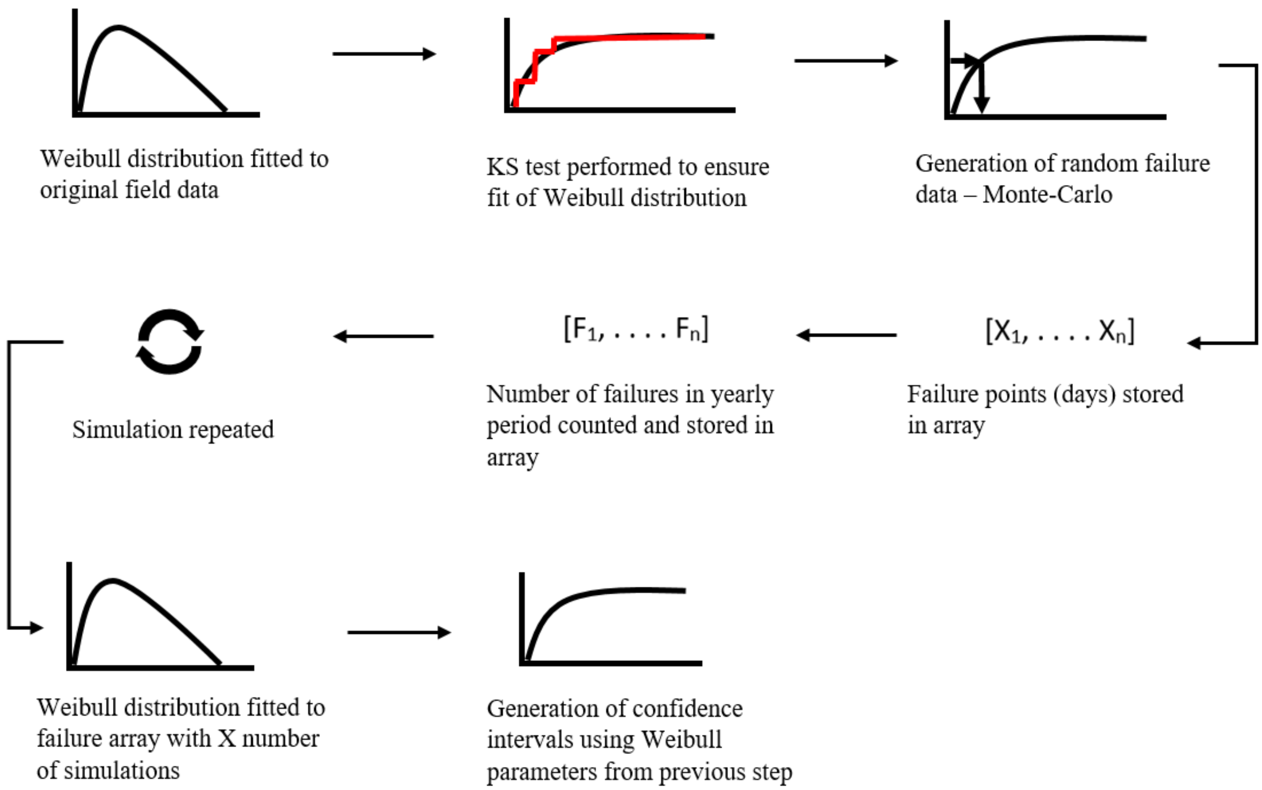

Figure 3.11: Diagrammatic simulation methodology

The optimum replacement time has been determined as the time at which, on average, the minimum cost per unit time, calculated using Equation 3.40, would be incurred. By definition, should this minimum average cost be used to determine an annual budget, in approximately 50% of years, the actual cost would be lower (fewer than the average failures would precede a preventative replacement) and in 50% of years, the actual cost will be higher (more than the average failures would precede a preventative replacement). This implies that using the average optimal cost as a budget, gives only a 50% confidence level that the budget would not be exceeded in any given year.

Since the outcome required from this exercise is an annual budget, given that the optimal replacement strategy is implemented, it is argued that it is necessary to provide a budget value as a function of confidence level, to decision makers. To achieve this goal, a Monte Carlo simulation was employed.

Figure 3.11 outlines the processes and functions used to generate the simulation. The first step of the simulation process is to fit the Weibull distribution to the original field data. Thereafter, the KS test is used to determine whether the Weibull distribution can be used to approximate the original data. Once this test has been completed, new random failure data can be generated using the original Weibull parameters from the field data. This random failure data is stored in an array. From this array, another array can be generated to store the number of failures within a yearly period ascertained from the random failure data. The simulation can then be repeated a number of times in order to store all the data in an array. Once this process has been completed, the Weibull distribution is chosen again to be fitted to the *failure count* array. Using the outputted Weibull parameters, confidence intervals around the budget can be computed for a yearly period.

This model is built on the basis that, instead of assuming an average cost of preventive maintenance for a specific period as the renewal theory does, simulations are run that generate failure data using the Weibull parameters. The actual number of failure and preventive actions within a certain period are recorded, which then allows a budgetary cost to be computed. The simulations are run *n* times in order to create confidence intervals around the outcome. Figure 3.12 outlines the simulation methodology that is followed where the Monte-Carlo methodology is seen as the driving element behind the simulation.

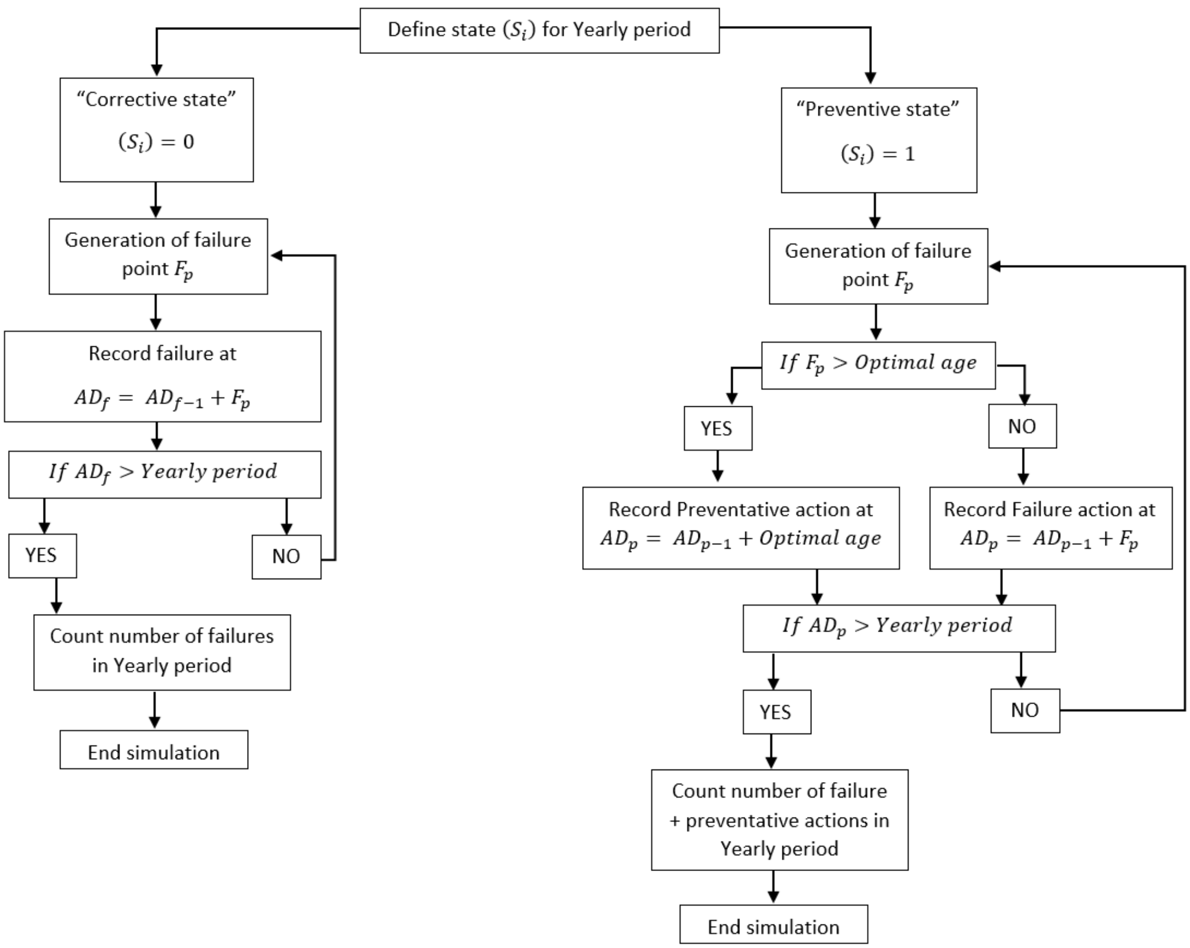

Figure 3.12: Novel Monte-Carlo simulation methodology for yearly budget

It is evident from Figure 3.12 that, before a simulation can take place, a state needs to be chosen for a specific annual period. Either a state of '0' which refers to a corrective maintenance strategy, or a state of '1' which refers to a preventive maintenance strategy, can be chosen for a respective yearly period. Once a state is chosen, it allows for a corrective strategy to be compared to a preventive strategy for a yearly interval. This enables the impact of preventive maintenance to be determined.

The next step in the simulation process is to generate failure data that is used throughout the balance of the simulation, following the steps presented in Figure 3.12. For the preventive case, the optimal age is determined by using the model presented in Section 3.6. The output of the simulation results in an array of data containing the number of preventive and failure actions that occur during a certain yearly period for a specific component. The length of the array is directly dependent on the number of simulations that are run. The greater the number of simulations run, the more accurate the outcome due to repeatability. The final step in this modelling process is to convert the array of failure and preventive actions within a yearly period into a cost array. This can then be compared to the average answer determined by the method discussed in Section 3.6. Equations 3.41 – 3.42 and Equations 3.43 – 3.47 are used to calculate this for the corrective and preventive case respectively.

3.7.2.1 Corrective case

$$\text{Simulation array} = [f_1, f_2, \cdots, f_n] \quad [3.41]$$

where: f_n is the number of failures counted in a yearly period.

$$\text{Simulation cost array} = [C_f \times f_1, C_f \times f_2, \cdots, C_f \times f_n] \quad [3.42]$$

From Equation 3.42 it is evident that only failure costs are considered in the corrective case since no preventive actions take place.

3.7.2.2 Preventive case

$$\text{Simulation array (failures)} = [f_1, f_2, \cdots, f_n] \quad [3.43]$$

$$\text{Simulation array (preventions)} = [p_1, p_2, \cdots, p_n] \quad [3.44]$$

where: f_n is the number of failure actions counted in a yearly period and p_n is the number of preventive actions counted in a yearly period.

$$\text{Simulation cost array (failures)} = [C_f \times f_1, C_f \times f_2, \cdots, C_f \times f_n] \quad [3.45]$$

$$\text{Simulation cost array (preventions)} = [C_p \times p_1, C_p \times p_2, \cdots, C_p \times p_n] \quad [3.46]$$

$$\text{Simulation cost array (total)} = [C_f \times f_1 + C_p \times p_1, C_f \times f_2 + C_p \times p_2, \cdots, C_f \times f_n + C_p \times p_n] \quad [3.47]$$

Unlike the corrective case, Equation 3.47 shows that both the preventive costs and the failure costs are considered when working out the total cost of preventive maintenance on a certain component.

3.7.3 Generation of failure data

As seen in Figure 3.12, failure data is one of the inputs into the simulation. This is not historical data but rather random data that has been generated using the historical data as well as the Weibull distribution. The failure data is produced utilising a Monte-Carlo simulation. The first step to running the Monte-Carlo simulation is determining a governing equation as the basis for the entire Monte-Carlo simulation. The Weibull cumulative probability density function is used as the governing equation, as seen in Equation 3.48. The reason is that a Monte-Carlo simulation works by creating a large quantity of random numbers which can then be used to generate a specific output. The output in this case is failure time, while the input is a random number between 0 and 1 which is the y-axis of a cumulative probability density function plot. Thus, it is evident that the cumulative probability density function is the appropriate equation to generate this failure data.

$$F(t) = 1 - e^{-\left(\frac{t}{\eta}\right)^{\beta}} \quad [3.48]$$

Figure 3.13 outlines how the failure data was generated using a Monte-Carlo simulation and Equation 3.48.

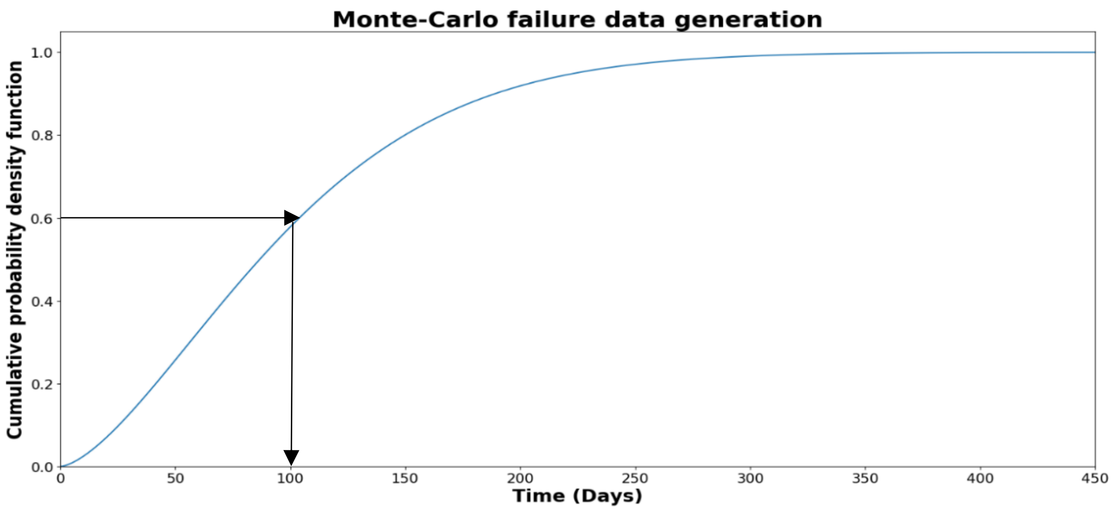

Figure 3.13: Random failure data generation using Monte Carlo simulation

Using Equation 3.48, Figure 3.13 was produced, which is the cumulative probability density function of a component. Coupled to a Monte-Carlo simulation, this function can generate failure data. The process is as follows: a random number of 0.6 is produced, which value is then matched to the cumulative probability density function. A corresponding value of 100 days is found as the failure point, as illustrated in Figure 3.13. This process can be repeated *n* times in order to create *n* failure points.

Through the generation and use of this random data utilising the simulation model presented in Figure 3.12, the variability of the model in Section 3.6 can now be found and confidence around the model can increase.

3.7.4 Generation of confidence intervals through the fitting of the Weibull distribution

Section 3.7.2 shows that the final output of the simulation is an array of cost data in which each element within the cost array represents the output of one simulation run. To create confidence levels in this outputted simulated data, it was necessary to fit it with a statistical distribution to indicate the variability around the dataset and the overall simulation. The Weibull distribution was chosen for this purpose. The reason for the choice is the versatility of the Weibull distribution, as outlined in Section 3.6.5. Thus, Equation 3.35 was applied to the simulated data array to compute β and η using the method outlined in Section 3.6.2. This resulted in the computation of the cumulative distribution function, which showed the probability of a certain value being reached. It thereby enabled the determination of the variability and confidence levels of the simulation, which were then compared to the outcome of the average answer found in Section 3.6.

3.7.5 Simulation solution procedure

This section outlines the simulation solution procedure that is followed to gain the results from the simulation. These can then be compared to the average solution computed in Section 3.6. The solution procedure is as follows:

1. Apply the renewal theory and cost optimisation model in Section 3.6 to gain the average optimum cost per unit time, as well as the optimum replacement age of a component.
2. Generate failure data by following the procedure in Section 3.7.3.
3. Run the simulation as outlined in Figure 3.12 with the given failure data inputs and the optimum replacement age input.
4. Repeat simulation *n* a number of times with the results of each simulation stored in an array.
5. Fit the Weibull distribution to the total outputted array of data using the method outlined in Section 3.7.4.
6. Apply Equation 3.48 to the Weibull outputted parameters.
7. Apply the statistical test in Section 3.4 to determine whether the Weibull distribution fits the actual data.

3.7.6 Illustrative example

An illustrative example is presented here to outline the methodology of the simulation process and to show the exact workings of the model. The example uses the same bearing data published by Coetzee (1997), as presented in Section 3.3.3.1. The solution procedure outlined in Section 3.7.5 is followed in order to gain all the desired results. Following this procedure, it is evident that the first step in the simulation process is the application of the renewal theory and the cost optimisation model to the given set of failure data. This process was implemented in Section 3.6.4 where it was found that the optimum age to replace the bearings is every 40 days with an optimum average cost of R173.58 per day.

Next, the average yearly budget was computed as follows:

$$C_{budget} = C(\text{optimal age}) \times T_b = R\ 173.58 \times 365 = R\ 63\ 356.7 \text{ per year}$$

This average annual budget represents what it will cost an organisation per year to maintain the bearings preventively. Thereafter, the simulation procedure outlined in Figure 3.11 was implemented in which random failure data was generated using the methodology in Section 3.7.3. Following steps 2 to 6 in the solution procedure with 1000 simulations run, Figure 3.14 was developed to show the results of the simulation.

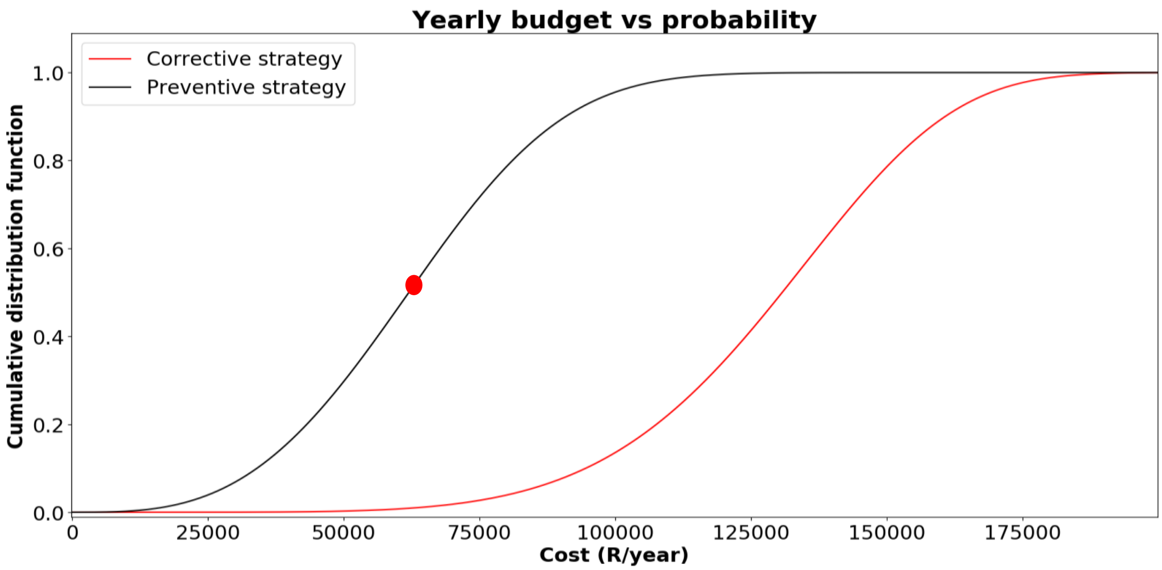

Figure 3.14: Monte-Carlo simulation results: yearly budget vs probability

Figure 3.14 shows the probability of having a specific budget within a yearly period for both a preventive strategy and a corrective strategy. From Figure 3.14 it can be seen that the result found in Section 3.6.4 using Coetzee (1997) method correlated to a value of R 63 356.7 which is seen as an average or 50% confidence if using Figure 3.14. This is shown by the red dot in Figure 3.14. From this it can be noted that organisations are unlikely to be satisfied with such low confidence in their annual budget for a year. Therefore, using Figure 3.14 allows the choice of a higher confidence and a corresponding budgetary value. This process enables organisations to gain a lot more certainty around their budget and a higher chance of not exceeding their budget within a yearly period. Figure 3.14 also shows that a preventive maintenance strategy results in a budget that is substantially less than a corrective maintenance strategy. This showcases the importance of the implementation of preventive maintenance.

The last step in the simulation process is to determine whether the Weibull distribution can be used to fit the actual data outputted from the simulation. This is achieved through the choice and implementation of the Goodness of fit test known as the Kolmogorov-Smirnoff (K-S) test.

The overall process for the K-S test is detailed in Section 3.4. A brief overview is presented here to illustrate its workings. The output of the test is defined by the following two hypotheses:

$$H_0\text{: The data follows a specified distribution } F_n(x) = F_0(x)$$

$$H_1\text{: The data does not follow the specified distribution } F_n(x) \neq F_0(x)$$

The main outcome of the K-S test is to determine the maximum vertical distance between the cumulative probability function and the empirical distribution. This is done using Equation 3.49.

$$D_n = max|F_n(x_i) - F_0(x_i)| \quad [3.49]$$

The maximum vertical distance known as D_n is the test statistic, which is then compared to a critical value to determine whether the null hypothesis can be rejected. Equation 3.50 gives this test condition:

$$D_n > c_n \quad [3.50]$$

where: c_n is determined from one sample K-S test statistical table.

Carstens (2012) states that if D_n exceeds c_n then there is significant evidence to reject the null hypothesis, which suggests that the two distributions do not fit each other well. In the simulation, there were six events for both the corrective case and the preventive case. Therefore, using the one sample K-S table at a confidence interval of 95%, $\alpha = 0.05$ results in a test statistic of 0.519 for both the corrective case and the preventive case. Using the procedure explained in Section 3.4, the empirical distribution function can be computed for the simulated data. Thus, the empirical distribution function was plotted against the Weibull distribution to enable the K-S test to take place. This is shown in Figure 3.15.

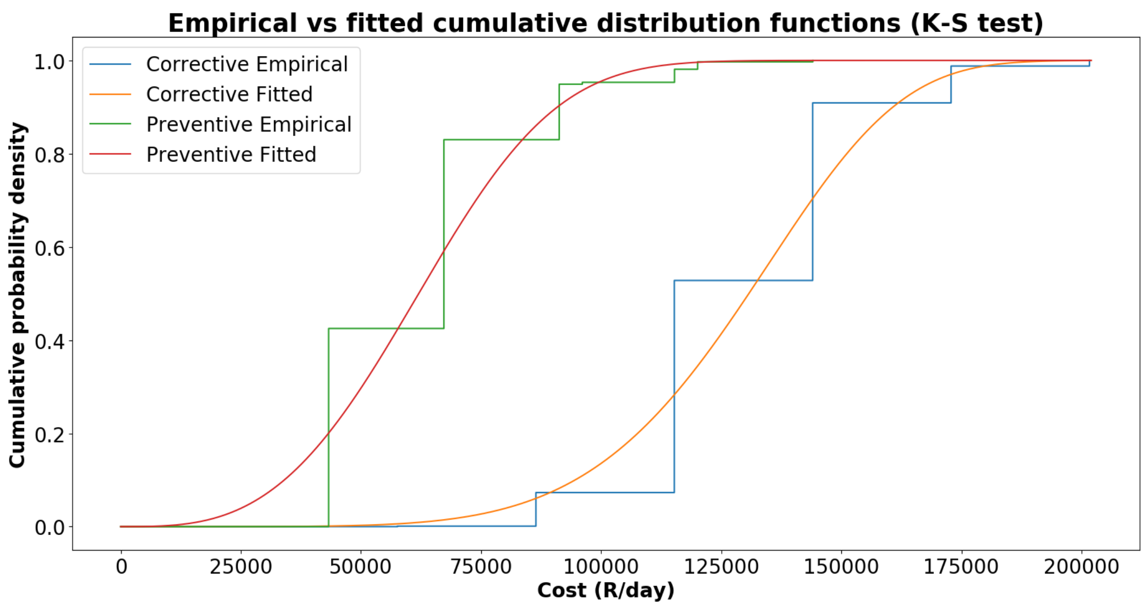

Figure 3.15: Kolmogorov-Smirnoff (K-S) test: empirical vs fitted cumulative distribution functions

Using Figure 3.15 and Equation 3.49, the D_n critical value for the corrective case and the preventive case were computed. These values were found to be 0.24 and 0.25. According to Equation 3.50, therefore, these values are both smaller than their respective test statistics which suggests there is not enough evidence to reject the null hypothesis. This results in an acceptable fit between the actual simulated data and the Weibull data. Thus, it is evident that this simulation method creates a lot more certainty around a budgetary requirement by using confidence intervals. This allows for the choice of a more realistic budget with a certain level of confidence rather than an average budget of possibilities that could take place within a specific yearly period.

3.8 Non-repairable systems budgetary validation over longer periods

In Section 3.7 a simulation methodology was outlined that showed the variability of a budget computed by using the renewal theory with its relevant cost optimisation model. This was achieved by developing confidence intervals around the budget for a yearly period. The budget for a preventive strategy was compared to that of a corrective strategy to enable conclusions to be drawn about the type of maintenance strategy to implement, based on the budget. This allows room for improvement within the model. Instead of simply looking at a certain annual period in which a preventive strategy can be compared to a corrective strategy, a finite period in years can be considered, enabling the application of a different maintenance technique each year within that finite period. The development of this model allows for budgets longer than just a year to be computed, demonstrating the effect of preventive maintenance compared to corrective maintenance over a finite period.

3.8.1 Model development

The model developed in this section is based on an extension of the simulation algorithm presented in Section 3.7. It looks at a longer period in years in which each year can be assigned a different maintenance technique. Figure 3.16 illustrates this methodology.

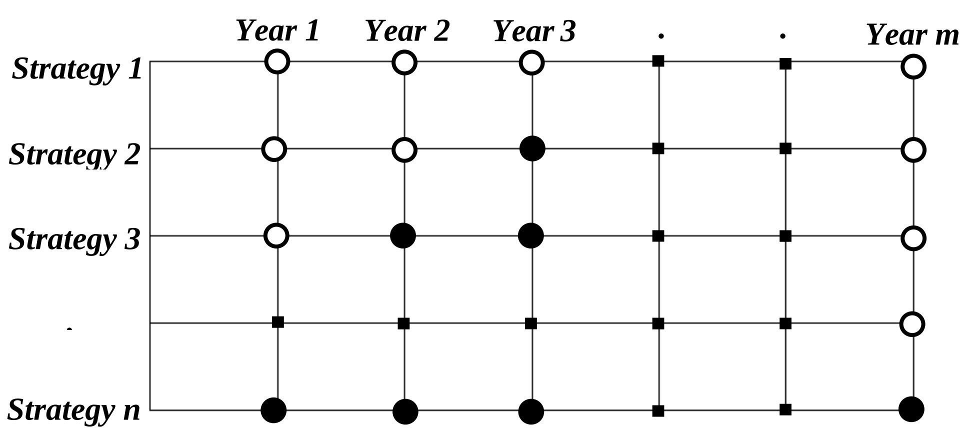

Figure 3.16: Yearly maintenance technique assignment

According to Wu and Lewins (1992), the first step to any simulation is to define the state of the system before any simulation is performed. The state of a certain component within the span of a year in the finite period can be denoted by b_i. The state of the system over the entire finite period can be described by the vector seen in Equation 3.51 (Wu & Lewins, 1992).

$$B = (b_1, b_2, \cdots, b_i) \qquad [3.51]$$

In terms of this study, b_i can have two possible states: one is an ‘up’ state in which preventive maintenance is being practised during a yearly period; the other is a ‘down’ state in which preventive maintenance is not being practised during the span of a year within the finite period. Wu and Lewins (1992) state that the vector B, given in Equation 3.51, contains the perception of what is happening in the system at a time point in its life. This logic is visually presented in Figure 3.16 where the solid black circles represent the practice of preventive maintenance and the outlined circles represent the practice of corrective maintenance.

In Figure 3.16 it is evident that a number of different strategies exist, depending on the longer period being considered. Here a strategy is defined as the maintenance plan over a longer period than a year. There can be a full corrective strategy or a full preventive strategy over the entire period. However, in-between these two full strategies, a number of other strategies exist that comprise a mixture of preventive maintenance techniques in some years and corrective maintenance techniques in other years.

To determine the total number of maintenance strategies that exist for a certain component over a longer period, binary values need to be assigned to the states that the system can be in. The author chose to assign a value of 1 to a system in an ‘up’ state and a value of 0 to a system in a ‘down’ state. Therefore, the total number of maintenance strategies that can exist for a component with two possible states over a finite period is:

$$2^{finite\ period}$$

The ‘free flight’ period is the interval in which nothing changes. The states given by Equation 3.51 are what occur during that interval. A collision point is where the state changes at an interval end from an ‘up’ state to a ‘down’ state, from a ‘down’ state to an ‘up’ state, from an ‘up’ state to an ‘up’ state, and finally from a ‘down’ state to a ‘down’ state. Thus, is evident that the system can change in four different ways at its collision points. To account for this, an algorithm must be developed that can factor in all these changes at the collision points over the entire finite period of the simulation.

Continuing from the simulation methodology outlined in Figure 3.12 in Section 3.7.2, Figure 3.17 was developed. It demonstrates the entire simulation process that is followed when the finite period considered is greater than a year and collision points are present.

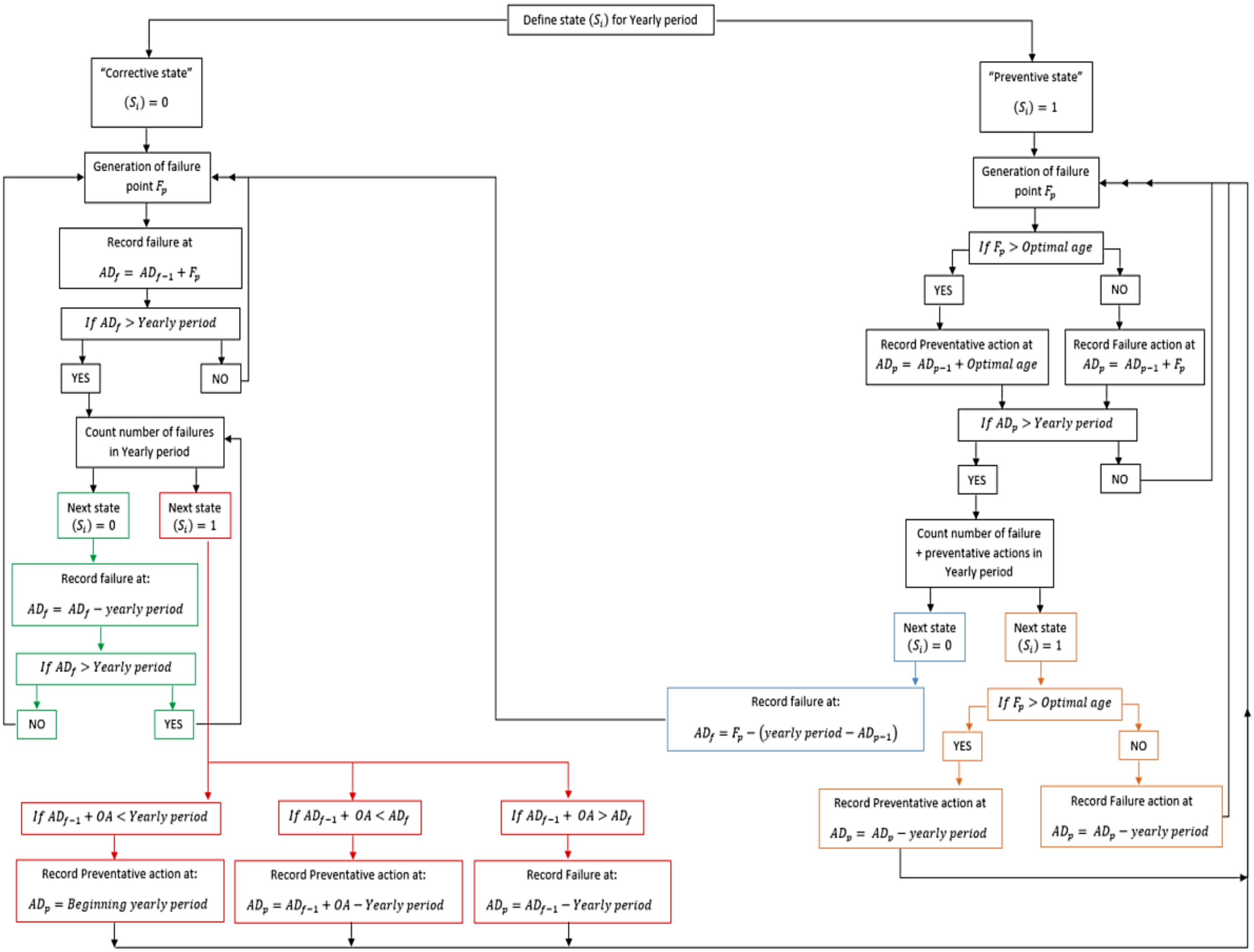

Figure 3.17: Novel Monte-Carlo simulation methodology for extended periods

Figure 3.17 shows that the outlined simulation methodology follows on from the methodology presented in Figure 3.11. Each of the four collision points uses one of the methods indicated by the coloured sections in the figure. Applying binary values to each of the collision points results in the latter being presented as follows: (0, 0), (0 ,1), (1, 0) and (1, 1). The development of these collision points allows the full life of the component to be considered when determining the age to replace the component within a specific yearly period. Depending on the collision point, this replacement age varies.

In Figure 3.17, the replacement age for a collision point of (0, 0) can be found by following the green section; the replacement age for a collision point of (0, 1) can be found by following the red section; the replacement age for a collision point of (1, 0) can be found by following the blue section; and, finally, the replacement age for a collision point of (1, 1) can be found by following the orange section. Thus, by following the methodology outlined in Figure 3.17 for all the different maintenance strategies over a long period, cost arrays such as those developed in Section 3.7.2 can be computed. This enables the comparison of all the different maintenance strategies over a longer period, which shows the effect of implementing certain maintenance strategies over others.

3.8.2 Simulation solution procedure

This section outlines the simulation solution procedure that is followed to gain the results of implementing all the different maintenance strategies for a certain component over a finite period. Thereby, a comparison between the strategies can occur.

1. Apply the renewal theory and cost optimisation model in Section 3.6 to gain the average optimum cost per unit time and the optimum replacement age of a component.
2. Develop all the maintenance strategies, depending on the finite period considered.
3. Generate failure data, following the procedure in Section 3.7.3.
4. Run the simulation on one maintenance strategy, as outlined in Figure 3.17, with the given failure data inputs and the optimum replacement age input.
5. Terminate the simulation once the finite period has been reached.
6. Repeat the simulation *n* number of times and store the results of each simulation in an array.
7. Repeat steps 3 – 6 until all the maintenance strategies have been looked at.
8. Fit the Weibull distribution to the total outputted array of data for each maintenance strategy, using the method outlined in Section 3.7.4.
9. Apply Equation 3.48 to the Weibull outputted parameters.
10. Apply the statistical test in Section 3.4 to determine whether or not the Weibull distribution fits the actual data.
11. Compare all the different maintenance strategies over a finite period.

3.8.3 Illustrative example

An example is presented here to illustrate the workings of the simulation model in Figure 3.17. Following on from the illustrative example presented in Section 3.7.6, it was decided that instead of only looking at a yearly budget, a three-year budget needed to be represented, accompanied by its relevant maintenance plan. The number of maintenance strategies that could be implemented over the three-year period are computed as $2^3 = 8$. Each maintenance strategy is presented in Table 3.5 by a vector B, in which a binary value of 0 or 1 is used, depending on whether a preventive or corrective maintenance technique is being practised within a certain year.

Table 3.5: Varying maintenance strategies over three years

Strategy 1	$B = (0, 0, 0)$
Strategy 2	$B = (0, 0, 1)$
Strategy 3	$B = (0, 1, 0)$
Strategy 4	$B = (0, 1, 1)$
Strategy 5	$B = (1, 0, 0)$
Strategy 6	$B = (1, 0, 1)$
Strategy 7	$B = (1, 1, 0)$
Strategy 8	$B = (1, 1, 1)$

Figure 3.18 was developed by applying the simulation solution procedure outlined in Section 3.8.2, with 1000 simulation runs for each maintenance strategy.

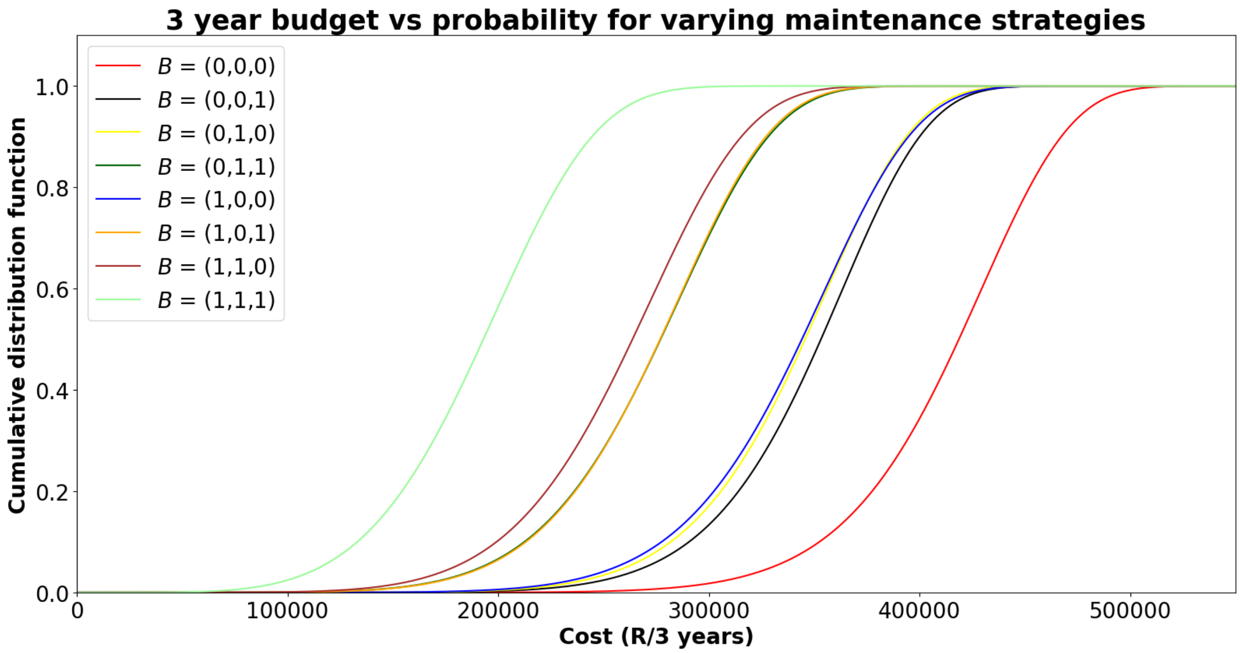

Figure 3.18: Monte-Carlo simulation results: 3 year budget vs probability for varying maintenance strategies

Figure 3.18 shows the probability of having a specific budget within a three-year period for all the different maintenance strategies outlined in Table 3.5. It is evident from Figure 3.18 that an entirely preventive maintenance strategy over the three years results in a budget that is substantially smaller than an entirely corrective strategy. All the other strategies lie between the entirely preventive strategy and the entirely corrective strategy. This indicates that an organisation can choose any one of the maintenance strategies, depending on how much preventive maintenance it is willing to do over a finite period of time. The effect of each strategy can be portrayed in terms of a budget that selects a confidence level in terms of the amount of reliability and certainty an organisation requires in its budget.

The final step in the simulation process is to determine whether the Weibull distribution can be used to fit the actual data outputted from the simulation. This can be achieved using a Kolmogorov-Smirnoff (K-S) Goodness of fit test. The same procedure as outlined in the illustrative example in Section 3.7.6 was followed, which resulted in the computation of Figure 3.19.

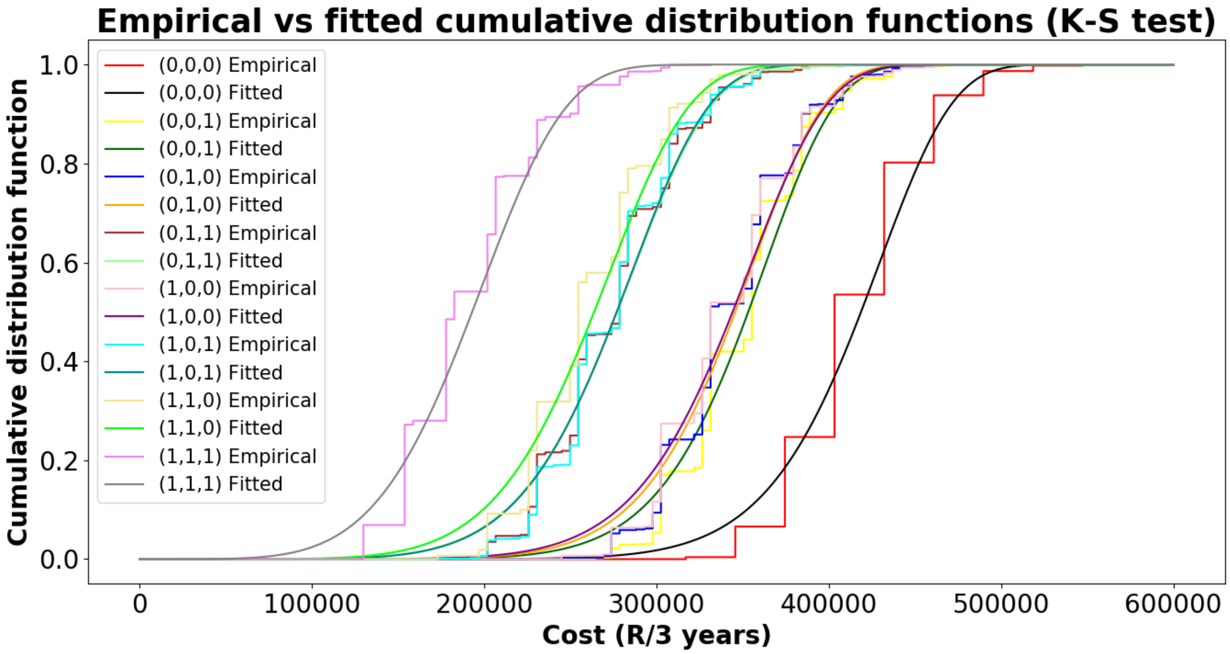

Figure 3.19: K-S test

Using Figure 3.19, Table 3.6 was drawn up to show the results of the K-S test in which c_n was found at a value of 95% confidence where $\alpha = 0.05$.

Table 3.6: K-S test results

Strategy	***Strategy vector***	***Number of events***	D_n	c_n
Strategy 1	$B = (0, 0, 0)$	9	0.178	0.430
Strategy 2	$B = (0, 0, 1)$	33	0.157	0.231
Strategy 3	$B = (0, 1, 0)$	32	0.139	0.234
Strategy 4	$B = (0, 1, 1)$	33	0.137	0.231
Strategy 5	$B = (1, 0, 0)$	31	0.127	0.238
Strategy 6	$B = (1, 0, 1)$	42	0.145	0.210
Strategy 7	$B = (1, 1, 0)$	32	0.139	0.234
Strategy 8	$B = (1, 1, 1)$	20	0.148	0.294

Table 3.6 shows that there was not enough evidence to reject the null hypothesis for any of the strategies, resulting in an acceptable fit between the actual simulated data and the Weibull data. In this illustrative example, it is evident that the simulation method allows for the development of a budget greater than one year. Certainty around the budget can also be developed using confidence intervals. Different maintenance strategies can be considered and the best strategy in terms of budgetary constraints can be chosen. The

outputted budget in this case is not an average budget as it would be if the renewal theory alone were applied. This results in a more realistic budget and minimises the probability of exceeding it as a confidence around the budget can be chosen.

3.9 Opportunistic/indirect grouping model to optimise the preventive maintenance strategy of a multi-component system

Section 3.6 shows that a component-based preventive maintenance strategy has been developed in which an optimum age and associated replacement cost have been computed. This strategy works well for components that do not belong to the same system and are not directly related to one another. An area in which it has been found that a strategy improvement can take place is the development of a multi-component preventive maintenance strategy for one system, comprised of various components. The functioning of the system relies on the functioning of all the components. The reason behind the development of this strategy is the recognition that it is more cost effective to group maintenance activities for components with similar failure statistics than to optimally replace each component separately. This is due to the fact that it can cost a company more to shut down a system for a preventive action than not to replace a component at its optimum age.

Therefore, continuing from the red section in Figure 3.1, the next model in the overall budgetary decision process considers n components within a system connected in series. Failure of any component in the system results in system failure, thus leading to complete shutdown. The overall model is based on a ‘minimal repair and partial periodic renewal’ policy for the complete system. This means that a specific number of components within the system will undergo partial renewal at a certain time period during the life cycle of the system. Laggoune et al. (2008) state that the system undergoes partial renewal at times:

$$t_j = j\tau; j = 1, 2, \dots, K$$

where: τ is the time interval between optimum replacements and K is the number of cycles until a complete overhaul.

In contrast to this, when a failure occurs before the preventive maintenance optimum replacement age, it is handled using a minimal repair strategy in which the component failure rate after the minimal repair is seen to be the same as just before the repair (Laggoune et al., 2008). Following this ‘minimal repair and partial periodic renewal’ policy, after a certain number of periods ($K\tau$) have been reached, an opportunity arises to replace all the components within the system simultaneously. This is regarded as a complete system overhaul, resulting in the return of the system to an ‘as good as new’ state.

The diagram in Figure 3.20 was created to outline how the different maintenance actions for the separate components within the system are scheduled. It shows that multiple component replacements can occur at different intervals, depending on the characteristics of the different components within the system. Here, τ is chosen as the smallest time interval based on an optimisation algorithm that is calculated using all the components within a system.

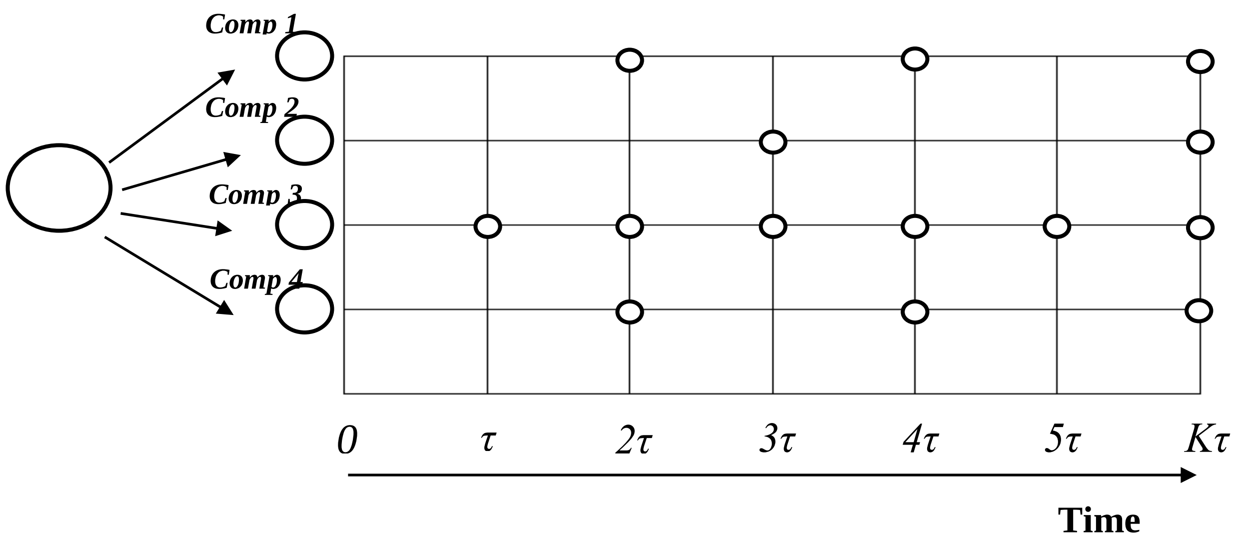

Figure 3.20: Grouping interval methodology

With τ as the smallest time interval in the optimisation algorithm, Figure 3.20 can be explained as follows. At time $t_1 = \tau$, the system undergoes a partial renewal in which component 3 is the only replacement. At time $t_2 = 2\tau$, the system undergoes its second partial renewal in which components 1, 3 and 4 are all preventively replaced. This process continues until time $t_k = K\tau$, in which all the components are replaced. This results in a completely overhauled system, returning it to the 'as good as new' state.

The total cost of system maintenance throughout the process of 'minimal repair and partial periodic renewal' includes all the failure costs over the time period analysed. These comprise, first, the cost due to minimal repair C_{mr}; second, the partial renewal cost which is seen as the preventive maintenance cost that occurs at the end of each period C_{pr}; and, third, the cost of a complete system overhaul which occurs at the end of a renewal cycle C_{ov}. Equation 3.52 shows the total expected cost of maintaining a system over its life cycle using this method.

$$C_{mr} + C_{pr} + C_{ov} \qquad [3.52]$$

Finally, the optimum cost of per unit time can be calculated using Equation 3.53, as stated by Laggoune et al. (2008).

$$C(t) = \lim_{t \to \infty} \frac{C(t)}{t} \qquad [3.53]$$

3.9.1 Comparison of maintenance models

To determine whether this indirect multi-component grouping method delivers better results than other models, a comparison is required. This section outlines the mathematics behind the variety of approaches, which enables this comparison to be performed.

3.9.1.1 Single component policy

This is the first policy to be outlined. The method makes use of a single component that is maintained according to the scheme of minimal repair with *complete* periodic renewal instead of minimal repair with *just* periodic renewal. Each component that follows this policy is maintained according to its own optimum strategy in which no grouping of preventive actions will occur. Laggoune et al. (2008) state that, under this policy, a component will fail according to the non-homogeneous Poisson process (NHPP). Gertsbakh (2000) states that the expected number of failures that will occur over the life cycle of the component can be given by Equation 3.54.

$$\Lambda_i(\tau) = \int_0^{\tau} \lambda_i(t)dt \qquad [3.54]$$

In Equation 3.54, $\lambda_i(t)$ can be seen as the intensity function that represents the failure rate for a non-repairable component. If the components being analysed are of a Weibull type, then the intensity function can be presented as seen in Equation 3.55, where $\beta_i \; and \; \eta_i$ are the unknowns of the Weibull function (Coetzee, 1997).

$$\lambda_i(t) = \frac{\beta_i}{\eta_i}\left(\frac{t}{\eta_i}\right)^{\beta_i - 1} \qquad [3.55]$$

The integral of the intensity function in Equation 3.56 results in the computation of the mean number of failures for a certain component over a time period (Laggoune et al., 2008).

$$\Lambda_i(\tau) = \int_0^{\tau_i} \lambda_i(t)dt = \left(\frac{\tau_i}{\eta_i}\right)^{\beta_i} \qquad [3.56]$$

Thus, using Equation 3.56 and incorporating cost, the cost function per unit time for the single component policy can be derived as seen in Equation 3.57 (Barlow & Hunter, 1960; Laggoune et al., 2008).

$$C(\tau_i) = \frac{C_i^C \int_0^{\tau_i} \lambda_i(t)dt \; + \; C_i^P}{\tau_i} = \frac{C_i^C \left(\frac{\tau_i}{\eta_i}\right)^{\beta_i} \; + \; C_i^P}{\tau_i} \qquad [3.57]$$

To determine the optimum time at which a component replacement should occur, two methods can be used. The first method involves plotting the function in Equation 3.57 where the optimum replacement time can be found by looking at the corresponding minimum cost. The second method involves deriving Equation 3.57 to result in Equation 3.58 in which the optimum replacement time interval can be established.

$$\tau_i^* = \left(\frac{C_i^P {\eta_i}^{\beta_i}}{C_i^C(\beta_i - 1)}\right)^{\frac{1}{\beta_i}} \qquad [3.58]$$

3.9.1.2 Multi-grouping approach

This section describes the detailed process that is followed to determine the best grouping strategy for a number of different components within one system. This reduces the downtime of the system as a whole and increases the availability, resulting in a more optimised model. Canh et al. (2015) state that the main advantage of maintenance grouping is to take advantage of the economic dependence between the different components. This implies that performing maintenance actions on a number of different components at once is cheaper than performing maintenance on the components separately.

The first assumption in this multi-grouping approach is that the downtime due to the performance of maintenance operations is negligible. This assumes that each maintenance action is performed instantaneously on the series system of components. Next, Equation 3.59 can be developed using the same failure rate as Equation 3.55 in Section 3.9.1.1 and knowing that each component cycle within the system will be repeated $K/_{k_i}$ times. K is the total number of cycles until a complete overhaul and k_i is the interval at which each preventive action takes place for the separate components. Equation 3.59 shows the expected number of failures of a component over the life cycle of the system (Laggoune et al., 2008).

$$\frac{K}{k_i}\Lambda_i(\tau) = \frac{K}{k_i}\int_0^{k_i\tau}\lambda_i(t)dt \qquad [3.59]$$

Using the same methodology as in Section 3.9.1.1, the failure cost for each component over the life cycle of the system can be computed using Equation 3.60.

$$C_i^C \cdot \frac{K}{k_i}\int_0^{k_i\tau}\lambda_i(t)dt \qquad [3.60]$$

From this, and under the assumption that simultaneous failures of the components within the system cannot occur (Laggoune et al., 2008), the total cost of the system over its life cycle due to failure can be expressed using Equation 3.61.

$$C_{mr} = \sum_{i=1}^{n}\left[C_i^C \cdot \frac{K}{k_i}\int_0^{k_i\tau}\lambda_i(t)dt\right] \qquad [3.61]$$

The cost of prevention is the next cost to make up the total maintenance cost, using this method. Figure 3.20 shows that specific components are replaced preventively only at certain intervals. Thus, at each j^{th}renewal, a group of components are replaced preventively, expressed as G_j. Using this rationale, the preventive cost at the j^{th}renewal can be expressed as shown in Equation 3.62, which also considers the preventive setup cost.

$$C_{prj} = \sum_{i \in Gj} C_i^P + C_0 \qquad [3.62]$$

Using Equation 3.62, the total expected preventive cost can be computed using Equation 3.63.

$$C_{pr} = \sum_{j=1}^{K-1} C_{prj} \qquad [3.63]$$

The last element to make up the total system costs endured is the cost of a complete overhaul, which occurs after K^{th}renewal. This cost comprises replacement of all the components and the setup cost for prevention, as expressed in Equation 3.64.

$$C_{ov} = \sum_{j=1}^{n} C_i^P + C_0 \quad [3.64]$$

The final cost equation can be computed by adding the preventive and failure costs. The total cycle length is given by $K\tau$. Equation 3.65 shows this cost equation.

$$C(\tau, k_1, k_2, \cdots k_n) = \frac{\sum_{i=1}^{n} \left[C_i^C \cdot \frac{K}{k_i} \int_0^{k_i\tau} \lambda_i(t)dt \right] + \sum_{j=1}^{K-1} C_{prj} + C_{ov}}{K\tau} \quad [3.65]$$

Laggoune et al. (2008) state that, at the K^{th}period, Equation 3.65 can be simplified to Equation 3.66 if it is assumed that $C_{ov} = C_{prk}$.

$$C(\tau, k_1, k_2, \cdots k_n) = \frac{\sum_{i=1}^{n} \left[C_i^C \cdot \frac{K}{k_i} \int_0^{k_i\tau} \lambda_i(t)dt \right] + \sum_{j=1}^{K} C_{prj}}{K\tau} \quad [3.66]$$

To gain an optimum result using this multi-component grouping approach, Equation 3.66 needs to be optimised. This can be achieved by looking at different time intervals τ and by iterating through all the different grouping intervals k_i for the various components.

3.9.1.3 Mono-grouping approach

The mono-grouping approach is a variation of the multi-grouping approach in which one optimum replacement age is found for all the components instead of replacing certain components at specific intervals. A disadvantage of this method is that systems are usually made up of components with varying failure statistics. This means that if all the components are replaced at one age, it could result in a large percentage of life being lost in certain components, thus increasing the overall system cost.

At the optimum age of replacement, a complete system overhaul is performed which means that the only costs involved in the model are the failure costs and the costs of a complete overhaul. The failure costs due to minimal repair on the system can be expressed using Equation 3.67.

$$C_{mr}^{mono} = \sum_{i=1}^{n} C_i^C \int_0^{\tau} \lambda_i(t)dt \quad [3.67]$$

The total cost per unit time for this method can be expressed by Equation 3.68. Here, the optimum cost can be found by minimising the time variable τ.

$$C^{mono}(\tau) = \frac{\sum_{i=1}^{n} C_i^C \int_0^{\tau} \lambda_i(t)dt + \sum_{i=1}^{n} C_i^P + C_0}{\tau} \quad [3.68]$$

3.9.1.4 Multi-grouping approach with an annual plant shutdown

The author has encountered various articles in literature, such as the one by Laggoune et al. (2008) on which this model is based, that outline different multi-grouping methods to optimise the overall cost of a system. One aspect that these articles fail to consider is the scenario of an annual plant shutdown over the festive season. The reasons this shutdown occurs are the inefficient work that takes place during this period and the safety aspect due to the poor condition in which some employees arrive at work. A number of organisations (certainly in South Africa) have found it more worthwhile to have a complete plant shutdown over this period during which only maintenance activities take place. The loss of production is accounted for in the annual budget. Bearing this factor in mind, the author decided to investigate the effect of pushing all the preventive maintenance activities into one annual shutdown compared to the other models.

This line of enquiry required a slight modification to the normal multi-grouping approach. The cost of lost production and the setup cost due to failure needed to become a separate variable factor. Thus, by modifying Equation 3.66 in Section 3.9.1.2, Equation 3.69 was developed.

$$C(\tau, k_1, k_2, \cdots k_n) = \frac{\sum_{i=1}^{n} \left[(C_i^C + C_0) \cdot \frac{K}{k_i} \int_0^{k_i \tau} \lambda_i(t) dt \right] + \sum_{j=1}^{K} C_{prj}}{K\tau} \qquad [3.69]$$

where: C_0 is the cost due to lost production that occurs throughout the yearly period, except for the annual plant shutdown.

3.9.1.5 Mathematical solution procedure

Laggoune et al. (2008) have outlined a solution procedure that can be followed to determine the optimum maintenance cost using this grouping methodology. Simple optimisation techniques cannot be used to find the best maintenance cost since the optimisation of τ is seen as a real variable and the optimisation of k_i, which is the best interval for all the components, is seen as an integer. To solve this problem, a combinatory optimisation algorithm is used in which both τ and k_i are optimised simultaneously. The solution procedure is as follows:

1. Determine the single component optimum replacement ages and costs using Equations 3.58 – 3.59.
2. Using these optimum replacement ages for all the components, an initial guess for the different component intervals can be computed using Equation 3.70.

$$k_i^0 = \frac{\tau_i^*}{\min(\tau_s^*)} \qquad [3.70]$$

3. Next, each component interval can only vary between a certain range, given by:

$$1 \le k_i^0 \le \min(k_s^0 | k_s^0 > k_i^0)$$

since the optimum replacement age for components is not expected to become larger than that of the components with higher reliabilities. This also reduces the search space for the model as it eliminates looking at unnecessary intervals. Using these intervals, all the different interval combinations for the grouping method can be computed.

4. All the combinations of intervals determined in step 3 are considered. A corresponding τ value is computed for each interval using optimisation techniques on Microsoft Excel.
5. From the optimum τ value found in step 3, the corresponding optimum interval can be computed. Thus, the optimum maintenance results are determined using this method.

3.9.1.6 Illustrative example

This section outlines an illustrative example using actual data to show how the model works and to demonstrate its effectiveness. Laggoune et al. (2009, 2010) have published data for a centrifugal compressor used in a Skikda refinery that will be utilised for this illustrative example. Table 3.7 shows all the reliability statistics and cost data. Note that R stands for rand, the South African currency (with the ISO currency code ZAR).

Table 3.7: Illustrative example Weibull parameters and associated costs (Laggoune et al., 2009, 2010)

			Failure cost	**Prevention cost**
Components	**Beta (β)**	**Eta (η)**	C_i^C	C_i^P
Common cost C_0			*R100 000.00*	*R4 000.00*
1	1,73	486	R14 868.00	R3 639.00
2	1,88	507	R39 204.00	R5 438.00
3	2,43	286	R44 880.00	R7 398.00
4	2,53	898	R57 876.00	R8 277.00
5	2,14	905	R73 860.00	R13 554.00
6	3,55	736	R46 752.00	R14 130.00
7	2,68	1094	R48 568.00	R21 356.00
8	2,09	1388	R74 232.00	R24 348.00
9	1,73	486	R11 281.84	R263.89
10	2,43	286	R33 244.00	R339.95

Using all the data in Table 3.7, and the mathematical model presented in Section 3.9, a comparison of all the different methods was completed, as represented in Table 3.8.

Table 3.8: Analysis results

	Single component		**Mono-grouping**		**Multi-grouping**		**Multi-grouping shutdown**	
Component	t_i^****(days)***	C_i^* ***(R/day)***	t_i^****(days)***	C_i^* ***(R/day)***	t_i^****(days)***	C_i^* ***(R/day)***	t_i^****(days)***	C_i^* ***(R/day)***
1	121,67	148,79	136	1409.98	71	985.02	365	812.52
2	129,67	155,49						
3	86,71	223,38						
4	276,59	73,39						
5	291,55	113,02						
6	313,71	80,46						
7	466,06	86,79						
8	558,67	97,29						
9	88,47	114,22						
10	60,32	122,27						
Total		1215.11						

Table 3.8 shows that the best solution to implement in this case is the multi-grouping shutdown approach. The final grouping was found to be (1, 1, 1, 1, 1, 1, 2, 2, 1, 1), which suggests that, to result in the optimal maintenance strategy, the components 1, 2, 3, 4, 5, 6, 9 and 10 should be replaced every 365 days and components 7 and 8 should be replaced every 730 days.

The single component strategy resulted in a better optimum value than the mono-grouping strategy. The reason was that, in the single component strategy, the optimum replacement ages for components ranged from 86 days to 558 days. Therefore, the optimum replacement age for the mono-grouping strategy resulted in a lot of wasted life in the components with a longer life, accounting for the increased optimum cost. A visual representation of this outcome is shown in Figure 3.21.

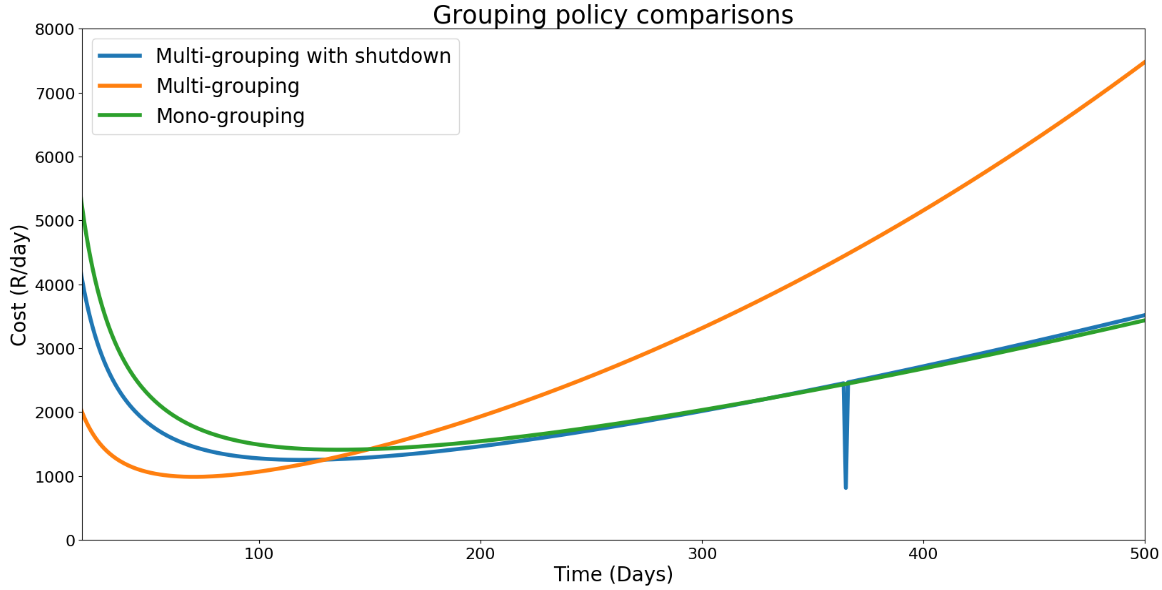

Figure 3.21: Optimum cost curves: grouping policy comparisons

Figure 3.21 shows that the grouping policies result in a much better maintenance strategy than a once off replacement for all the components, as well as individual separate replacements. The reason for the dip in the blue line in the multi-grouping approach with shutdown is the failure to consider the R100 000.00 for lost production because there is no lost production during this shutdown period.

The author found that a main uncertainty in the model centred around the variable cost of lost production. It became evident that if the cost of lost production is low, then the multi-grouping approach results in the best solution. In other words, this approach delivers the optimum if the cost of pushing all the components into one annual shutdown is greater than the cost of lost production for the interval groupings. If the cost of lost production is high, then the multi-grouping approach with an annual shutdown is the best solution. In other words, it was found to be optimal not to endure this cost at set intervals and rather to push all the maintenance activities into one annual shutdown where this cost did not feature, as seen in Figure 3.21.

3.10 Block replacement model

In Sections 3.5, 3.6 and 3.9, system replacements have been managed using repairable systems analysis; non-dependent component replacements have been managed using non-repairable systems theory; and, finally, multiple component replacements within one system have been managed using indirect grouping methodologies. One untouched area is the scenario of multiple identical components within one system. In order to tackle this topic, the block replacement model was developed as outlined by Jardine and Tsang (2013) (see also Section 2.7.4). This model falls under a similar category in preventive maintenance to the indirect grouping model discussed in Section 3.9. The major difference between the block replacement model and the indirect grouping model is that the former assumes all the components to be replaced are identical, such as the idlers in a conveyor system, while the latter compares a number of different components with varying failure statistics for an optimum replacement interval. Jardine and Tsang (2013) state that the main reason for the development of the block replacement model is that sometimes replacing all components with identical failure statistics can result in a more economical solution than replacing them individually when they fail. Certain resource requirements stay constant whether one component or a number of components are replaced. Thus, replacing many identical components at once results in an overall cost reduction. A typical example is streetlights.

This section gives a detailed explanation of the block replacement model (Jardine & Tsang, 2013). In normal circumstances, when an item within a system fails, it is replaced with a new one and the process continues. However, if a number of similar components within a system have similar failure statistics, the option of block replacement at fixed intervals can be viable based on the economics involved. To optimise the economics and reach the best solution that can be compared to single component replacement, the balance between how often a block replacement occurs and how many failure replacements are mitigated needs to be investigated. Obviously, the earlier a block replacement occurs, the less failure replacements will happen. However, it will also cost more due to an increased number of block replacements and the increased loss of life of a component. Therefore, a balance between these two factors needs to be determined.

This model is based on the underlying assumption that the cost of a group replacement is less than that of a failure replacement. The model performs group replacements at certain intervals and failure replacements when necessary (Jardine & Tsang, 2013). This rationale can be seen in Figure 3.22.

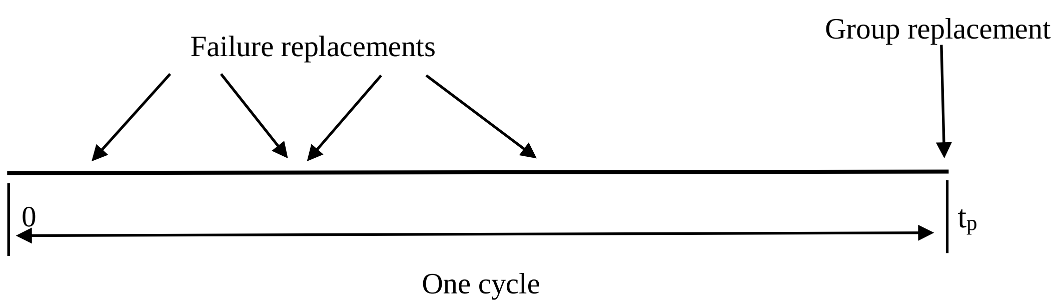

Figure 3.22: Replacement cycle

The total expected cost per unit time for a block replacement at a certain interval t_p can be given as $C(t_p)$, as seen in Equation 3.71 (Jardine and Tsang, 2013).

$$C(t_p) = \frac{\text{Total expected cost in interval } (0, t_p)}{\text{Interval length}} \qquad [3.71]$$

The total expected cost in an interval of $(0,\ t_p)$ can be regarded as the cost of prevention due to group replacement, plus the total cost of the expected number of failures within that interval. This is expressed in Equation 3.72.

$$C(t_p) = \frac{C_g + C_f H(t_p)}{t_p} \quad [3.72]$$

Equation 3.72 shows that $H(t_p)$ is the expected number of times one component fails within a certain interval. Jardine and Tsang (2013) have outlined a discrete approach to determine $H(t_p)$. An example is presented to demonstrate this aspect.

Assuming a three-month interval between preventive replacements, $H(3)$ can be computed as follows:

$$\begin{aligned} H(3) = {} & \text{number of failures that occur in interval } (0,3) \text{ when the first failure occurs in month 1} \\ & \times \text{ probability of failure occurring in interval } (0,1) \\ & + \\ & \text{number of failures that occur in interval } (0,3) \text{ when the first failure occurs in month 2} \\ & \times \text{ probability of failure occurring in interval } (1,2) \\ & + \\ & \text{number of failures that occur in interval } (0,3) \text{ when the first failure occurs in month 3} \\ & \times \text{ probability of failure occurring in interval } (2,3) \end{aligned}$$

The mathematical representation of this discrete process can be seen in Equation 3.73.

$$H(3) = [1 + H(2)]\int_0^1 f(t)dt + [1 + H(1)]\int_1^2 f(t)dt + [1 + H(0)]\int_2^3 f(t)dt \quad [3.73]$$

Thus, simplifying Equation 3.73 to a generic equation results in Equation 3.74.

$$H(t) = \sum_{i=0}^{T-1}[1 + H(T - i - 1)]\int_i^{i+1} f(t)dt, T \geq 1 \quad [3.74]$$

$H(0) = 0$ and $f(t)$ are the probability density function for a Weibull distribution with a set β and η.

Using this discrete approach, the calculation of $H(t)$ always requires $H(t-1)$ to have been calculated first, which suggests a recurrence relation. Therefore, an iterative method must be implemented for the calculation of $H(t)$.

Once $H(t)$ has been computed, the total expected cost per unit time for multiple components can be calculated using Equation 3.75. N is the number of components to be block replaced.

$$C(t_p) = \frac{NC_g + NC_f H(t_p)}{t_p} \quad [3.75]$$

Thus, using Equation 3.75, an optimum block replacement interval can be found that determines the most economical replacement age for a group of similar components within a system.

3.10.1 Illustrative example

An illustrative example is presented to demonstrate the workings of the block replacement model. It uses data from the Weibull Database (2010) for mechanical couplings that connect shafts together. The database gives a value of 2 for β and 3125 days for η. Using these values for β and η, $H(t_p)$ was computed using Microsoft Excel for t_p values ranging from (0, ∞). From Incledon (2019), it was found that the cost of shaft couplings ranges from between R450 and R2 500. By selecting a value around the midpoint of this range, the preventive maintenance cost per component was taken to be R1000. It was assumed that a failure would result in a cost 10 times greater than the prevention cost due to lost production and immediate setup costs. It was also assumed that the system had 50 couplings for block replacement. Therefore, using all this data and Equation 3.75, Figure 3.23 was computed. It shows the optimum replacement age vs cost of replacement for the 50 couplings, utilising the block replacement method.

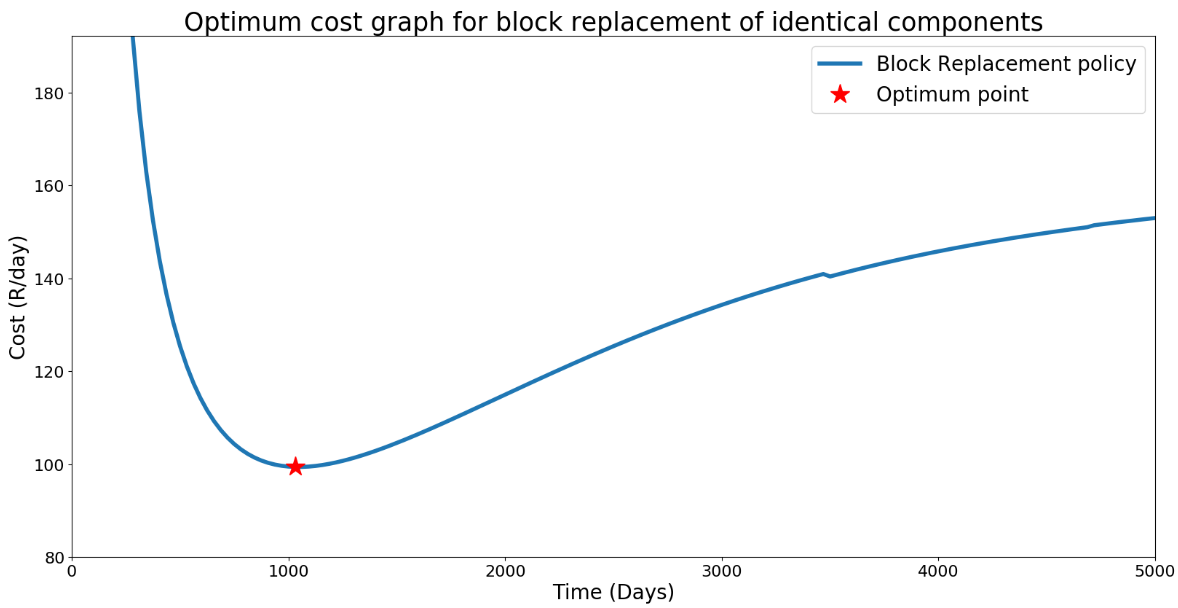

Figure 3.23: Optimum cost curve: block replacement of identical components

From Figure 3.23 it was determined that the optimum block replacement interval for the couplings is 1047 days at a cost of R99.71 per day. For a single component replacement policy, using the mathematics in Section 3.10, it was assumed that the preventive maintenance cost is 1.5 times greater than the preventive block replacement cost. The reasons for the increase in cost for this method are the rise in setup costs, labour hours and system availability since only one component is being replaced at a time compared to a number of components. Using the same data, it was determined that a single component replacement policy would result in a cost of R145.33 per day. This cost is 45.8% greater than the block replacement cost, which demonstrates the advantage of using the block replacement maintenance method compared to the single component method.

3.10.2 Model development

In Section 3.10 the block replacement model was discussed. The optimum replacement age and the optimum cost associated with a replacement were found by minimising the cost function, expressed in Equation 3.75. Like the non-repairable systems model presented in Section 3.6, a main disadvantage of the block replacement model is that it outputs an average cost per unit time due to the computation of $H(t)$ and the division by the time constant, as seen in Equation 3.75. This results in the computation of an average yearly budget, if the method illustrated in Section 3.10 is used alone, which suggests that the budget presented is an average representation of the yearly cost rather than an accurate representation of the likely budget. In terms of the overall budgetary requirements of an organisation, this budget variability may not be acceptable and more certainty around the budget may be required.

This section outlines a methodology that can be followed to create more certainty around the answers found using the model discussed in Section 3.10. It was achieved by developing an extensive program using Monte-Carlo simulations.

3.10.3 Simulation methodology

As stated previously, the general block replacement model discussed in Section 3.10 results in the output of an average yearly cost associated with this optimisation model. This section illustrates a methodology that can be implemented on the general block replacement model, resulting in confidence and certainty around the optimum output to be obtained. The model is based on a simulation methodology, as outlined in Figure 3.24. Failure data is generated in the same manner as in Section 3.7.3, after which the data can be put into the simulation to generate confidence around the average solution. The simulation is run n number of times in order to create confidence intervals around the outcome. Figure 3.24 outlines the simulation methodology that is followed.

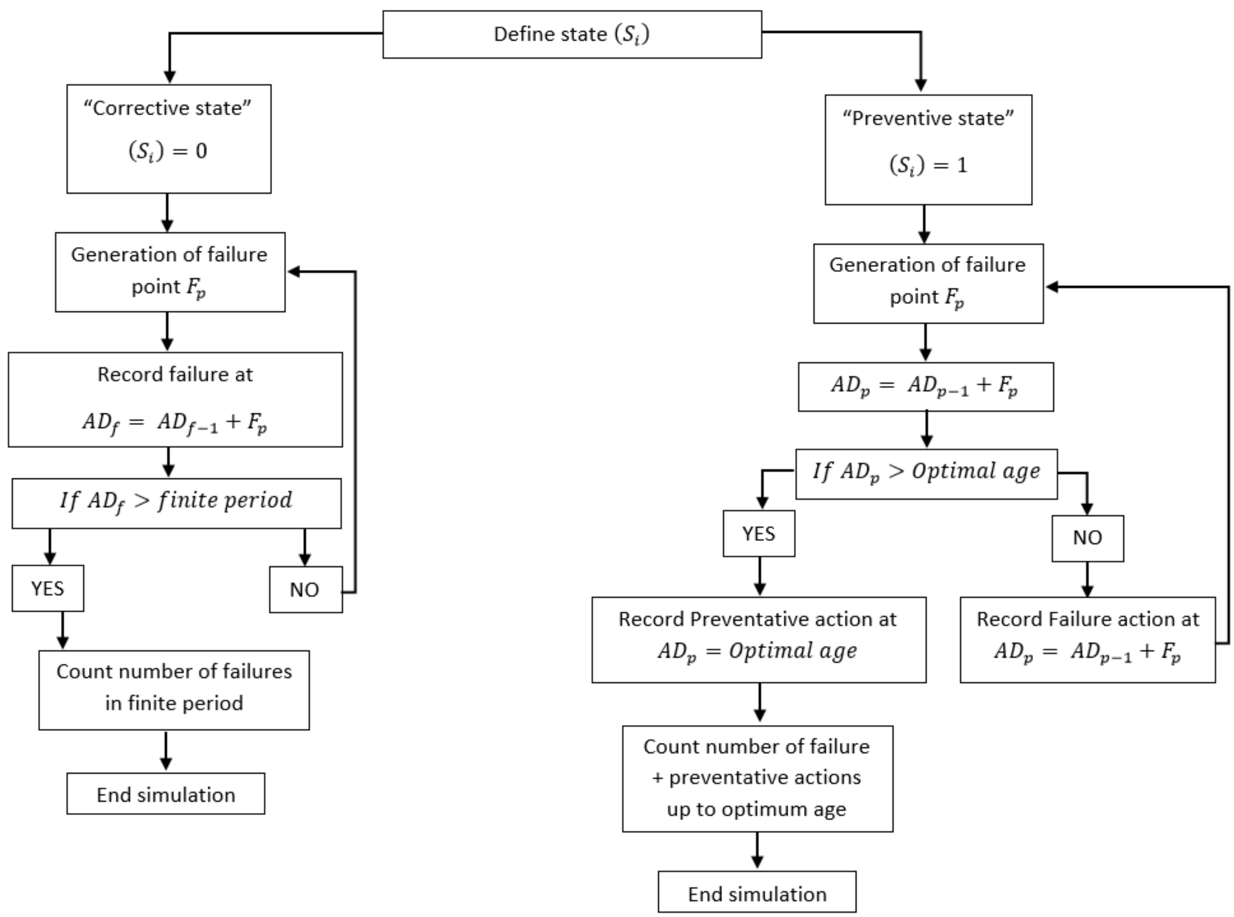

Figure 3.24: Novel Monte-Carlo simulation methodology for block replacement model

Figure 3.24 shows that, before a simulation can take place, a state needs to be chosen for a specific annual period. Either a state of '0', which refers to a corrective maintenance strategy, or a state of '1', which refers to a preventive maintenance strategy, can be chosen for a respective yearly period. Once a state has been chosen, it enables the comparison of a corrective strategy to a preventive strategy for a yearly interval. This allows the impact of preventive maintenance to be determined.

The next step in the simulation process is to generate failure data. This is used during the balance of the simulation, following the steps presented in Figure 3.24. For the preventive strategy, the optimal age is determined using the model presented in Section 3.10. The output of the simulation results in an array of data containing the number of preventive and failure actions that occur during a certain period for a specific component. The length of the array is directly dependent on the number of simulations that are run. The greater the number of simulations run, the more accurate the outcome due to repeatability.

The final step in this modelling process is to convert the array of failure and preventive actions within a yearly period into a cost array that can be compared to the average answer determined by the method discussed in Section 3.10. Equations 3.41 – 3.42 and Equations 3.43 – 3.47 in Section 3.7.2 are used for this purpose for the corrective and preventive strategies respectively.

Following the methodology in Section 3.7.4, the Weibull distribution can be used to fit the cost arrays outputted. This enables the development of the confidence intervals around the general block replacement model.

3.10.4 Solution procedure

The solution procedure for the generation of confidence and certainty around the block replacement model, using Figure 3.24, is presented as follows:

1. Apply the general block replacement model in Section 3.10 to gain an average optimum replacement cost per unit time and the optimum replacement age of a component.
2. Generate failure data, following the procedure in Section 3.7.3.
3. Run the simulation as outlined in Figure 3.24, using the given failure data inputs and the optimum replacement age input.
4. Repeat the simulation *n* number of times and store the results of each simulation in an array.
5. Fit the Weibull distribution to the total outputted array of data, using the method outlined in Section 3.7.4.
6. Apply Equation 3.48 to the Weibull outputted parameters.
7. Apply the statistical test in Section 3.4 to determine whether the Weibull distribution fits the actual data.

3.10.5 Illustrative example

The illustrative example in Section 3.10.1 is extended into this section for two reasons: to show the functioning of the simulation methodology, and to show how to develop certainty and confidence around the general block replacement model. Following the solution procedure in Section 3.10.4, the first step in the simulation process is the application of the general block replacement model to gain optimum values. From Section 3.10.1, the optimum replacement age and cost for the illustrative example were found to be 1047 days and R99.71 per day respectively, following the general block replacement model. This is the average daily cost that an organisation must carry per year to maintain the bearings preventively using this maintenance strategy.

With these optimum values determined, the simulation procedure outlined in Figure 3.24 can now be implemented. The random failure data for the simulation was generated using the methodology in Section 3.7.3. Following steps 2 to 6 in the solution procedure with 1000 simulations run, Figure 3.25 was developed to demonstrate the results of the simulation.

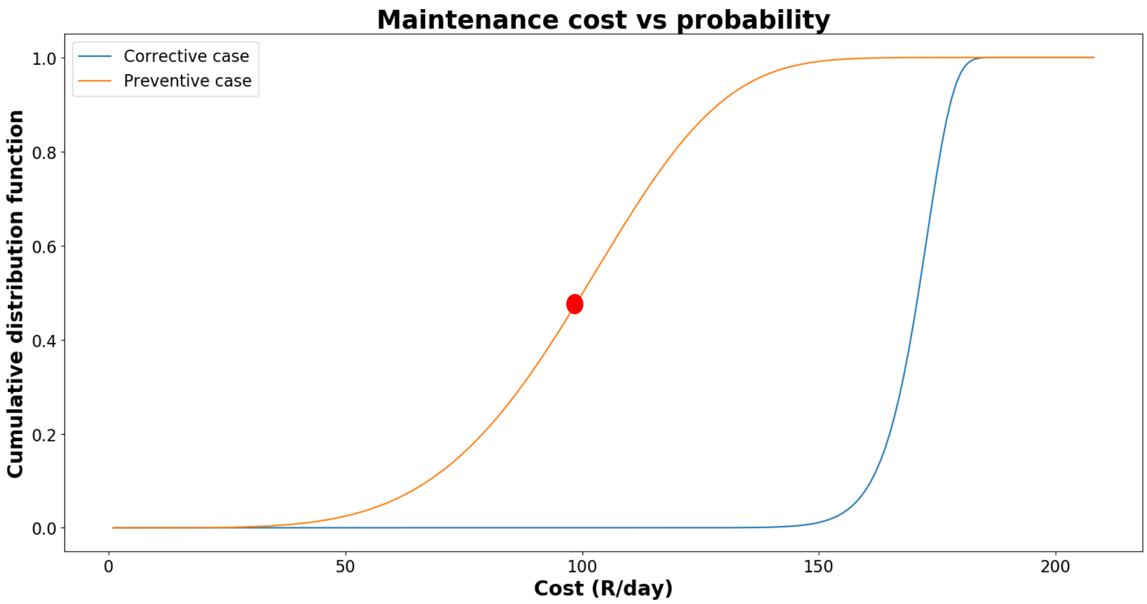

Figure 3.25: Monte-Carlo simulation results: maintenance cost vs probability

Figure 3.25 shows the confidence intervals around having a specific budget within a yearly period for both a preventive strategy and a corrective strategy. There is only 50% confidence in keeping to the budget obtained just using the method outlined in Section 3.10.1, which is shown by the red dot in Figure 3.25. Like the case in the illustrative example presented in Section 3.7.6, organisations are unlikely to be satisfied with such a low confidence in their yearly budget. By developing Figure 3.25, higher confidence levels around a budget can now be chosen. This process gives organisations a lot more certainty around their budgets and a higher chance of not exceeding their budgets within a yearly period. At a higher confidence level, there will be more certainty around a budget, but the budget will also be substantially more. Therefore, a number of factors need to be considered when making decisions about the choice of confidence interval. In addition, Figure 3.25 demonstrates that a preventive maintenance strategy results in a budget that is substantially less than a corrective maintenance strategy. This showcases the importance of the implementation of preventive maintenance.

The last step in the simulation process is to determine whether the Weibull distribution can be used to fit the actual data outputted from the simulation. Again, this is achieved by using the Kolmogorov-Smirnoff (K-S) Goodness of fit test. Following the methodology in Section 3.4, the empirical distribution function was plotted against the Weibull fitted function, resulting in the development of Figure 3.26.

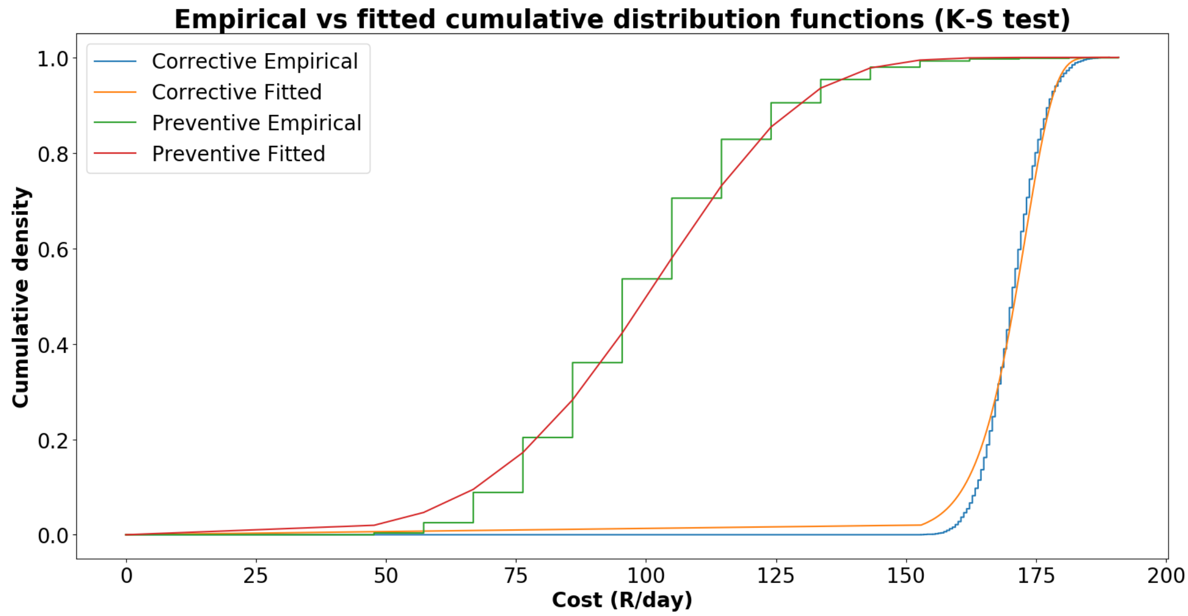

Figure 3.26: K-S test results

Using the one sample K-S table, the critical values for the preventive case and the corrective case were found to be $c_n = 0.327$ and $c_n = 0.17$ respectively, at a confidence interval of 95% where $\alpha = 0.05$. Using Figure 3.26, the test statistic D_n could be computed as $D_n = 0.069$ for the preventive case and $D_n = 0.125$ for the corrective case. In both cases it is evident that $D_n < c_n$, which suggests there is not enough evidence to reject the null hypothesis. This means that the Weibull distribution fits the data with a good enough fit.

Since the fit of the Weibull data to the Monte-Carlo simulated data is acceptable, the cumulative distribution function of the Weibull distribution can be used to generate confidence intervals for the block replacement model. In Section 3.10.1 it was found that the optimum age to replace the components in the block model was at 1047 days, resulting in a cost of R99.71/day. The Monte-Carlo simulation determined only a 50% certainty of having a cost of R99.71/day. This reveals the uncertainly around taking just the answer in Section 3.10 into account. Thus, it is evident that this simulation method creates a lot more certainty around a budgetary requirement by using confidence intervals. This allows a more realistic budget to be chosen with a certain level of confidence rather than just an average budget of what could happen within a certain yearly period. Figure 3.25 also indicates that there is significant benefit to performing preventive maintenance compared to corrective maintenance, as shown by the confidence intervals.

3.11 Forecast model

Thus far, in the mathematical Section 3, only models pertaining to historical failure data have been considered. The question that remains is what happens when no historical failure data is present, but a budgetary estimate is still needed for certain components/systems. The one piece of information that is rarely not recorded is the amount spent on a certain piece of machinery within one financial year due to maintenance and repair. The presence of this information enables a better answer than just heuristics with regard to the expected cost of maintenance and repair in the next financial year using forecasting methods.

Hyndman et al. (1998) affirm that a number of different forecasting techniques are available in literature. These include quantitative techniques, such as time series and explanatory modelling, if sufficient quantitative data is available; qualitative techniques if little or no quantitative data is available but sufficient qualitative knowledge exists; and, finally, unpredictable techniques that give a forecast when there is little or no information available. To apply the quantitative forecasting technique, three conditions first need to be met. These conditions are: first, information about the needs of the past is available; second, the information from the past can be quantified into numerical data; and, third, it can be assumed that aspects of the past pattern of the historical data can be continued into the future (Hyndman et al., 1998).

This research study uses the quantitative technique as it meets all three criteria. First, sufficient historical maintenance cost data can be drawn from industry; second, the data is in the form of a cost, thus it meets the numerical criterion; and, third, it can be assumed that the past pattern in the historical data can be continued into the future since maintenance actions and repairs such as major overhauls and service repairs are seasonal.

3.11.1 Exponential smoothing

Bagio (2017) states that exponential smoothing forecasting techniques are some of the most robust and widely used as they can be employed in a vast number of different applications. According to Chase and Jacobs (2018), a major reason for the emergence of exponential smoothing was the finding that more recent occurrences in the historical data offer more indicative predictions about the future than those in the distant past. Exponential smoothing is a time series forecasting method that uses weights which decrease exponentially for each past period (Chase & Jacobs, 2018). A number of different weights and methods are associated with exponential smoothing. The choice of the method and weights is dependent on the available data and whether trends, seasonality or both are present within the data.

There are a variety of exponential smoothing methods (Bagio, 2017). Only the three main methods will be discussed, which include simple exponential smoothing, double exponential smoothing and triple exponential smoothing. The simple exponential smoothing model requires minimal computation and is only used when there is no trend or seasonal variation within the historical data. For the model to be implemented, only one past actual value and one past predicted value are needed, as seen in Equation 3.76, illustrated by Bagio (2017):

$$S_t = \alpha y_{t-1} + (1-\alpha)S_{t-1} \qquad [3.76]$$

where: S_t represents the predicted value at time t and α ranges between $0\ to\ 1$, which is seen as the smoothing factor.

Since the computation of S_t only needs two numerical values, a major advantage of this exponential smoothing method is its computational efficiency. This means it can be used on very large datasets (Bagio, 2017).

The double exponential smoothing model, also commonly known as Holt's exponential smoothing method, is used extensively when a trend is present within the historical dataset (Bagio, 2017). The presence of a trend within this data always causes the exponential forecast to lag behind the actual occurrences (Chase &

Jacobs, 2018). Therefore, to minimise the effect of lag, the double exponential smoothing model was developed to introduce an additional parameter to allow for some correction to the forecast. This new parameter accounts for the trend within the data and adjusts the forecast, thus reducing the error between the forecasted values and the actual values. The development of Holt's exponential smoothing model, as stated by Bagio (2017), is expressed in Equations 3.77 – 3.79:

$$S_t = \alpha y_t + (1-\alpha)(S_{t-1} + T_{t-1}) \quad [3.77]$$

$$T_t = \gamma(S_t + S_{t-1}) + (1-\gamma)T_{t-1} \quad [3.78]$$

$$\hat{y}_{t+k} = S_t + kT_t \quad [3.79]$$

where: S_t *and* T_t are the smoothed level and trend respectively; α *and* γ are the smoothing parameters; and $\hat{y}_{t+k}$ is the forecast into the future with k as the step ahead forecast made from origin t.

To solve Equations 3.77 – 3.79, initialisation values are needed for S_1 *and* T_1. Equations 3.80 – 3.81 are the governing equations for these values.

$$S_1 = y_2 - y_1 \quad [3.80]$$

$$T_1 = 0 \quad [3.81]$$

The triple exponential smoothing method is also commonly known as the Holt-Winters technique. The significant advantage of this forecasting method is that, if the historical data shows signs of both a trend and seasonality, it can take these into account. Bagio (2017) states that the formulation of the Holt-Winters method treats the level, trend and seasonality as separate factors, thus allowing all these factors to be considered in the forecasting model.

There are two types of triple exponential smoothing methods: additive and multiplicative (Bagio, 2017). The additive method assumes that the seasonal fluctuations within the data are stable, while the multiplicative method assumes that they are variable. The additive triple exponential smoothing model is expressed in Equations 3.82 – 3.85:

$$L_t = \alpha(Y_t - S_{t-1}) + (1-\alpha)(L_{t-1} + T_{t-1}) \quad [3.82]$$

$$T_t = \beta(L_t + L_{t-1}) + (1-\beta)T_{t-1} \quad [3.83]$$

$$S_t = \gamma(Y_t + L_t) + (1-\gamma)S_{t-1} \quad [3.84]$$

$$\hat{y}_{t+p} = L_t + pT_t + S_{t-1+p} \quad [3.85]$$

where: L_t represents the level affected by α; T_t represents the trend affected by β; S_t represents the seasonality affected by γ; p represents the seasonal period of the historical data; and $\hat{y}_{t+p}$ represents the forecast for a certain time period.

As with the double exponential smoothing method, to solve Equations 3.82 – 3.85 initialisation values of some sort are needed for L_t, T_t and S_t. Equations 3.86 – 3.88 outline the process of determining these initialisation values where s is the seasonal length.

$$L_s = \frac{1}{s}(Y_1 + Y_2 + \ldots + Y_s) \quad [3.86]$$

$$T_s = \frac{1}{s}\left[\frac{Y_{s+1} - Y_1}{s} + \frac{Y_{s+2} - Y_2}{s} + \ldots + \frac{Y_{s+s} - Y_s}{s}\right] \quad [3.87]$$

$$S_1 = Y_1 - L_s, \qquad S_2 = Y_2 - L_s, \ldots\ S_s = Y_s - L_s \quad [3.88]$$

Amiruddin (2016) and Bagio (2017) state that one of the main problems with the triple exponential smoothing forecasting method is determining the optimum values of $\alpha,\ \beta\ and\ \gamma$, which will minimise the error between the actual values and the forecasted values. To establish these optimum values, an optimisation algorithm needs to be developed that outputs the optimum $\alpha,\ \beta\ and\ \gamma$ based on the minimum error.

3.11.2 Optimisation algorithm

As stated in Section 3.11.1, an optimisation algorithm needs to be developed for this forecasting method that optimises $\alpha,\ \beta\ and\ \gamma$ by minimising the error function between the actual data and the forecasted data. To obtain these optimum values of $\alpha,\ \beta\ and\ \gamma$, a forecasting error function is needed. The three most used error functions in forecasting are the mean absolute error (MAE), the mean squared error (MSE) and the mean absolute percent error (MAPE) (Amiruddin, 2016; Bagio, 2017).

Mean absolute error function:

For each value within a given dataset, the MAE function takes the absolute error between the actual value and the forecasted value. The sum of these values from the dataset is then computed and divided by the number of values within the dataset to reach the MAE. The MAE can be seen in Equation 3.89.

$$\text{MAE} = \frac{\sum_{i=1}^{n} |X_i - F_i|}{n} \quad [3.89]$$

Mean squared error function:

The MSE gives the squared average between the actual values and the forecasted values within a dataset. Hyndman et al. (1998) state that this method for determining the error function is the most used in statistical analysis. It has the advantage of being easy to handle mathematically while, at the same time, gives an answer that is interpretable. Equation 3.90 outlines the MSE.

$$\text{MSE} = \frac{\sum_{i=1}^{n} (X_i - F_i)^2}{n} \quad [3.90]$$

Mean absolute percent error:

The MAPE is calculated as the absolute average differentiation between the actual values and the forecasted values within a dataset. It is expressed as a percentage of the actual value for each value within a dataset. This method of determining the error for a specific forecast gives a clear and interpretable answer in which quantity ranges can be assigned to the error to determine the accuracy of the forecast. Equation 3.91 outlines the MAPE mathematics and Table 3.9 gives the linguistic forecast ranges of the MAPE function to establish the accuracy of the forecast, as stated by Amiruddin (2016).

$$\mathrm{MAPE} = \frac{\sum_{i=1}^{n} \left| \frac{X_i - F_i}{X_i} \times 100 \right|}{n} \qquad [3.91]$$

Table 3.9: MAPE linguistic representation

MAPE	Definition
< 10%	Excellent
10%–20%	Good
20%–50%	Adequate
> 50%	Poor

The optimum values of $\alpha,\ \beta\ and\ \gamma$ can be computed using Equations 3.89 – 3.91.

3.11.3 Selection of optimum values

It is evident from the equations in Section 3.11.1 for single, double and triple exponential smoothing that all describe a repetition relationship in which the next value is computed using the previous value. This means that the choice of $\alpha,\ \beta\ and\ \gamma$ plays a significant role in the accuracy of the forecast model and needs to be determined precisely. The best way to achieve this accuracy is by doing testing on data training as many as n times with different combinations of $\alpha,\ \beta\ and\ \gamma$ with specific values (Anggrainingsih et al., 2015).

Using Equations 3.89 – 3.91, the combination that gives the lowest error is chosen as the optimum constants. Since there are three constant values that need to be optimised, all of which are bounded between $0\ and\ 1$, numerous different combinations exist among the constants. A trial and error approach to find the optimum values will not work as it would take too long to go through all the different combinations. For this reason, the author developed an optimisation algorithm in Python with the use of the *scipy.optimize* function to determine the optimal values of $\alpha,\ \beta\ and\ \gamma$. The MSE error function was optimised in the algorithm and the MAPE function was also computed to show the accuracy of the forecast linguistically.

3.11.4 Determination of the seasonality index

Before the triple exponential smoothing model can be applied to any dataset with seasonality and a trend, the seasonality index needs to be determined. This is the index that shows how often a pattern repeats itself within a dataset. It can be determined by simply plotting the data and establishing how often the points repeat themselves. A problem with this manual method is that, in the event of needing to apply the model to a large number of datasets, the process will take far too long, which makes it unviable.

Microsoft Excel 2016 has a built-in triple exponential smoothing function – *forecast.ets* – which can automatically determine the seasonality index of a given dataset. The author found that the automatic function does not detect seasonality effectively and works a lot better when data is inserted manually. For this reason, a VBA macro was coded to run through a number of different seasonality indexes. The output was a confidence interval at a certain value. The confidence interval was chosen as the output parameter because it looks at the uncertainty and risk within an answer. The seasonality index that gave the smallest confidence interval at the certain value was chosen because it directly results in less uncertainty around the answer and hence provides a more accurate forecast.

3.11.5 Illustrative example

To demonstrate the functioning of the exponential smoothing forecasting model, an illustrative example is presented. Hyndman et al. (1998) have published a set of data, as seen in Table 3.10, which details the sales of a company over a certain time period.

Table 3.10: Illustrative example dataset

Period	***Sales***	***Period***	***Sales***
1	362	13	544
2	385	14	582
3	432	15	681
4	341	16	557
5	382	17	628
6	409	18	707
7	498	19	773
8	387	20	592
9	473	21	627
10	513	22	725
11	582	23	854
12	474	24	661

The first step to applying any exponential smoothing model to a dataset is to determine the correct type of method to be applied. This is done by establishing whether there is a trend and/or seasonality within the data. The *slope* function of Microsoft Excel 2016 is used for this purpose. If the outputted value is positive, it suggests an increasing trend in the data. If the slope is negative, it suggests a decreasing trend in the data. A positive or negative trend within the dataset suggests that the single exponential smoothing model cannot be used, and either the double or triple exponential smoothing model should be applied, depending on whether seasonality is present or not. To determine the presence of seasonality within the data, it is necessary to implement the method described in Section 3.11.4. If the seasonality index outputted is greater than 2, it means that the outputted value is the seasonality index and the triple exponential smoothing method must be applied to the dataset. If the value outputted is 0, it means there is no seasonality within the data and the double exponential smoothing method must be applied to the dataset. Applying this rationale to the dataset in Table 3.10, the slope was found to be 17.8 and the seasonality index was found to be 4. To validate these findings, the data in Table 3.10 was plotted, as shown in Figure 3.27.

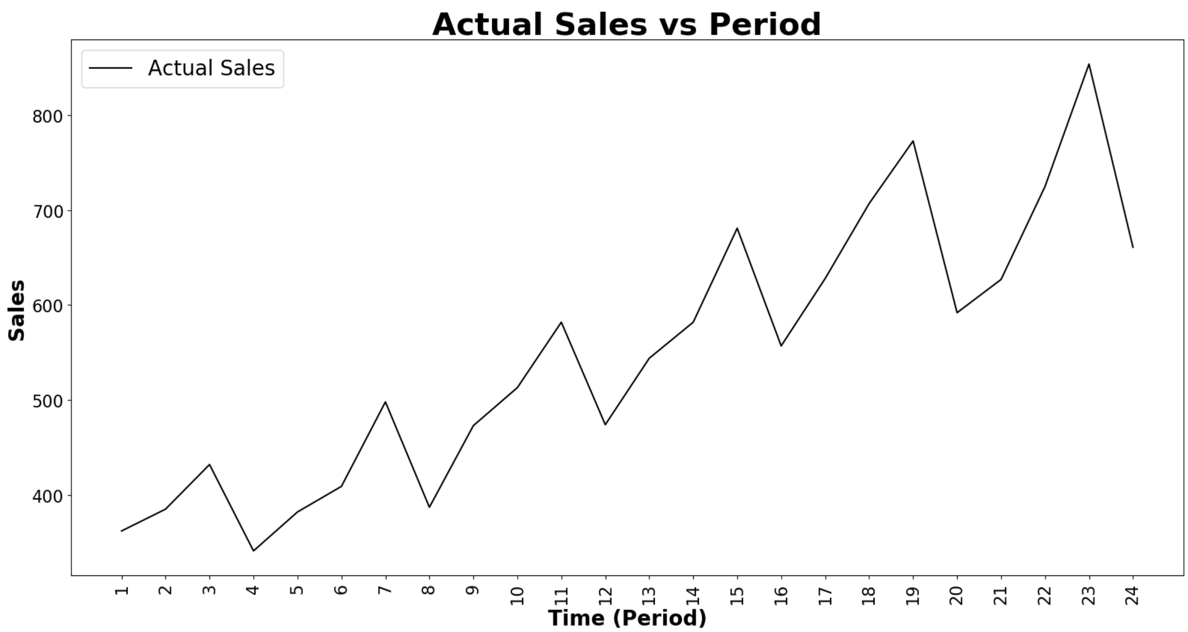

Figure 3.27: Illustrative example of actual costs

The increasing trend in the dataset, as seen in Figure 3.27, validates the positive increasing trend of 17.8, as found by the slope function in Microsoft Excel. The seasonality index of 4, computed using the method described in Section 3.11.4, is also validated since it is evident in Figure 3.27 that the same pattern repeats itself every 4 data points. Therefore, knowing that both a trend and seasonality are present within the data, the triple exponential smoothing model is clearly the best model to apply to the dataset for the forecast.

Knowing that the triple exponential smoothing model can be applied to the dataset, the next step in the forecasting process is to determine the optimum values of $\alpha,\ \beta\ and\ \gamma$. This was done using the process explained in Section 3.11.2 in which the MSE is minimised, resulting in optimum values of $\alpha = 0.512$, $\beta = 0.025$ and $\gamma = 0.977$. Utilising these optimum values and Equations 3.82 – 3.85, Figure 3.28 was developed to show the actual sales vs the forecasted sales for the dataset.

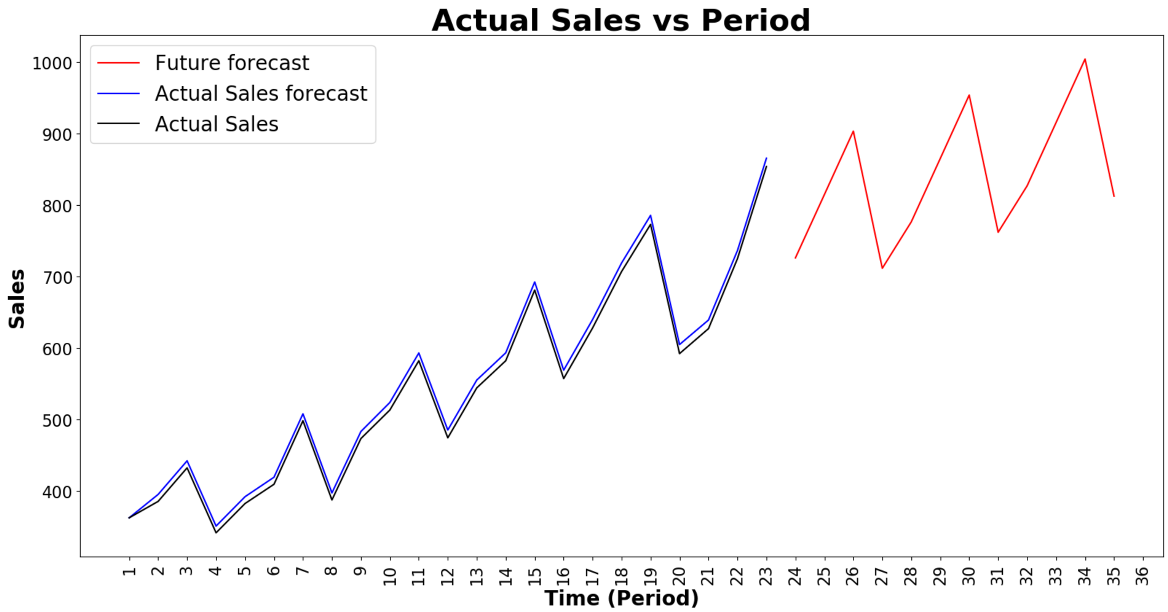

Figure 3.28: Illustrative example of forecasted costs

Figure 3.28 shows that the forecasted data follows the actual data closely. The MAPE was found to be 2.11%. Thus, using Table 3.9, it was established that the forecast is regarded as *Excellent*. This suggests that it can be used to predict values into the future, as seen by the red line in Figure 3.28.

This section has outlined all the mathematics around forecasting datasets, whether trends, seasonality or neither of these are present. The main outcome is to show the reader what methods can be used to predict costs when no failure data is available, which means that the methods discussed in Sections 3.5 – 3.10 cannot be used. As in any prediction method, there is always uncertainty around the answer. However, this method does give more validated answers than just pure heuristics and can be applied to gain information about the budgetary requirements of an organisation.

3.12 Life cycle cost analysis

The forecasting model described in Section 3.11 is an excellent model to implement when only historical maintenance cost data is available and an estimate is needed for the budgetary requirements of the succeeding year. However, if a piece of capital equipment is being analysed in which maintenance costs, capital acquisition costs and resale costs are available, a more accurate model can be developed for the budget than simply a cost estimate from a forecast. The model developed in this section is a life cycle costing model that determines the optimum replacement age of a piece of capital equipment by minimising the total cost. Jardine and Tsang (2013) state that the main reason for the development of such a model is the fact that equipment deteriorates over time. This deterioration is measured by the increase in the maintenance costs over the lifespan of the equipment. Due to this increase, a point in time will eventually come when replacement of the equipment will be economically justifiable. For the model developed, it was assumed that the piece of equipment is replaced by an identical item, thereby bringing the system back to an as ‘good as new condition’. It was also assumed that the trend in the maintenance costs after each replacement, in which periodic replacements occur at certain intervals, remains the same.

Jardine and Tsang (2013) state that the underlying equation to such a model is Equation 3.92, in which the objective is to minimise the optimal interval between replacements by minimising the total discounted cost.

$$EAC(n) = \frac{A + \sum_{i=1}^{n} C_i r^{i-1} - r^n S_n}{1 - r^n} \times i \qquad [3.92]$$

Equation 3.92 gives the equivalent annual cost of operating and maintaining a piece of equipment if this model is followed. To solve Equation 3.92, the acquisition cost (A), the operations and maintenance cost (C_i), the resale value (S_n) and the discount factor (r) are all needed. For the model developed here, it is assumed that the acquisition cost is incurred at the beginning of the replacement cycle and the costs associated with each year are also incurred at the start of the year. This results in year 1 costs not being discounted, which suggests a more realistic model as outlined by Jardine and Tsang (2013). Figure 3.29 depicts all the assumptions around the cash flows of the piece of capital equipment.

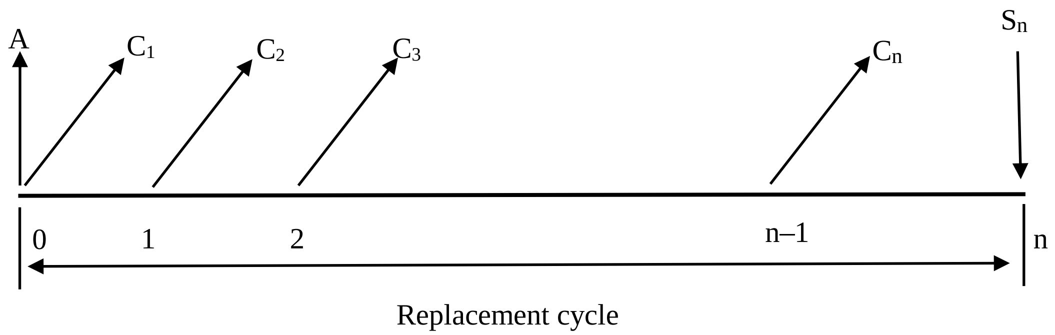

Figure 3.29: LCC replacement cycle

Thus, if capital cost data is available for a piece of capital equipment, Equation 3.92 can be followed to obtain the optimal point of replacement and a relevant annual cost of implementing such a method. The cost flows in Figure 4.5 are used for this procedure. The results can be put into an overall budgetary requirement for the maintenance of such a piece of equipment within an organisation.

3.12.1 Illustrative example

In this section, the methodology of the life cycle cost analysis is presented, as outlined by Jardine and Tsang (2013), using an illustrative example. A sample set of equipment cost data is shown in Table 3.11.

Table 3.11: Illustrative example of O & M and disposal costs

Year	Operation and maintenance cost (R)	Resale value (R)
1	500	7000
2	1000	5000
3	2000	4000
4	3000	3000
5	4000	2000

Table 3.11 outlines all the operation and maintenance costs and the resale value of the piece of equipment over a five-year period. An interest rate of 10% was assumed for use in the model. The capital acquisition cost of the piece of equipment was assumed to be R10 000. The LCC analysis could be applied using all the information in Table 3.11 and Equation 3.92, resulting in the development of Figure 3.30.

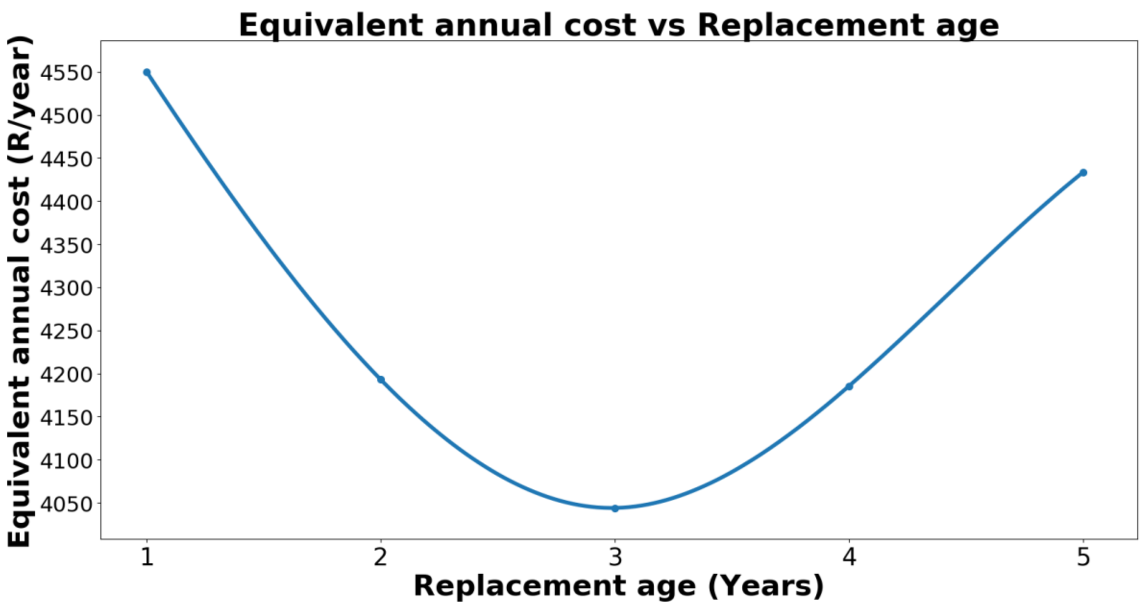

Figure 3.30: Equivalent annual cost vs replacement age

Figure 3.30 shows the results of the life cycle cost model implemented on the information on the piece of equipment, as given in Table 3.11. From Figure 3.30 it is evident that the optimum time to replace the equipment is at an age of 3 years, with an associated cost of R4 044 per year. This is the amount it would cost an organisation each year if this maintenance strategy were to be followed. It is also evident that the curve on either side of the optimum value is steep. This suggests that any deviation from the optimum replacement age is going to result in a significantly increased cost as the penalty for extending the life of the piece of capital equipment.

This section has presented a life cycle cost model. A detailed description of all the mathematics has been given, as well as the benefits of such a model in an overall maintenance model. An illustrative example has been presented to show the functioning of the model with all the relevant outputs. It was demonstrated that the model outputs an optimum replacement age with an associated cost which can be used in an overall budgetary requirement for an organisation within a yearly period.

3.13 Conclusion

In this chapter, a detailed methodology and mathematical outline of the overall maintenance model was presented in order to provide the tools to apply a complete maintenance analysis. The overall maintenance model developed made used of six different maintenance models, namely: a repairable systems analysis, a non-repairable systems analysis, a block replacement model, a grouping model, a forecasting model and a life cycle costing analysis. This resulted in the development of a generic model that can be used in a variety of scenarios where different types of datasets do not affect the implementation of the model. Monte-Carlo algorithms were developed for certain models within the overall maintenance model to create more certainty and less risk around the final outputted budgetary requirement for a specific application. Goodness of fit tests were employed to validate the use of the models. Finally, a complete maintenance methodology was presented, as shown in Figure 3.1, which demonstrated how all the individual models interlink to produce one budgetary requirement in which all the inputs and outputs to the model are evident.

4 Case study

Section 4 outlines a case study performed on a contrived plant with the aim of demonstrating the application of the proposed solution methodology outlined in Section 3. The case study aims to show that an overall maintenance decision model can be applied to a real-world problem. The outcome of the implementation of such a model results in a condensed budgetary requirement for the preventive maintenance of an entire plant. This section initially provides an overview of the case study, outlining all the system boundaries, data requirements and assumptions made in the case study. Thereafter, a detailed analysis is performed on a variety of different systems and components with varying requirements in the plant, following the methodology in Figure 3.1.

4.1 Overview of Anglo American

For the case study presented in this section, real-world data was acquired from the Anglo American PLC group to validate the model detailed in Section 3. Anglo American PLC is a British mining company with its main headquarters based in London in the United Kingdom and Johannesburg in South Africa. Anglo American also operates in numerous other countries throughout Africa, Asia, Europe, and North and South America. Its primary listing is on the London Stock Exchange and it has a secondary listing on the Johannesburg Stock Exchange.

Anglo American is the largest producer of platinum, with 40% of the world's annual production. The company is also a major contributor to the production of diamonds, copper, iron ore and nickel. It has $31 billion in property, plant and equipment assets, which are the main contributors to the total assets of the company, and $39 billion in non-current assets (Anglo American, 2018).

The case study considered here makes use of data from the Sishen and Kolomela mines, both of which are situated in the Northern Cape province, South Africa. Other data was also extracted and used from the Mogalakwena mine in Limpopo, South Africa and the Minas Rio mine in Brazil. The Sishen, Kolomela and Minas Rio mines are some of the largest iron ore mining operations in the world, while the Mogalakwena mine is the largest open-pit platinum mine globally. Anglo American has the largest stake in all the mines – it controls operations and distributes tasks to other companies. The data extracted from the different mines comprises failure and operations data, as well as failure cost data.

4.2 Case study design

As stated in Section 1, a major gap found in the literature on the topic of maintenance is the development of an overall maintenance model that can be implemented on any plant with a variety of data inputs. In the literature, a number of different maintenance models have been looked at on an individual basis. The incorporation of all these individual models into one overall maintenance model has not commonly been considered in literature. There is also limited literature on the development of a systematic approach on when to use what model.

In this study, with the acquisition of real-world data from Anglo American, a solution to the problem outlined in Section 1 is given to determine whether the proposed overall maintenance methodology presented in Section 3 will give a valid outcome to the problem. The main aim of this case study is to present a detailed integrated analysis of the methodology in Section 3 on a real-world problem. Different maintenance models found in literature are used to analyse available plant data, resulting in an annual overall budgetary requirement for a specific plant.

In addition, the analysis procedure can be used as a decision-making tool. The individual models outlined in Section 3 utilise a number of different statistical distributions as well as forecasting and LCC methods, depending on the available data, in order to gain one budgetary requirement for an overall plant. Ultimately, by following the entire methodology detailed in this dissertation, a deep understanding and validation of the overall maintenance model developed should be gained, resulting in a decision tool that can be used to develop an annual budgetary requirement for the preventive maintenance of an organisation.

As stated earlier, the main intention of this case study was to implement the overall maintenance model in Section 3 on a real-world problem. In any industrial plant, there are a huge number of different systems and components, all in need of their own maintenance strategy. Thus, a large variety of different components and systems could be chosen for the implementation of the proposed maintenance model. In terms of the outcome of this work, an entire power plant or mining operation was considered too large; the validation of this procedure on a smaller operation was regarded as justifiable. It is believed that similar outcomes could be expected if the model was implemented on a larger scale example. Therefore, a simpler representative plant was contrived, comprising a number of different systems and components that allowed for the functioning of the maintenance model to be illustrated and validated.

After numerous discussions with various staff members from industry who were directly responsible for the extraction of the available system/component data, it was concluded that the plant would comprise all the systems and components seen in Figure 4.1.

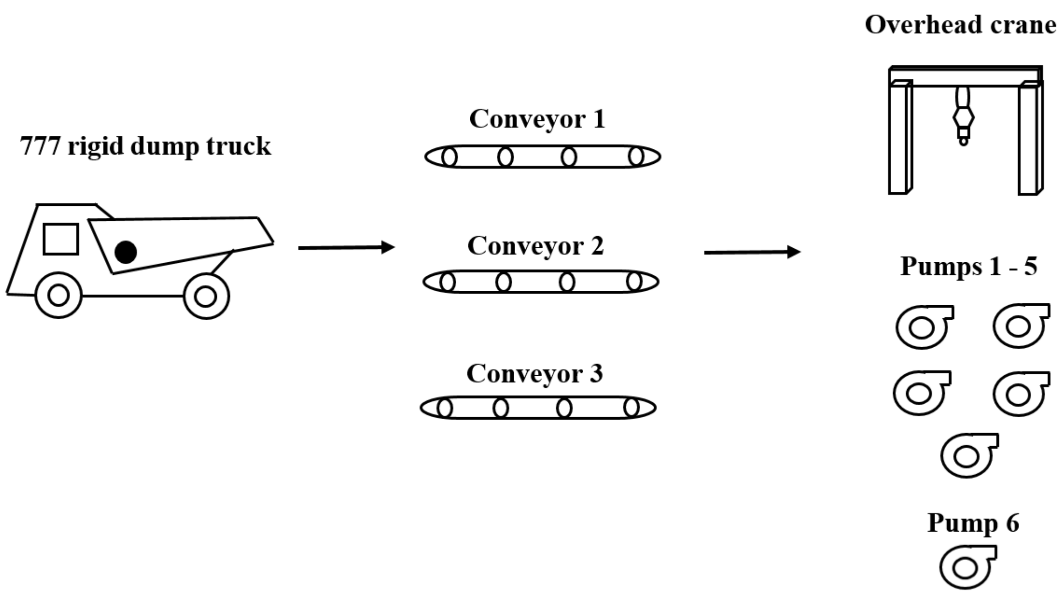

Figure 4.1: The composition of the plant to be analysed

Figure 4.1 shows that the plant developed is made up of various different systems and components, including a rigid dump truck, a selection of conveyor systems, a variety of different pumps, and an overhead crane. The reason for the choice of the systems and components was the availability of data for each element within the plant, and to illustrate the functioning of all the sub-models and maintenance methods in the overall maintenance model described in Section 3.

4.3 System boundaries and data requirements

Section 4.2 indicates that the plant being analysed comprises a number of different systems and components, which make up the contents of the entire plant for the case study. Figure 4.1 outlines the composition of the plant. The plant functions by taking material from a mine using a dump truck. Different conveyor systems transport the material from the truck to a plant consisting of pumps and an overhead crane where a refining process can begin. Figure 4.2 outlines the system boundaries of the different elements in the plant.

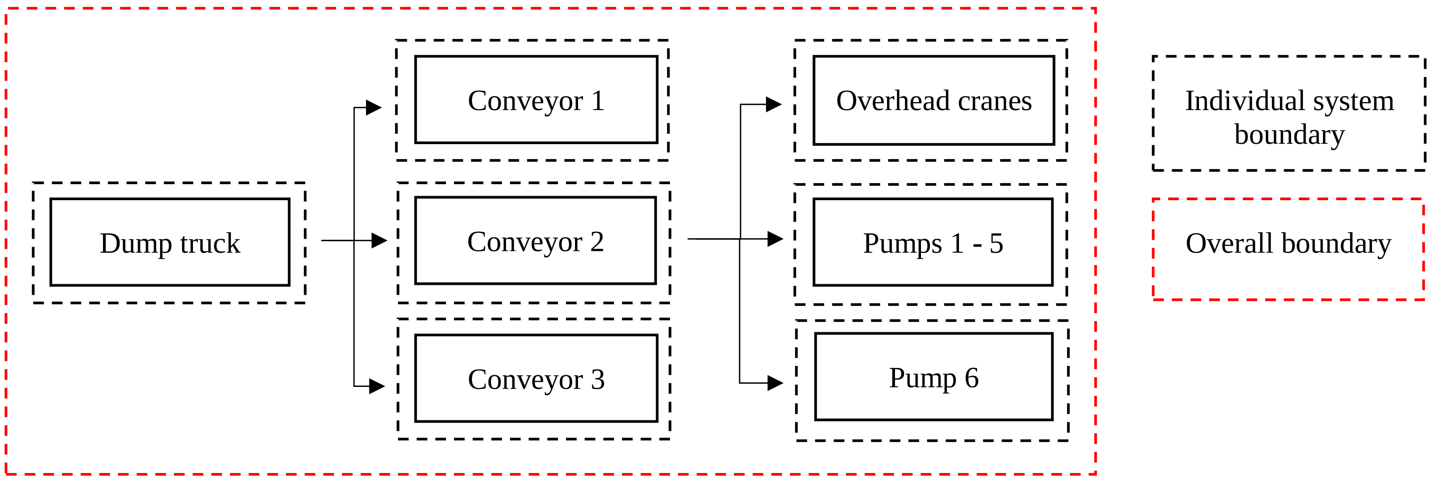

Figure 4.2: System boundaries

Figure 4.2 shows that each element within the plant has individual boundaries. The reason is that one single maintenance technique will not suit all the varied types of data that were gathered for the different elements. This suggests that different maintenance methods may be needed to analyse each element. Figure 4.2 also shows an overall boundary around the entire plant to include all the different budgetary requirements of the individual elements. The outcome is one overall budgetary requirement for the entire plant.

To enable the application of the maintenance methodology in Figure 3.1, the plant in Figure 4.1 has specific data requirements. Each different model outlined in Section 3 needs either historical failure data or historical cost data, depending on the type of model used. For each individual element within the plant, either failure data, cost data or both were extracted, depending on their availability. The data was drawn from the Anglo Operating Platform, which is the data base used by the company to store all its data records. It was obtained for all the relevant elements within the plant for varying periods between 2007 and 2019, contingent on the available historical records in the stored data for each element. A long extraction period was used to ensure that a sufficient number of historical data points were available for the analysis. The data was stored in Microsoft Excel for future post-processing.

All the historical failure data extracted was classified as a failure point for the maintenance analysis. The cost data obtained was classified as the cost incurred by an organisation as the result of a failure.

4.4 Analysis of 777 rigid dump truck

This section outlines the preventive maintenance methodology that was implemented on the 777 rigid dump truck to gain a yearly budgetary requirement for its maintenance. A selection of maintenance data was collected from the Anglo Operating Platform with a time period for the dataset from 1 January 2012 – 31 May 2019. General assumptions were made throughout the analysis, as seen in Section 3, due both to certain factors being unattainable and to the selection of the optimisation model used.

4.4.1 Dataset analysis

The data collected for the 777 rigid dump truck was only in the form of historical maintenance cost data as historical failure data could not be obtained. It considered the cost of materials and resources used, as well as labour costs for maintenance actions during a certain period. Production losses as a result of the downtime due to maintenance actions on the dump truck were not taken into account. The historical maintenance cost data was collected in yearly periods, that is, the total sum spent on different maintenance activities on the dump truck within a specific year was recorded. There were 92 different maintenance-related activities recorded for the dump truck each year, as well as the cost surrounding each one. The records indicated every maintenance cost related to the dump truck, ranging from electrical, flexible hose and general service costs to complete engine repair costs.

With this relevant cost data available, the next step in the analysis process was to determine which maintenance optimisation technique to apply to the dump truck dataset to result in an optimum yearly budgetary requirement for an organisation. From Figure 3.1, it was evident that none of the historical failure data models could be used to analyse the dataset since this data was not accessible. This left the option of either the forecasting model or the LCC analysis. The data collected from the Anglo Operating Platform was in the form of maintenance cost data for one complete system – the dump truck, which can be regarded as a piece of capital equipment due to its finite life and substantially high acquisition cost. For these reasons, the life cycle cost analysis (LCC) was chosen as the best optimisation model to implement.

4.5 Life cycle cost analysis implementation

The life cycle costing model is explained in detail in Section 3.12, with Equation 3.92 as its main output. This equation allows the computation of the equivalent annual cost of maintaining a piece of capital equipment for a certain life. A number of inputs are needed in order to solve Equation 3.92. These include the capital acquisition cost of the dump truck; the resale value of the dump truck per year in use; every maintenance-related cost over the analysis period; the useful life of the dump truck; and the interest rate per year. This data was all obtained after extensive conversations with Anglo personnel.

Table 4.1 outlines the capital acquisition cost of a new dump truck, the useful life of the dump truck before it is decommissioned by the company, and the company interest rate.

Table 4.1: Life cycle costs for rigid dump truck

Capital acquisition cost	R16 368 833
Useful life	8 years
Interest rate (per year)	6.5%

Table 4.1 outlines all the maintenance-related costs of the dump truck over the eight-year period analysed. The costs in Table 4.2 detail the total maintenance cost of the dump truck within a specific year.

Table 4.2: Maintenance cost for rigid dump truck

Year	Maintenance cost (R)
1	12 490
2	16 382
3	41 234
4	2 280 937
5	1 020 210
6	1 014 028
7	986 018
8	67 242

Two other costs extracted from the Anglo Operating Platform were those of a midlife service and a rebuild. These costs were part of company policy in which, after every 2 years of use, the dump truck underwent a midlife service costing R562 020 and, after every 4 years in use, it underwent a complete rebuild costing R8 390 630. To ensure an accurate model, all these costs needed to be included.

The final cost required was the resale value of the dump truck per year in use. To obtain these costs, a depreciation value was needed. Anglo personnel supplied a disposal percentage, which is the percent of the acquisition cost at which the company values the worth of the dump truck after a year in use. For the dump truck's useful life of 8 years, a disposal percentage was obtained for each year, as seen in Table 4.3. The corresponding resale value was also calculated.

Table 4.3: Disposal costs for rigid dump truck

Year	Disposal percentage (%)	Resale value (R)
1	58	9 493 923
2	43	7 038 598
3	30	4 910 649
4	24	3 928 519
5	18	2 946 389
6	14	2 291 636
7	10	1 636 883
8	8	1 309 506

Therefore, using all the information available in Tables 4.1 – 4.3 and implementing Equation 3.92, Figure 4.3 was computed to demonstrate the equivalent annual cost of the dump truck over its useful life.

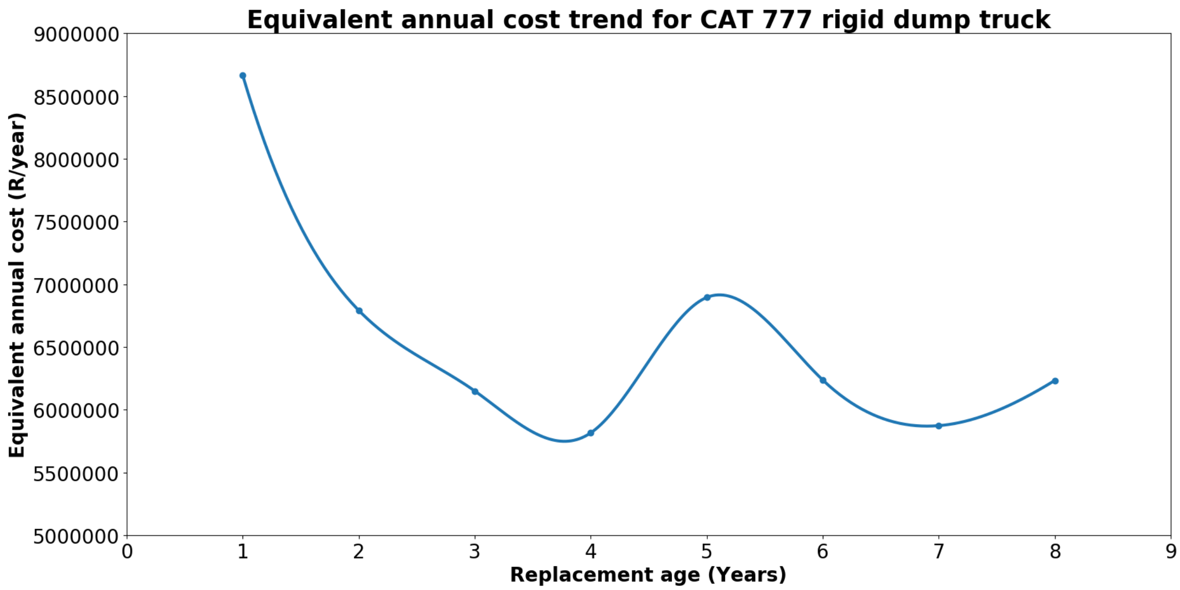

Figure 4.3: Equivalent annual cost graph for a 777 rigid dump truck

In Figure 4.3 there are two distinctive dips in the graph which occur at a replacement age of 4 years and 7 years. The equivalent annual cost at a replacement age of 4 years was found to be the optimum, with a cost of R5 815 182. This represents the cost that an organisation will endure each year if this replacement policy is followed. The large increase in cost between the fourth and fifth year resulted from the rebuild cost incurred at the end of the fourth year. After the fifth year, the cost graph again decreases until the seventh year. The reason for this decrease is the major rebuild that occurred in the fourth year, which reduces maintenance costs for a few succeeding years because the dump truck has been restored to a nearly 'as good as new' condition.

To show the cost effect of not replacing the dump truck at its optimum of every 4 years, Figure 4.4 was developed.

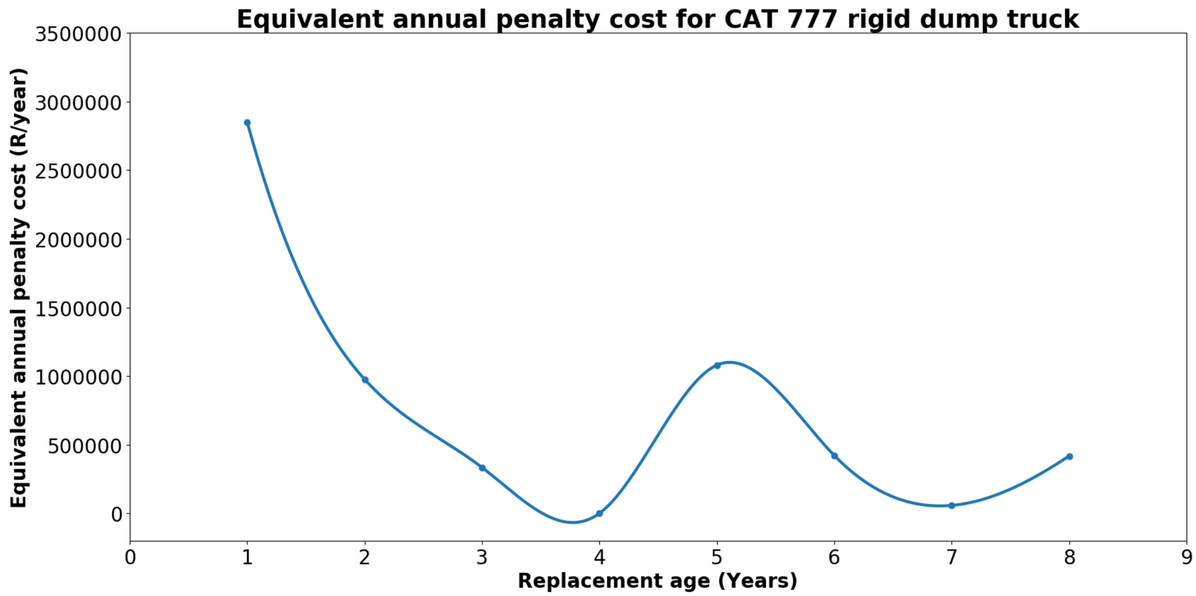

Figure 4.4: Equivalent annual penalty cost for a 777 rigid dump truck

Figure 4.4 shows the equivalent annual penalty if the dump truck is not replaced every 4 years. Again, two dips are evident in the graph. The first is at 4 years with no penalty present as this is the optimum. The second is at 7 years with an equivalent annual penalty of R57 649. A decision needs to be made, either to replace the dump truck every 4 years, resulting in an equivalent annual cost of R5 815 182 and the need for the capital acquisition cost of R16 368 833 to be available every 4 years; or, to extend the life of the dump truck by another 3 years and replace it every 7 years with an extra equivalent annual penalty cost of R57 649, but a capital acquisition cost that only needs to be available every 7 years. Therefore, in terms of the model presented here, and assuming that the capital acquisition cost will be available when replacement is needed for the dump truck, it is evident that the best age to replace it is every 4 years to result in the lowest equivalent annual cost.

4.5.1 Summary

This section outlined the preventive maintenance optimisation technique that was implemented to analyse the dump truck dataset present within the plant. It was found that the best model to implement was the life cycle costing model since the dump truck was a capital asset and maintenance-related costs were attainable, but historical failure data was not. On implementation of the model, an equivalent annual cost of R5 815 182 was computed and it was determined that the best maintenance strategy to follow would be replacement of the dump truck every 4 years. Under this policy, maintaining the dump truck would cost a company the amount stated above each year within the 4-year period.

A penalty cost graph was also developed, which indicated the cost effect of not replacing the dump truck at the optimum age of 4 years. It was found that, if the 4-year rebuild cost was endured, the next best age to replace the dump truck would be every 7 years, resulting in an equivalent annual penalty of R57 649.

Therefore, a financial decision needed to be made to determine whether an organisation could endure the cost of acquiring a new dump truck every 4 years, or would benefit from extending the life of the dump truck by 3 years, paying an equivalent annual penalty each year and only acquiring a new dump truck every 7 years. In this case, it was assumed that the organisation would have the funds to acquire a new dump truck every 4 years, which was the optimal choice. Thus, the optimum equivalent annual cost of R5 815 182 will be used in the overall yearly maintenance budget of the plant.

4.6 Analysis of conveyor 1

This section analyses the preventive maintenance methodology for the first of the three conveyors within the plant. The time period used for the data collected from the Anglo Operating Platform was 1 November 2014 – 30 September 2018. As seen in Section 3, specific assumptions were made throughout the analysis as a result of certain factors not being attainable.

4.6.1 Failure dataset analysis

The maintenance data collected was in the form of failure data, along with a recorded corresponding cost for each failure activity. This represented the cost an organisation incurred when the failure happened. The cost of lost production due to downtime was not considered. The failure data collected was for one conveyor that comprised various different components, including idlers, troughing idlers, pulleys and belts. The failure data was given in days and 409 failure points were collected within the analysis period.

Since failure data and cost data were collected, Figure 3.1 shows that a trend test needed to be performed first to determine the most appropriate preventive maintenance optimisation method to apply to the dataset. The test performed was the Laplace trend test, as outlined in Section 3.3.2. Using Equation 3.1 for the given dataset, the result was $L = 6.01$. This clearly shows a strong trend in reliability degradation within the dataset, as seen in Figure 3.5, which suggests that the Lewis-Robinson test is irrelevant in this case.

As indicated above, the results of the Laplace trend test demonstrate a strong trend in reliability degradation within the dataset. From Figure 3.1, this suggests that the repairable systems analysis methodology (following the first NHPP model) should be used as the preventive maintenance optimisation method for the dataset on conveyor 1. The methodology is discussed in Section 3.5, which presents all the related mathematics for repairable systems analysis. The first NHPP model, described in Section 3.5, was used to model the system to determine the expected number of failures at a certain time. From here, an optimum replacement age with a corresponding cost was computed, which could then be added to a yearly budget if this maintenance strategy is followed. The parameters of the first NHPP model were computed using the maximum likelihood method, as outlined in Section 3.5 (Coetzee, 1997). These parameters were found utilising the Goal Seek optimisation tool in Microsoft Excel. Table 4.4 gives the optimised parameters.

Table 4.4: NHPP model parameters

Parameter	Value
α_0	–5,346483
α_1	0,000022

Therefore, using the parameters in Table 4.4, the modelled NHPP function for the first model found to follow the actual failure events (see Section 3.5) is shown below:

$$\rho_1(T) = e^{-5.3464+0.000022T}$$

A main outcome of using this NHPP method was to show that it could be utilised to model actual failure events at a specific time instance, which could then be converted into a cost analysis for the conveyor. To demonstrate this, the actual failure events were plotted against the modelled failure events using Equation 4.1 (Coetzee, 1997).

$$E\{N(T)\} = \frac{e^{\alpha_0}}{\alpha_1}(e^{\alpha_1 T} - 1) \quad [4.1]$$

Thus, using Equation 4.1, Figure 4.5 was developed.

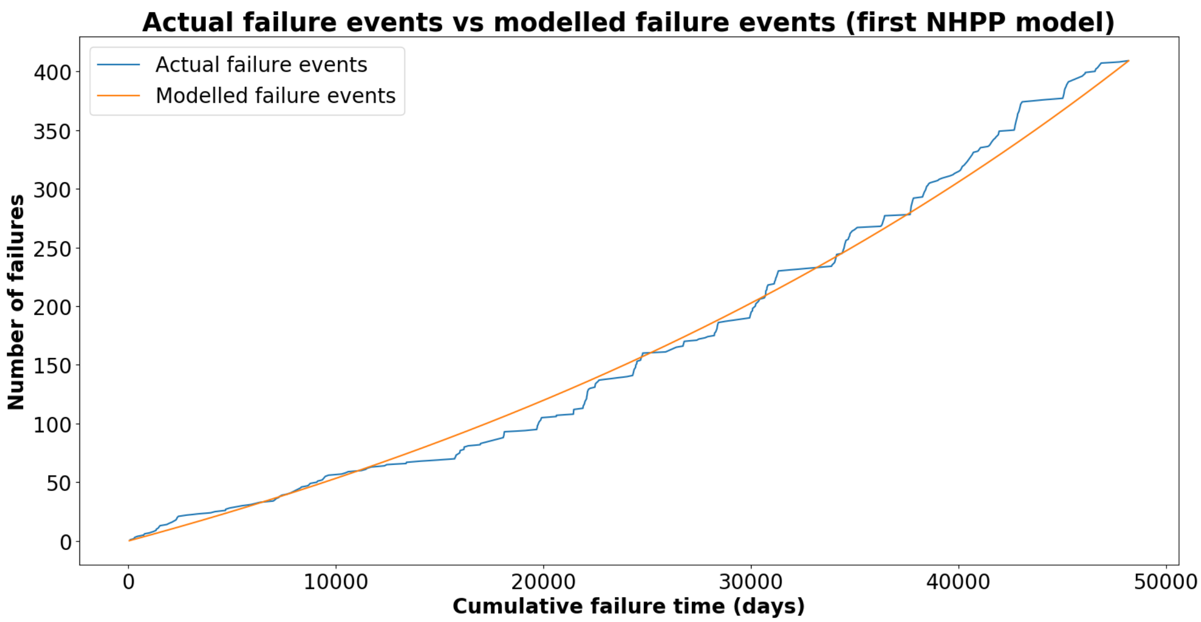

Figure 4.5: Actual vs modelled failure events

From Figure 4.5, it is clear that the modelled failure events using the first NHPP model follow a similar trend to the actual failure events of the conveyor. This suggests that the first NHPP model is ideal to model the failure events of the conveyor.

4.6.2 Budgetary calculation for conveyor 1

The yearly budgetary calculations for conveyor 1 are shown in this section. In Section 4.6.1, it was found that the dataset for conveyor 1 follows a reliability degradation trend. Therefore, it was modelled using the repairable systems analysis, following the first NHPP model as described in Section 3.5. The parameters

α_0 and α_1 were computed in Section 4.6.1 and will be needed for the cost analysis. To determine the yearly budgetary requirements of the conveyor, the methodology described in Section 3.5.3 will be used.

In Section 3.5.3, Coetzee (1997) outlines three methods that can be utilised to determine the point in time to replace the conveyor and the relevant cost associated with that point. The three methods are, namely, an optimum replacement time method using Equation 3.24; an optimum number of failures method using Equation 3.25; and, lastly, a graphical method using Equation 3.29. All three methods should yield similar answers and each method will be investigated here.

It is evident from Equations 3.24, 3.25 and 3.29 that the main driving factors behind determining this budgetary cost are the cost of failure and the cost of an entire new system, in this case, the conveyor. As mentioned above, for each recorded failure point, an associated cost of failure was also recorded on the Anglo Operating Platform. This cost of failure did not consider the cost of lost production due to downtime. For the cost optimisation model, an average of all these failure points was taken as the cost of failure. The cost for an entire new conveyor was not attainable. However, a study performed by Sandvik for Anglo Platinum estimated that the cost of a new conveyor is R15 000 per metre. In this plant, it was assumed that conveyor 1 was 250 m long. Thus, using this information, Table 4.5 was generated to show all the costs associated with conveyor 1.

Table 4.5: Conveyor 1 associated costs

Failure cost C_f	**Conveyor replacement cost C_p**
R61 395.77	R3 750 000

Using the cost data in Table 4.5, the first NHPP model parameters in Table 4.4, and Equations 3.24, 3.25 and 3.29, the optimum replacement point and the cost of the conveyor for all three methods was computed, as seen in Table 4.6.

Table 4.6: NHPP model optimum outcomes

Method (Equation)	**Optimum replacement point**	**Optimum replacement cost (R/day)**
1 (3.24)	27 669 days	539.37
2 (3.25)	182 failures	537.15
3 (3.29)	27 650 days	538.71

From Table 4.6, it is evident that all three methods give similar answers in terms of the optimum age to replace the entire conveyor, as well as the price incurred each day to maintain the conveyor. Using Equation 3.29, Figure 4.6 was computed to demonstrate the effect of the replacement age vs the cost of replacement.

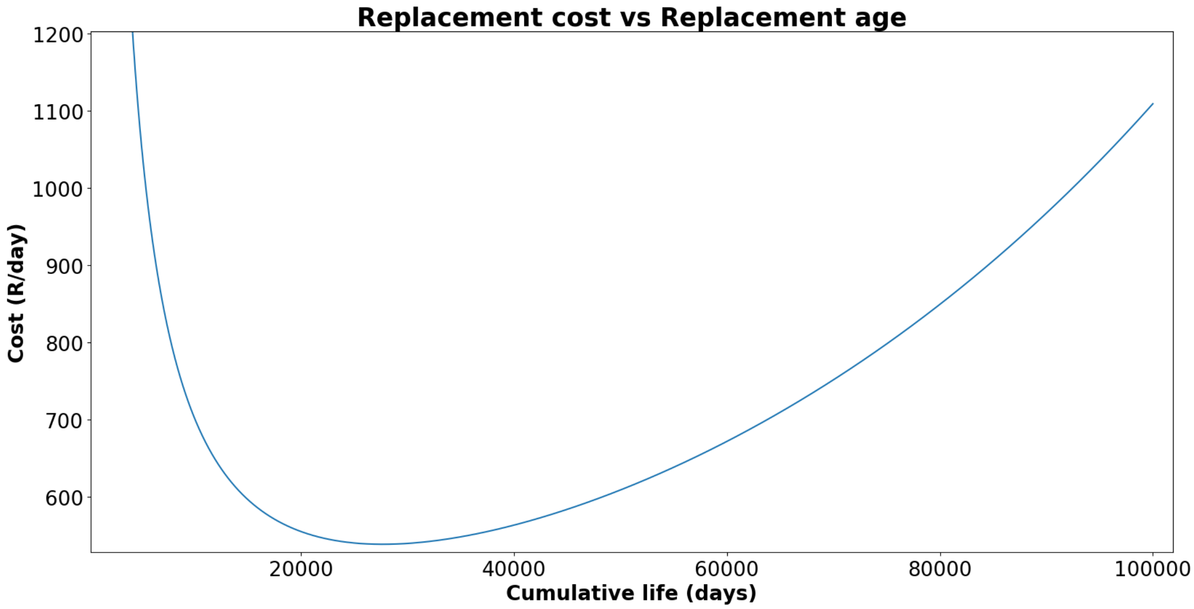

Figure 4.6: Conveyor 1 optimum cost curve

Figure 4.6 shows that the cost associated with the replacement of the conveyor is more sensitive to the lagging end than to the leading end of the graph. This suggests that it would be preferable to extend the life of the conveyor by a set period than to replace it early. It is also evident that, after 40 000 days, the cost of replacement increases more sharply, which indicates that any extension over this time frame will result in a large cost increase per day.

The final step in the repairable systems analysis is to present the results found in terms of a yearly budgetary requirement for use in the overall budget of an organisation. To achieve this, Equation 4.2 can be applied to convert the daily cost of maintaining the conveyor to a yearly cost.

$$C_{yearly} = C_{daily} \times 365 \quad [4.2]$$

Using Equation 4.2, the annual budgetary requirement for maintaining conveyor 1 was calculated to be R196 871.40. This is the amount that needs to be set aside each year in order to maintain the conveyor in terms of the repairable systems analysis.

4.6.3 Summary

This section indicates that the cost model utilised for conveyor 1 in the plant was the repairable systems analysis approach. The Laplace test found that the failure data gathered showed reliability degradation, which suggested that this approach was the best method for the analysis. Using the repairable systems analysis approach, it was determined that the conveyor should be entirely replaced after 27 650 days or 76 years, with an associated cost of R196 871.40 per year. This optimum yearly cost did not consider production losses due to downtime since these were not attainable. However, if they could be obtained, it would be straightforward to implement them into the optimum yearly cost model.

Figure 4.6 showed that the replacement age was more sensitive to an early replacement than a late replacement, which suggests it is more cost effective to extend the replacement age than to reduce it. However, neither of these methods are better than replacing the conveyor at its optimum age. Finally, the optimum yearly cost of maintaining the conveyor can be implemented into the overall budgetary requirements of an organisation for a year. Decisions surrounding whether to follow this budget can be made based on the sensitivity of Figure 4.6 and the budget of an organisation within a certain yearly period.

4.7 Analysis of conveyor 2

In this section, the preventive maintenance methodology for the second of the three conveyors within the plant is analysed. The time period for the dataset collected from the Anglo Operating Platform was 1 December 2014 – 31 October 2018. As seen in Section 3, specific assumptions were made throughout the analysis as a result of certain factors not being attainable.

4.7.1 Failure dataset analysis

The selection of failure data collected for conveyor 2 was for one component, namely, an idler. A number of idlers exist within the conveyor system. For each failure point collected, its associated failure cost to the organisation was recorded, as well as the replacement cost of the component. The failure data points were recorded in days and 8 idler failure points were found in the given study period.

As for conveyor 1, failure data and cost data were available for the analysis. Using this information, Figure 3.1 indicates that the next step in the analysis process for conveyor 2 was to perform a trend test on the dataset to determine what preventive maintenance optimisation method should be chosen. The Laplace trend test was used, as outlined in Section 3.3.2. The Laplace value was computed using Equation 3.1 and a value of $L = -0.286$ was found. Using Figure 3.5, it is clear that this value lies within the non-committal area, which suggests that no trend is present within the dataset and there is no need to perform the Lewis-Robinson test.

As stated above, the failure data collected for conveyor 2 was one set of idler data. A number of identical idlers are present within the conveyor system. Since the Laplace value showed no trend within the dataset, it is clear from Figure 3.1 that the best preventive maintenance optimisation method to implement in this case is the block replacement model, as outlined in Section 3.10. The reasons are the multiple identical components within one system with identical failure characteristics for analysis and no trend in the failure data. The mathematics surrounding the block replacement model is presented in Section 3.10, in which Equation 3.75 is the underlying function of the entire model. It is evident in Equation 3.75 that the main input into the equation is $H(t)$, which is the expected number of times a component fails within a certain interval. To calculate $H(t)$, $f(t)$ is needed, which is the probability density function for a Weibull distribution. To calculate $f(t)$, the Weibull analysis outlined in Section 3.6.2 needs to be performed to find β and η.

Following the methodology in Section 3.6.2 and using the maximum likelihood method (Coetzee, 1997), β and η were computed, as seen in Table 4.7.

Table 4.7: Weibull parameters

Parameter	**Value**
β	2.354
η	311.94

Using the parameters in Table 4.7, $f(t)$ could be computed:

$$f(t) = \frac{2.354}{311.94}\left(\frac{t}{311.94}\right)^{2.354-1} e^{-\left(\frac{t}{2.354}\right)^{311.94}}$$

Before $f(t)$ can be used conclusively in the block replacement model, it first needs to be determined whether the Weibull distribution fits the failure data with a good enough fit. As discussed in Section 3.4, the K-S test will be used to test the fit of the actual data to the modelled Weibull distribution. Following the methodology for the K-S test in Section 3.4, the critical value was found to be $c_n = 0.454$ at a confidence interval of 95% where $\alpha = 0.05$. Plotting the cumulative distribution function over the empirical distribution function, Figure 4.7 was computed.

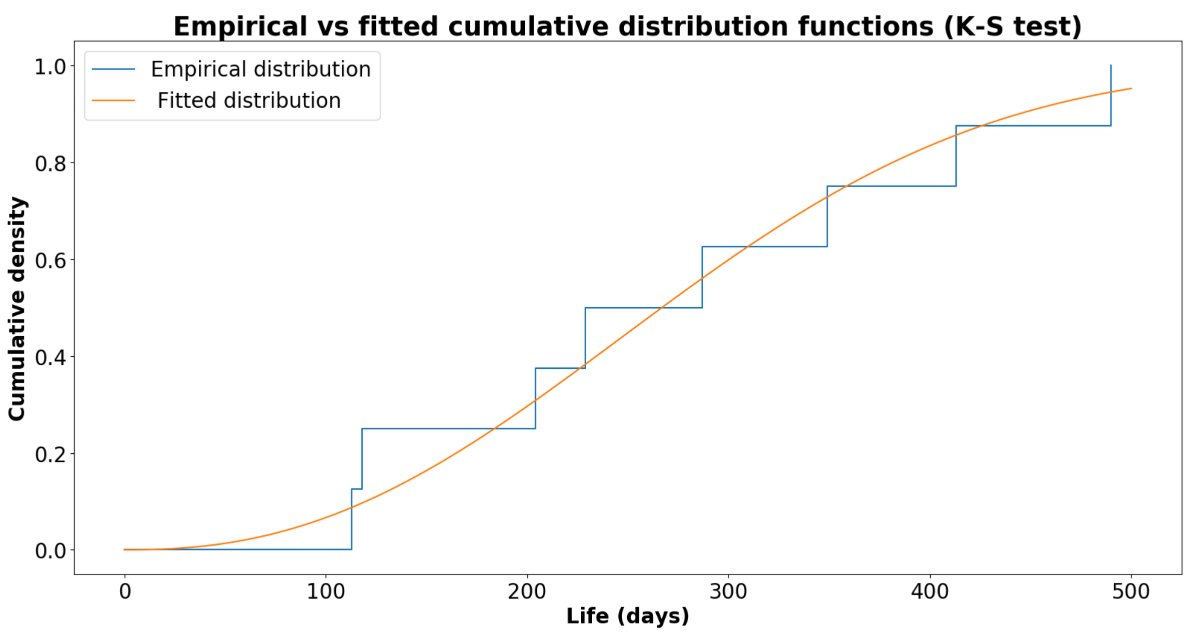

Figure 4.7: Graphical K-S test: empirical vs fitted cumulative distribution functions

Using Figure 4.7, the test statistic D_n was computed as $D_n = 0.154$. It is evident, therefore, that $D_n < c_n$ which suggests there is not enough evidence to reject the null hypothesis. This means that the Weibull distribution fits the data with a good enough fit.

4.7.2 Budgetary calculation for conveyor 2

In Section 4.7.1 it was determined that the block replacement model needs to be implemented on the set of idler conveyor data as the optimum preventive maintenance strategy. It was also found that the Weibull distribution fits the idler failure data with a good enough fit, which enables the use of the block replacement model to analyse the failure data. This section outlines the process that was followed to establish the budgetary cost of maintaining the idlers in conveyor 2, utilising the block replacement model. In Section 3.10, it was indicated that the underlying equation for this model is Equation 3.75. The first step in calculating the budgetary requirement using this method is the computation of $H(t)$. Applying the results of Section 4.7.1 and Equation 3.74, $H(t)$ was computed by developing an extensive Microsoft Excel program.

Equation 3.75 indicates that the other driving factors behind determining the budgetary cost are the cost of failure and the cost of a preventive block replacement for an individual component. As stated in Section 4.7.1, for each of the failure points recorded, a cost of failure was also recorded which did not consider the cost of lost production due to downtime. By extracting these costs from the Anglo Operating Platform and averaging them out, a cost of failure for the idlers within conveyor 2 could be determined. The preventive cost for the model was not attainable as it had never been recorded. Soccio (2016) states that the true cost of a machine breakdown can be reasonably estimated as between 4–15 times the maintenance cost. Thus, taking the end value of this interval, and using the block replacement model, it was assumed that the cost of preventive maintenance would be 15 times less than the cost of failure. Since the cost of a new component is fixed, the costs associated with the model were found as shown in Table 4.8.

Table 4.8: Conveyor 2 associated costs

Failure cost C_f	**Individual group replacement cost C_g**
R21 731.10	R1 855.50

For this plant, it was assumed that conveyor 2 is 500 m long with an idler present on either side of the conveyor every 2 m. This results in 500 idlers being modelled. Using the cost data in Table 4.8 and $H(t)$, Equation 3.75 was solved, resulting in the development of Figure 4.8.

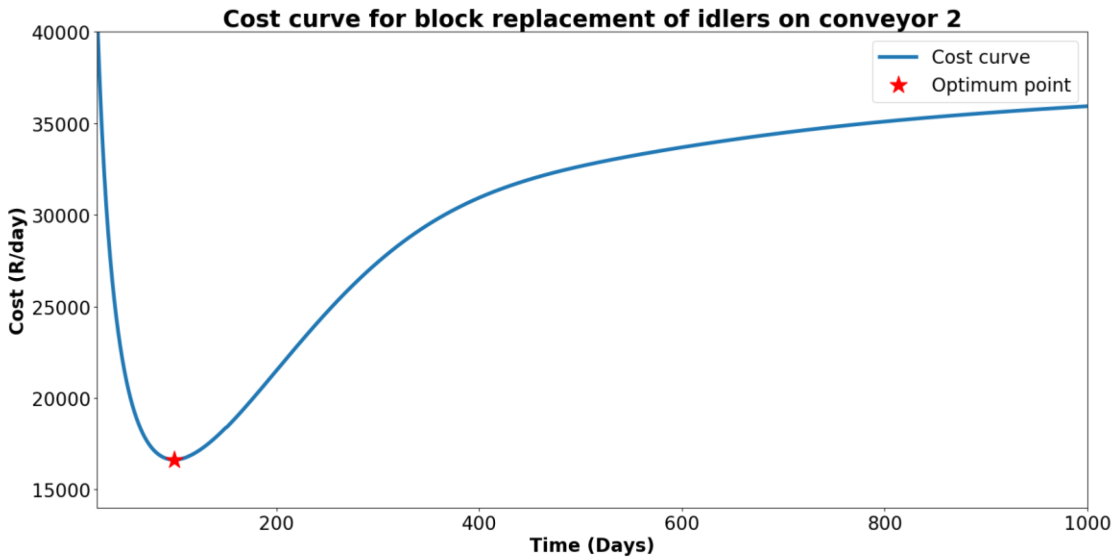

Figure 4.8: Conveyor 2 optimum cost curve

Figure 4.8 shows there is a clear optimum point to preventively block replace the idlers within the conveyor. The sensitivity around this optimum point is also high, as seen by the steep curve around it. Table 4.9 outlines the results of the model.

Table 4.9: Conveyor 2 outcomes

Optimum block replacement age (days)	Optimum block replacement cost (R/day)	Run to failure cost (R/day)
99	16 627.58	38 050.30

Table 4.9 shows that all 500 idlers on the conveyor must be block replaced every 99 days for the optimum cost to be endured. If this policy is not followed, it will result in a large cost increase annually due to the sensitivity around the optimum replacement point. The run to failure cost was also computed by letting the model run until a stable value was reached on the leading edge of Figure 4.8. This cost was found to be 129% greater than the optimum cost, indicating how vital it is to implement this preventive maintenance strategy to result in the lowest possible budget. Finally, applying Equation 4.2, the yearly budget for maintaining the idlers was found to be R6 069 065.74. This is the amount of money that needs to be set aside each year in order to maintain the idlers within conveyor 2.

Due to the presence of the integral divided by the time period in Equation 3.75, the output of this block replacement model results in an average cost being determined that has only a 50% chance of reaching the optimum cost. In terms of a budgetary requirement, too much uncertainty was found in this answer. For this reason, the author developed a model that allowed more certainty to be found around the budget. This is implemented in Section 4.7.3.

4.7.3 Monte-Carlo simulation certainty validation

As stated in Section 4.7.2, only using the block replacement model (see Section 3.10) results in an optimum cost value with too much uncertainty surrounding it to allow its use in an organisation's annual budget. The purpose of this section is to implement the simulation model to create certainty around the optimum budget for the maintenance of the idlers in conveyor 2 in the plant.

The simulation methodology outlined in Section 3.10.3 will be followed. Figure 3.24 shows that a number of inputs are needed before the simulation can take place, namely the cost of failure, the cost of group prevention and the optimum block replacement age. These values have all been found, as seen in Section 4.7.2. The next step is to generate failure data that can then be run through the simulation model. The failure data for the block replacement model was generated using the method presented in Section 3.7.3. Once the simulated failure data was generated, it was run through the simulation model outlined in Figure 3.24. Therefore, following the simulation procedure in Section 3.10.4, Figure 4.9 was developed. It shows the confidence levels around the average block replacement answer from Section 4.7.2 with 2000 simulations run.

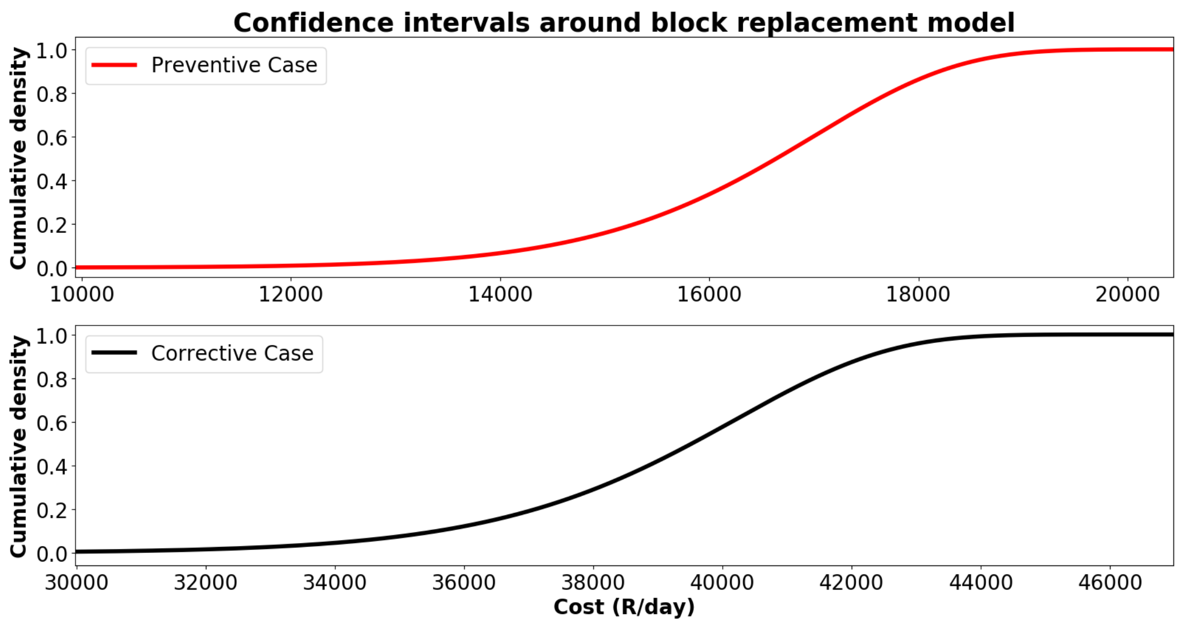

Figure 4.9: Confidence intervals around conveyor 2 budgetary requirements

The results of the simulation validate the average possible values of the budget incurred within a certain year given by the block replacement model. This can be seen by comparing the values at a confidence of 50% in Figure 4.9 with the values in Table 4.9 and noting that they are identical. Figure 4.9 indicates the importance of running this simulation. In terms of budgetary requirements, a 50% certainty within a budget could be regarded as too risky. Therefore, following this model, an organisation has the opportunity to increase the certainty and reduce the risk. However, this choice is accompanied by an increased budget. For the plant, a certainty of 80% around the budget for the preventive case would result in a cost of R17 725/day. This cost is 6.6% greater than the 50% confidence cost, but it allows for more certainty around the answer. In terms of a budgetary decision-making process, it is evident that all the odds must be weighed up to determine if it would better to have more certainty around the budget at a higher cost, or a lower budget with more risk and uncertainty surrounding it.

The final step in the simulation process is to determine whether the Weibull distribution can be used to fit the simulated data to generate the confidence intervals. The K-S test was used to accomplish this, as described in Section 3.4. The critical values for the preventive case and the corrective case were found to be $c_n = 0.218$ *and* $c_n = 0.259$ respectively, at a confidence interval of 95% where $\alpha = 0.05$. Figure 4.10 was computed by plotting the cumulative distribution function over the empirical distribution function.

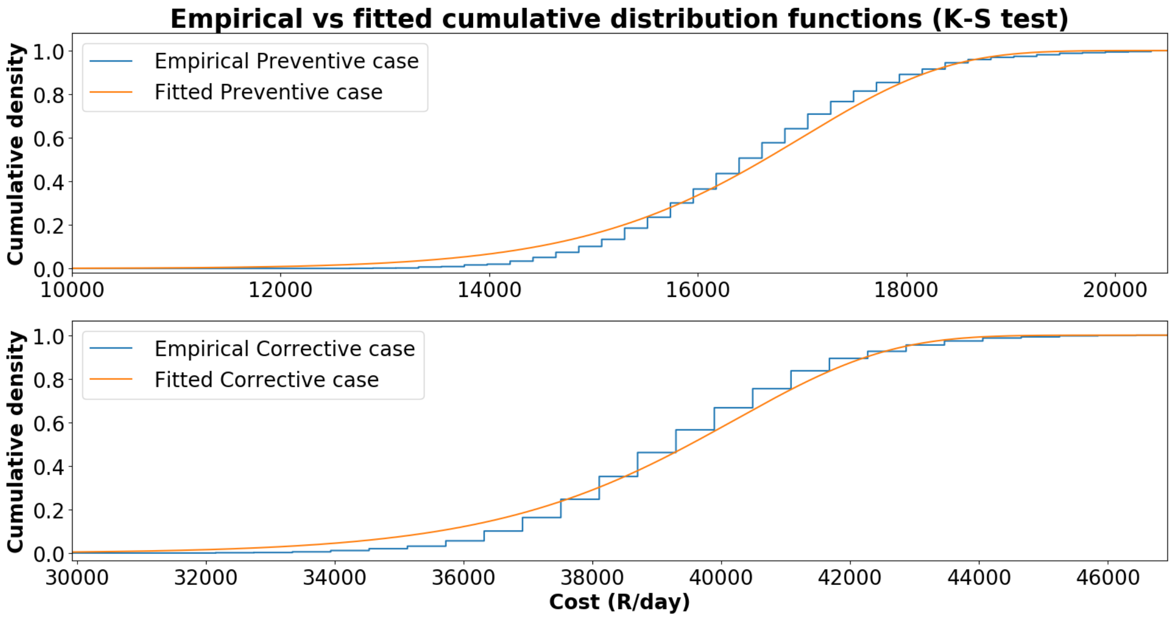

Figure 4.10: K-S test validation around conveyor 2 confidence intervals

Using Figure 4.10, the test statistic D_n was computed as $D_n = 0.091$ for the preventive case and $D_n = 0.108$ for the corrective case. In both cases $D_n < c_n$, which suggests there is insufficient evidence to reject the null hypothesis. This means that the Weibull distribution fits the data with a good enough fit.

4.7.4 Summary

This section illustrated the block replacement method that was used to determine the yearly budget for maintaining the 500 idlers on conveyor 2 in the plant. The failure data of the idlers showed no trend. Multiple identical idlers were present in the conveyor system, which allowed the block replacement model to be implemented. Through its application, it was determined that all the idlers should be replaced every 99 days, resulting in an annual maintenance cost of R6 069 065.74. This represented the average cost of maintaining the idlers using the block replacement model. Production losses were not considered since these were not attainable. The answer obtained utilising this model only resulted in a 50% certainty because it was an average value. For this reason, the author developed a model that enabled an increase in the certainty around the block replacement optimum cost answer. By implementing this new model, confidence intervals could be created around the optimum cost. This necessitated decisions about whether to increase the certainty around a budget at a higher cost or have less certainty and more risk in a lower budget. Finally, it is evident from this section that the implementation of the preventive block replacement model results in a drastically reduced maintenance budget (by 129%) compared to the run to failure strategy. This indicates that it is imperative for an organisation to implement this preventive strategy to benefit from the huge cost saving in the budget.

4.8 Analysis of conveyor 3

In this section, the preventive maintenance methodology for the last of the three conveyors in the plant is analysed. Eight different sets of component data from one conveyor system were collected from the Anglo Operating Platform. The time period used for the dataset was from 1 July 2014 – 30 September 2018. As seen in Section 3, specific assumptions were made throughout the analysis as a result of being unable to obtain certain factors.

4.8.1 Failure dataset analysis

The maintenance data collected was in the form of failure data with a recorded corresponding cost to each failure activity. This was the cost that an organisation incurred at the time of the failure. It did not factor in the cost of lost production due to downtime, labour costs or setup costs. It was simply a record of the cost of the materials and resources needed to fix the failure. The failure data collected was for one conveyor comprised of 8 different components, including idlers, troughing idlers, idler sets, pulleys and belts. The failure data was given in days and 12–49 failure points were collected within the analysis period, depending on the component in the conveyor system being analysed.

With the available cost and failure data on hand, and using Figure 3.1, the next step in the analysis process was to perform a trend test on all the collected data. From the results, the choice of a preventive maintenance optimisation technique to determine the budgetary requirements for the conveyor could be made. The Laplace trend test was chosen (see Section 3.3.2). If the results of the Laplace test for a given set of component failure data ended up in the ‘grey’ area in Figure 3.5, the Lewis-Robinson test was performed, as illustrated in Section 3.3.3. Table 4.10 outlines the results of the trend test performed on all 8 components in the conveyor system.

Table 4.10: Conveyor 3 trend test results

Component	Laplace trend test result	Lewis-Robinson test result
1	0.076	n/a
2	0.229	n/a
3	–1.19	–1.459
4	0.951	n/a
5	–1.07	–1.208
6	–0.792	n/a
7	1.00	n/a
8	0.224	n/a

Table 3.3.3 shows that all the components, except for components 3 and 5, lie within the non-committal section of Figure 3.5. This suggests there is no trend for these components in the failure data. Components 3 and 5 yielded Laplace values which resulted in them lying within the 'grey' area in Figure 3.5. This indicated that the Lewis-Robinsion test needed to be performed in order to make a correct assumption about the trend present within these datasets. Applying this test to components 3 and 5 failure datasets resulted in values that still remained in the 'grey' area of Figure 3.5. To gain a definite answer on the trend within these datasets, the data was plotted for both components. Visually, it was found that neither of the datasets possessed any trends. Thus, the datasets for all 8 components within the conveyor showed no trend.

Following the methodology outlined in Figure 3.5, and noting that multiple components within one system require analysis, all of which show no trend within their datasets, it can be concluded that the grouping preventive maintenance model should be applied to this conveyor. Section 3.9 discusses all the mathematics surrounding this model. It is evident from Section 3.9 that four different models need to be analysed before any validation about implementating this grouping model can be made. These include the single component, mono-grouping, multi-grouping and multi-grouping shutdown approaches that will all be compared to one another. The underlying element of the cost curves in all these different approaches is Equation 3.56, which is the intensity function that has been analysed using the Weibull distribution in this case. Thus, two unknowns need to be calculated, namely β and η. As for conveyor 2, the Weibull analysis outlined in Section 3.6.2 needs to be performed to find β and η. Therefore, following the methodology in Section 3.6.2 and using the maximum likelihood method (Coetzee, 1997), β and η were computed for all 8 components within conveyor 3, as seen in Table 4.11.

Table 4.11: Conveyor 3 Weibull parameters

Component	**β**	**η (days)**
1	1.798	233.26
2	1.680	505.87
3	1.294	100.58
4	1.369	180.68
5	1.281	251.40
6	1.137	277.94
7	1.218	152.14
8	1.581	413.88

Using the parameters in Table 4.11, the intensity function for component 2 was computed, as shown below. The intensity functions of the other components were computed in the same manner.

$$\lambda_i(t) = \frac{1.68}{505.87}\left(\frac{t}{505.87}\right)^{1.68-1}$$

Before $\lambda_i(t)$ can conclusively be used in the group replacement model, it first needs to be determined whether the Weibull distribution fits the failure data with a good enough fit. As discussed in Section 3.4, the K-S test will be used to test the fit of the actual data to the modelled Weibull distribution. Following the methodology for the K-S test in Section 3.4, the critical value for all 8 components within the conveyor was found at a confidence interval of 95% where $\alpha = 0.05$, as seen in Table 4.12. Figure 4.11 was computed by plotting the cumulative distribution function over the empirical distribution function for all 8 components.

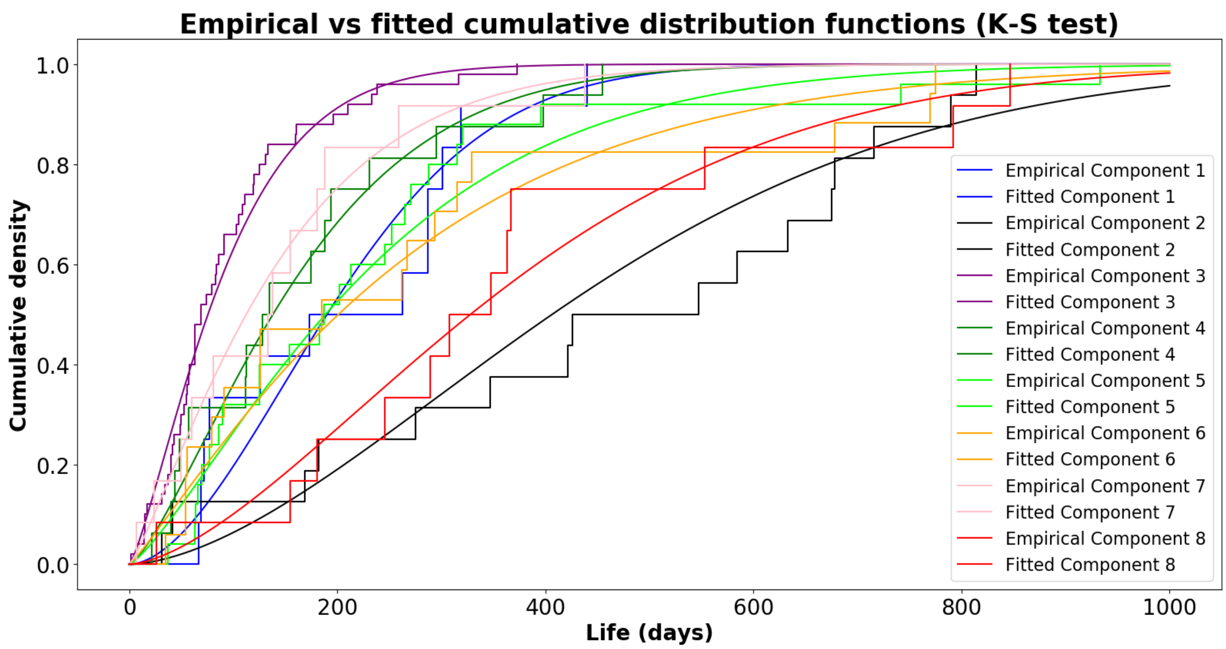

Figure 4.11: Conveyor 3 K-S test validation

Using Figure 4.11, the test statistic D_n was computed for all 8 components, as seen in Table 4.12.

Table 4.12: Conveyor 3 K-S test results

Component	c_n	D_n
1	0.375	0.211
2	0.327	0.180
3	0.194	0.082
4	0.327	0.126
5	0.264	0.136
6	0.318	0.136
7	0.375	0.55
8	0.375	0.187

Thus, from Table 4.12, it can be seen that $D_n < c_n$ for all the components, which suggests there is not enough evidence to reject the null hypothesis. This means that the Weibull distribution fits the data with a good enough fit for all the components analysed in conveyor 3.

4.8.2 Budgetary calculation for conveyor 3

This section outlines the process that was followed to determine the budgetary requirements for maintaining conveyor 3. In Section 4.8.1, the grouping replacement model was found to be the best preventive maintenance strategy to implement on the different sets of component data within the conveyor because this data shows no trend and the conveyor system has multiple different components. The use of the Weibull distribution within the intensity function for this approach was validated using the K-S test.

As indicated above, the implementation of this grouping model requires four different methods (see Section 3.9) to be considered to determine whether they result in the optimal maintenance strategy being applied, and to show the cost benefit of using this method compared to others. These four methods include the single component approach, the mono-grouping approach, the multi-grouping approach and the multi-grouping shutdown approach. To compare these approaches, cost Equations 3.57, 3.66, 3.68 and 3.69 are used. The main inputs into these equations are the intensity function as computed in Section 4.8.1, the cost of prevention and failure for the different components within the conveyor, and the setup costs for a preventive action and a failure action.

As stated in Section 4.8.1, for each failure point recorded for the 8 components within the conveyor, a cost of failure was also recorded which did not take into account the cost of lost production due to downtime, labour costs or setup costs. It merely indicated the cost of the materials and the resources needed to fix the failure. The preventive cost was not attainable on the Anglo Operating Platform as it had not been recorded. In this case, it was assumed that the preventive cost was the same as the failure cost because the latter only included the material and resource costs, making it a constant whether there was a failure or a prevention. The setup cost for a preventive and failure action was also not attainable. To gain an accurate estimate of this cost, the 2017 Sishen mine annual report (from which all the component data was obtained) was consulted. The setup cost for a failure was found to be R509 457.76 per hour. The calculations for this cost can be seen in Appendix D.

As for conveyor 2, the true cost of a machine breakdown can be reasonably estimated to lie between 4–15 times the maintenance cost (Soccio, 2016). Thus, for conveyor 3 it was assumed that the setup cost for a preventive action was 10 times less than that of a failure action. Laggoune et al. (2009) also justify this assumption by stating that the setup cost, which includes mobilising repair crews, safety provisions, transportation and production losses related to these tasks, can be prepared in advance in a preventive situation where the production penalty is low. However, in a failure scenario there is an element of emergency which does not allow for the advanced preparation, hence the increased setup cost. Therefore, bearing in mind all these assumptions and obtaining the failure costs from the Anglo Operating Platform, the total preventive and failure costs for all 8 components within the conveyor are presented in Table 4.13.

Table 4.13: Conveyor 3 associated costs

	Failure cost	Prevention cost
Components	C_i^C	C_i^P
Common cost C_0	R509 457.76	R50 945.78
1	R23 933.05	R23 933.05
2	R135038.88	R135038.88
3	R21 298.98	R21 298.98
4	R35 518.00	R35 518.00
5	R34 721.93	R34 721.93
6	R45 651.98	R45 651.98
7	R9 958.26	R9 958.26
8	R113 789.96	R113 789.96

The cost data in Table 4.13 and the Weibull data in Table 4.11 are used throughout the rest of the analysis.

4.8.3 Single component approach

This is the first approach to be analysed to determine the optimum age and cost to preventively replace the components within the conveyor individually. This general individual replacement strategy will be compared to the grouping strategies to ascertain which approach results in the optimal preventive strategy. Thus, following the methodology in Section 3.9.1.1 for the single component approach and using Equations 3.58 and 3.57, the optimum replacement age and cost for all 8 components within the conveyor were computed, as seen in Table 4.14.

Table 4.14: Conveyor 3 single component approach results

Component	Optimum replacement age (days)	Optimum replacement cost (R/day)
1	88	1901.81
2	303	1512.94
3	55	5731.33
4	97	3289.01
5	159	2441.73
6	343	2337.15
7	91	3721.41
8	251	1782.45

The optimal solutions for the individual components are depicted in Table 4.14. It is evident that the optimal values for all the separate components within the conveyor are vastly different. To show this visually, Equation 3.57 was used to develop Figure 4.12, which shows the cost vs replacement age for all 8 components within the conveyor system.

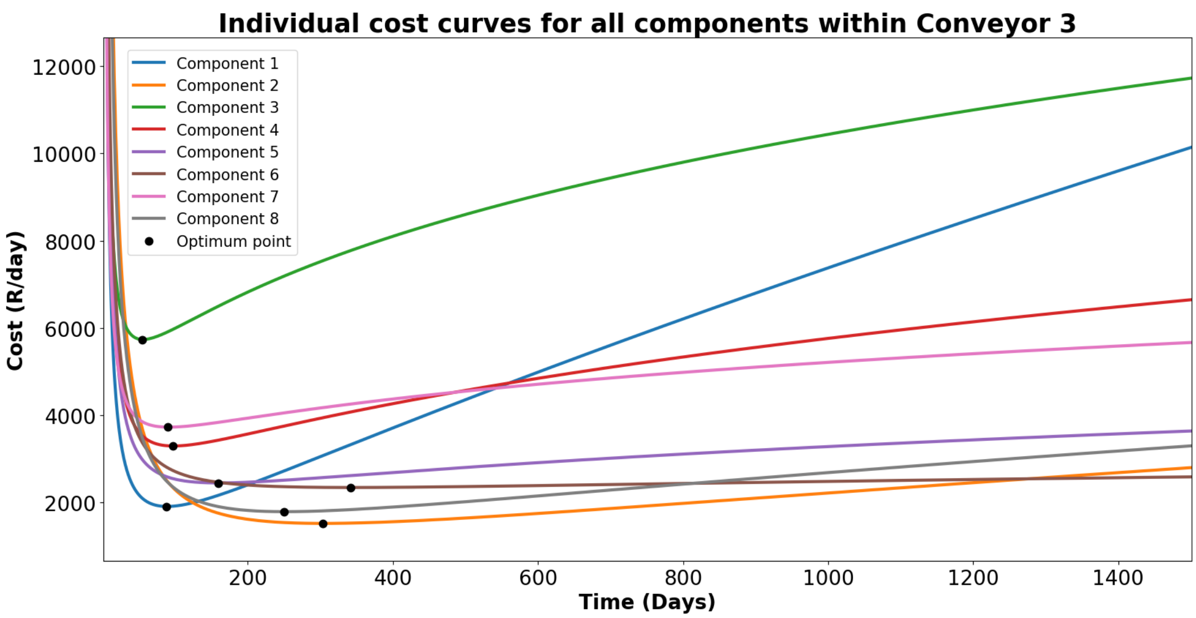

Figure 4.12: Conveyor 3 individual optimum cost curves

Figure 4.12 validates the results in Table 4.14 through the different cost curves it presents. The summary of the optimum replacement costs for all 8 components in Table 4.14 and their conversion into an annual cost, resulted in a cost of R8 292 011.26 per year being obtained. This is the budget that needs to be set aside each year if the conveyor is to be preventively maintained using this method. Thus, with this information available, the single component replacement strategy can now be compared to the grouping strategies.

4.8.4 Grouping approaches

This section outlines the method that was followed to develop all the results for the grouping strategies, if implemented on conveyor 3. The first approach considered, called the mono-grouping approach, comprises jointly replacing all the components within the conveyor in one set replacement interval. Following the methodology in Section 3.9.1.3 and applying Equation 3.68, Figure 4.13 was developed to show the results of implementing this method. It was found that the optimum age to replace all the components within the system was every 90 days, at a cost of R21 134.04 per day.

The second approach considered was the multi-grouping approach. This comprises replacing all the components within the conveyor at variable intervals. Following the methodology in Section 3.9.1.2 and applying Equation 3.66 and the solution procedure in Section 3.9.1.5, Figure 4.13 was developed. It was established that the optimum interval replacement age is 47 days with an associated cost of R19 382.43 per day. The optimum multi-grouping strategy was found to replace components 1, 3, 4 and 7 every interval;

component 5 every second interval; components 4 and 8 every fourth interval; and component 2 every fifth interval (i.e. 1, 5, 1, 1, 2, 4, 1, 4, 1, 1).

The third approach considered was the multi-grouping shutdown approach in which all the preventive actions were pushed into one annual plant shutdown. The lost production setup cost was assumed to be zero during this annual shutdown since the entire plant had ceased operation. Following the methodology in Section 3.9.1.4 and implementing Equation 3.69, Figure 4.13 was developed. The highlighted section shows the results of implementing the shutdown policy. It was found that an annual shutdown of every 365 days resulted in a cost of R31 109.93 per day to maintain the conveyor. The dip in the cost curve resulted from the preventive setup cost not being considered due to the planned plant shutdown.

The results of all the grouping approaches and the single component approach can be seen in Table 4.15.

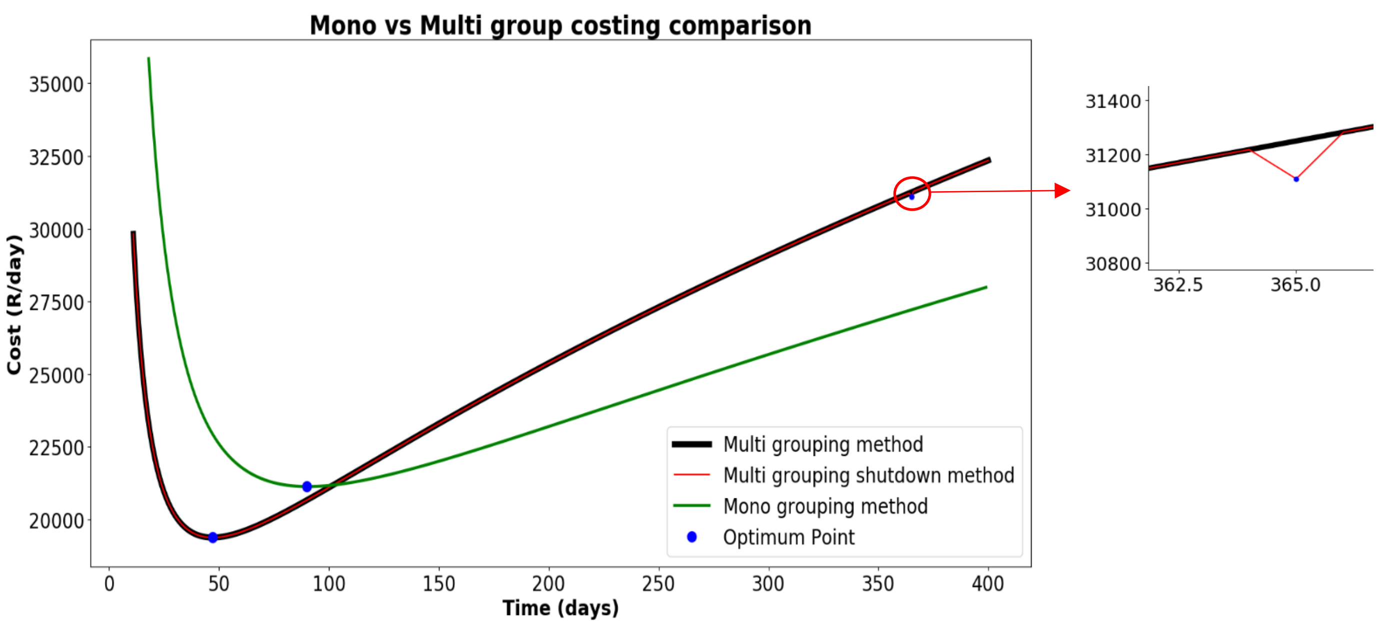

Figure 4.13: Conveyor 3 optimum cost curves

Table 4.15: Conveyor 3 analysis results

Strategy	Optimum cost (R/day)	Optimum cost (R/year)
Single component	22 717.84	8 292 011.26
Mono-grouping	21 134.04	7 713 924.08
Multi-grouping	19 382.43	7 074 586.79
Multi-grouping shutdown	31 109.93	11 355 125.63

From Table 4.15 and Figure 4.13 it can be seen that the best policy to implement for the preventive maintenance of conveyor 3 is the multi-grouping approach. This approach resulted in a cost reduction of 17.2% compared to the single component replacement policy, indicating how vital it is to implement such a policy in terms of overall savings for an annual budget. The multi-grouping shutdown policy was found to be the worst policy to implement because the optimum replacement ages for all the single components were less than 365 days. This suggests that pushing all the replacements into a yearly shutdown would result in many failures prior to the preventive replacements, hence the escalated cost. In addition, the preventive setup cost was not high enough to outweigh the cost of failures by pushing all the replacements into one annual shutdown. The mono-grouping approach was found to be the next best option, after the multi-grouping approach, but still resulted in a cost increase of 9% over the multi-grouping approach.

4.8.5 Summary

This section outlined the entire methodology and implementation of the grouping preventive maintenance strategy on conveyor 3 in the plant. By following the rationale in Figure 3.1 and the mathematics in Section 3.9, it was determined that the best grouping approach to implement in order to maintain the 8 components within the conveyor was the multi-grouping approach. This resulted in a yearly maintenance cost of R7 074 586.79 being computed, which needs to be budgeted each year in order to keep the conveyor up and running according to this optimum solution. The multi-grouping approach was also compared to the other approaches. It was found to result in a 17.2% cost reduction compared to the single component replacement policy, and a 9% cost reduction compared to the mono-grouping approach. This demonstrates how essential it is to consider all options before a budgetary decision is made about the maintenance strategy to be implemented on a system. The chosen decision can have a huge impact on the yearly cost saving in terms of the planned maintenance budget of an organisation.

4.9 Analysis of set of pumps

This section outlines the preventive maintenance methodology that was implemented on the set of pumps, pumps 1–5, within the plant. From this, a yearly budgetary requirement could be determined. Data was collected from the Anglo Operating Platform. The time period used for the different sets of pump data varied from 1 April 2014 – 31 July 2019. As seen in Section 3, specific assumptions were made throughout the analysis as a result of certain factors not being attainable.

4.9.1 Failure dataset analysis

In this section, a failure data analysis is performed on all the failure data obtained from the Anglo Operating Platform for all the pumps within the plant to determine which preventive maintenance optimisation technique is best suited to analyse the failure data. This would result in the development of a yearly budgetary requirement for the maintenance of the pumps. There are five pumps present in the plant, each one in need of a maintenance strategy. The pumps are not aligned in series, which suggests that the failure of one pump will not result in the shutdown of the rest of the pumps. However, one budgetary requirement for all the pumps is needed as they are regarded as similar components within a larger system. From the Anglo Operating Platform, failure data was recorded for each of the five pumps within the plant. For each failure point recorded for each pump, a corresponding cost of failure was also recorded. This was the cost incurred by the organisation when the failure occurred. It did not consider the cost of lost production due to downtime, labour costs or setup costs, but was simply the cost of the materials and resources needed to fix the failure. The failure data collected for each pump in the plant was given in days and 9–22 failure points were collected within the analysis period, depending on the pump being analysed.

As stated previously, failure data and cost data were attainable for each pump within the plant. Using Figure 3.1 and this data, the next step in the analysis process is to perform a trend test on all the pump failure data to determine which preventive maintenance technique should be applied to each pump. The Laplace trend test was chosen for this purpose (Section 3.3.2). If the results of the Laplace test for a given set of pump failure data ended up in the 'grey' area on Figure 3.5, the Lewis-Robinson test was performed (Section 3.3.3). Table 4.16 outlines the results of the trend tests performed on all five pumps in the plant.

Table 4.16: Pumps 1–5 trend test results

Pump	Laplace trend test result	Lewis-Robinson test result
1	–1.326	–1.919
2	–0.957	n/a
3	–0.843	n/a
4	–1.038	–1.916
5	0.243	n/a

Table 4.16 shows that the outcome of the Laplace trend test for pumps 2, 3 and 5 all resulted in the failure data lying within the non-committal area of Figure 3.5, which suggests there is no trend present for these pumps. The results for pumps 1 and 4 led to the failure data lying in the 'grey' area of Figure 3.5, indicating that another trend test needed to be performed to validate whether a trend is present within the datasets. The Lewis-Robinson trend test results for both pumps 1 and 4 still showed the failure data lying within the 'grey' area of Figure 3.5. Therefore, to gain a definite answer on the trend within these datasets, the data was plotted for both pumps. Visually, it was found that neither dataset carried any trend. Thus, the datasets for the five pumps within the plant showed no trend.

The next step in the analysis process is to determine which preventive maintenance optimisation technique to apply to each pump. Following the methodology in Figure 3.1, the best optimisation technique to apply to the pumps is the non-repairable systems analysis technique. The reason is that the pumps can be seen as separate components within varying sub-systems because the failure of one pump does not result in the shutdown of another pump. This enables the application of the non-repairable systems technique to the pump failure data. A detailed description of all the mathematics surrounding this method can be seen in Section 3.6. The main outcome of this method is the development of Equation 3.37, which allows the optimum replacement age and cost of the maintenance strategy to be computed. The two driving factors behind the implementation of Equation 3.37 are $R(t_p)$ and $f(t)$. These are the reliability and probability density functions, respectively, of the Weibull distribution. Section 3.6 indicates that, to calculate these two functions, the Weibull parameters β and η need to be determined. Thus, following the methodology in Section 3.6.2 and applying the maximum likelihood method, β and η were computed for each of the five sets of pump failure data as detailed in Table 4.17.

Table 4.17: Pumps 1–5 Weibull parameters

Pump	β	η (days)
1	1.54	110.75
2	1.57	131.32
3	2.17	165.31
4	1.85	505.79
5	1.71	355.60

Using the parameters in Table 4.17, the reliability and probability density functions for pump 1 were computed, as shown below. The other pump functions were computed in the same manner.

$$R(t) = e^{-\left(\frac{t}{110.75}\right)^{1.54}}$$

$$f(t) = \frac{1.54}{110.75}\left(\frac{t}{110.75}\right)^{1.54-1} e^{-\left(\frac{t}{110.75}\right)^{1.54}}$$

Before $R(t_p)$ and $f(t)$ can be used conclusively in the non-repairable systems model, it first needs to be determined whether the results of the Weibull distribution fit the different sets of pump failure data with a good enough fit. As discussed in Section 3.4, the K-S test will be used to test the fit of the actual data to the modelled Weibull distribution. Following the K-S test methodology (Section 3.4), the critical value for all five pumps in the plant were found at a confidence interval of 95% where $\alpha = 0.05$, as seen in Table 4.18. Figure 4.14 was computed by plotting the cumulative distribution function in Equation 3.31 over the empirical distribution function in Equation 3.6.

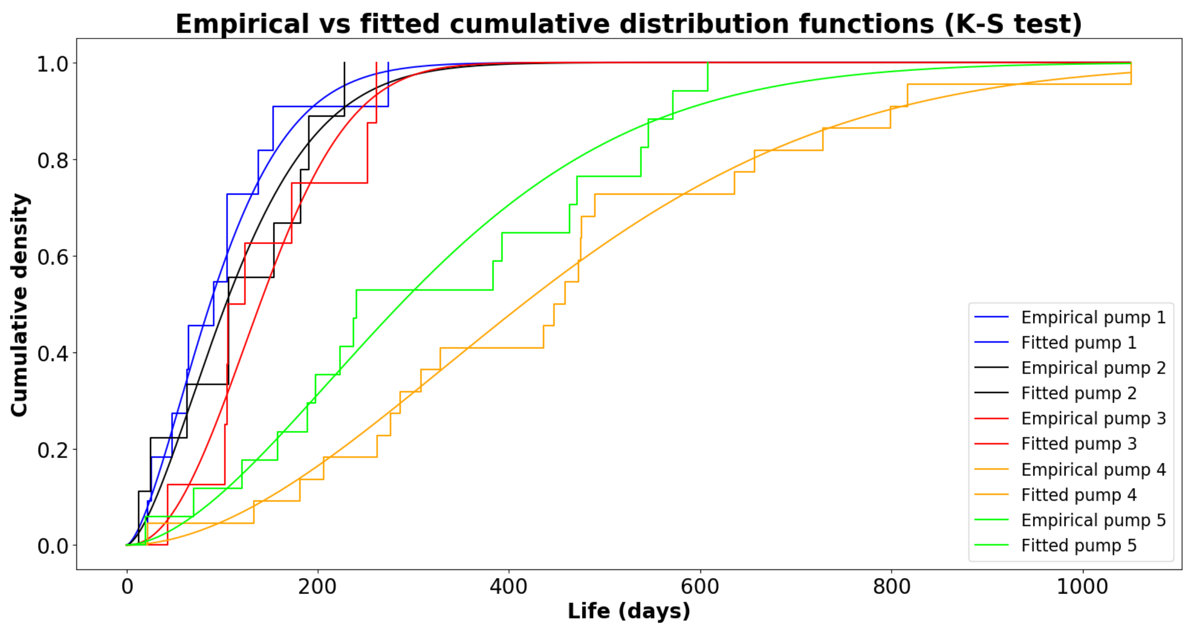

Figure 4.14: Pumps 1–5 K-S test

Using Figure 4.14, the test statistic D_n was computed for all five pumps, as seen in Table 4.18.

Table 4.18: Pumps 1–5 K-S test results

Pump	c_n	D_n
1	0.391	0.125
2	0.430	0.182
3	0.430	0.210
4	0.281	0.123
5	0.318	0.149

Table 4.18 shows that $D_n < c_n$ for all five pumps within the plant, which suggests there is not enough evidence to reject the null hypothesis. This means that the Weibull distribution fits the data with a good enough fit for all the pumps analysed.

4.9.2 Budgetary calculation for all five pumps within the plant

This section outlines the process that was followed in order to gain an overall yearly budgetary requirement for maintaining the five pumps within the plant. In Section 4.9.1, it was found and validated that the best maintenance optimisation technique to apply to all the sets of pump data was the non-repairable systems analysis model. Equation 3.37 is the underlying equation for the output of this technique. It comprises five different elements: a time element, which is a variable constant; $R(t_p)$ and $f(t)$, which have both been calculated in Section 4.9.1; the cost of a preventive action and the cost of a failure action. As stated in Section 4.9.1, the data for the cost of a failure action was documented on the Anglo Operating Platform for each failure point recorded for each pump. This data was extracted for each pump and averaged out to determine the cost of failure for each pump. The preventive maintenance cost for each pump was not attainable as it had never been recorded. The true cost of a machine breakdown can be reasonably estimated to be between 4–15 times the maintenance cost (Soccio, 2016). Thus, taking a value between this interval, it was assumed that the cost of preventive maintenance would be 10 times less than that of a failure action. Using this assumption, the fixed costs associated with this non-repairable systems model were found for all five pumps, as seen in Table 4.19.

Table 4.19: Pumps 1–5 associated costs

Pump	Failure cost C_f	Preventive cost C_p
1	R223 564.85	R22 356.49
2	R81 700.84	R8 170.08
3	R117 239.09	R11 723.91
4	R216 206.05	R21 620.61
5	R69 417.78	R6 941.78

Using the cost values in Table 4.19 and the results of $R(t_p)$ and $f(t)$ found in Section 4.9.1, Equation 3.37 was applied to each set of pump data to find the budgetary requirement for each pump. This process is illustrated in Figure 4.15.

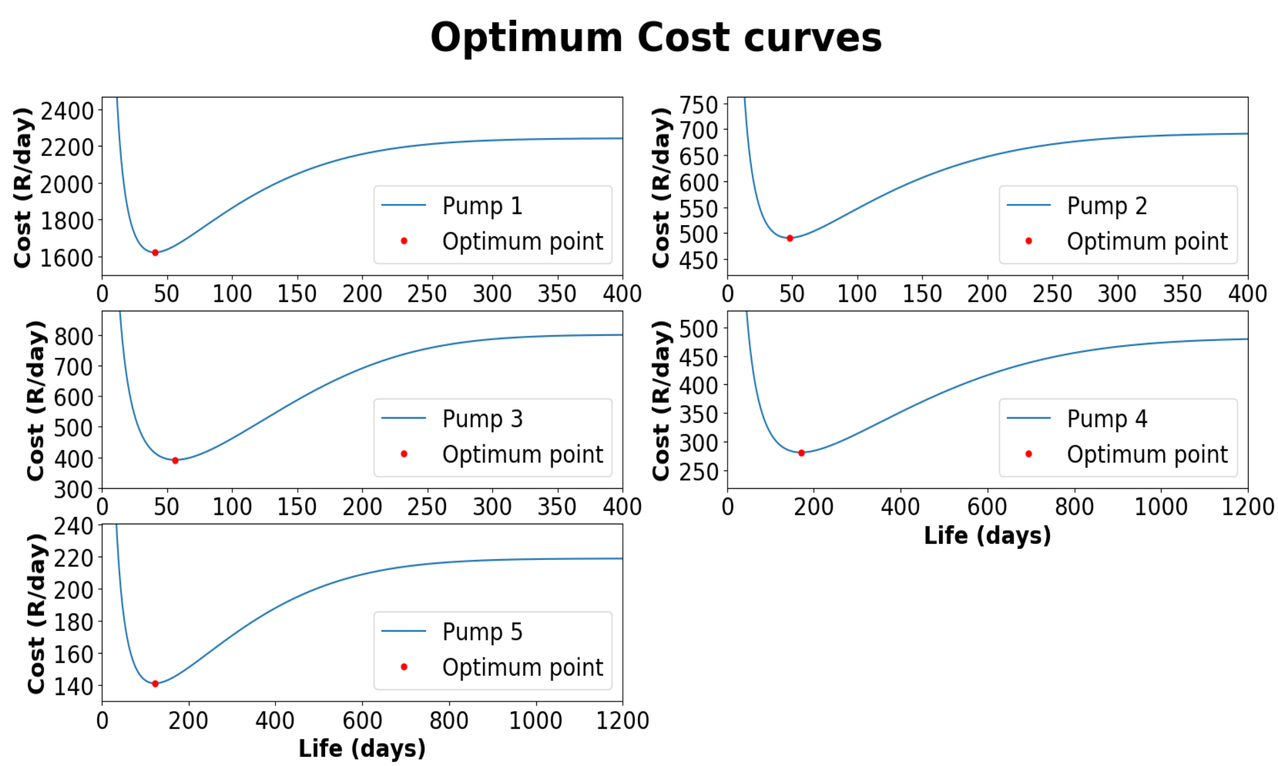

Figure 4.15: Pumps 1–5 optimum cost curves

Figure 4.15 shows the optimum point to replace each pump in the plant. This optimum replacement age, its associated cost and the cost of run to failure if no preventive maintenance is implemented, are outlined in Table 4.20 for each pump in the plant.

Table 4.20: Pumps 1–5 analysis results

Pump	Optimum replacement cost (R/day)	Optimum replacement age	Run to failure cost (R/day)
1	1 621.18	41	2 243.43
2	490.65	48	694.23
3	391.38	56	805.07
4	281.72	171	483.13
5	141.02	122	219.52

Table 4.20 shows the optimum replacement ages and optimum replacement costs for each pump. The values obtained are vastly different for each pump. The results of Table 4.20 indicate that each pump needs to be replaced at its relevant optimum age in order to attain its optimum cost for the preventive maintenance strategy. If the strategy is not followed for the pumps, it is evident that their maintenance costs grow substantially, as outlined by the run to failure cost. The cost increase was found to range between 38–105%, depending on the pump analysed. Therefore, it is clear how important it is to implement a preventive maintenance strategy within a plant to ensure the lowest possible budget for system and component maintenance. The yearly budget for each pump was computed using Equation 4.2, following the non-repairable systems analysis technique within the plant. The results are presented in Table 4.21.

Table 4.21: Pump 1–5 yearly maintenance budgets

Pump	Yearly budget (R)
1	591 730.70
2	179 087.25
3	142 853.70
4	102 827.80
5	51 472.30

From Table 4.21, it can be calculated that the total yearly budget needed to maintain all five pumps within the plant is R1 067 971.75. This value was found to be 52% less than run to failure costs over a yearly period, emphasising the importance of implementing this maintenance strategy.

As found in Section 3.6, due to the presence of the integral in Equation 3.37, the output of this non-repairable systems model leads to an average cost being determined for each pump. This results in only a 50% chance of the optimum cost being reached. In terms of a budgetary requirement, there is too much uncertainty around this answer. Thus, the author developed a model, as seen in Section 3.8, that allows more certainty to surround the budget. This model is implemented in Section 4.9.3.

4.9.3 Implementation of Monte-Carlo simulation

This section outlines the process that was followed to gain more certainty and confidence around the optimum budgetary costs obtained in Section 4.9.2. These were established by implementing the non-repairable systems analysis on all five components within the plant. As stated in Section 3.6, the output of the general non-repairable systems model results in an average cost per time period being determined due to the presence of the integral function and the time step in the cost Equation 3.37. For a basic budgetary estimate in which the effect of exceeding budget is not important to an organisation, this general non-repairable systems model will suffice. For most organisations, however, the effect of going over budget is significant and can be detrimental to their success. Therefore, the model developed in Section 3.8 was applied to the pump data in order to gain more confidence and certainty around the budget required to maintain the five pumps in the system within a specific annual period.

Sections 3.7 and 3.8 demonstrate that two possible models can be applied to gain confidence around the budget. These include a yearly validation model that runs a simulation only looking at a yearly period, as outlined in Section 3.7, and a longer period validation model that considers a certain preventive maintenance strategy over a set period to determine the best maintenance strategy to implement for a period longer than a year, as described in Section 3.8. The latter model allows organisations to plan in advance if they require funds and gives them a future budgetary outlook that can be hugely beneficial. For the plant in this case study, the second model will be applied to establish the best maintenance strategy over a finite period from which the yearly budgetary requirements can be found.

A five-year future budgetary outlook was utilised for the five pumps within the plant. Each year within the overall five years could either implement a preventive strategy or a corrective strategy. By applying the methodology in Section 3.8, a total of 32 different maintenance decisions could be looked at for a five-year finite period, ranging from a fully preventive strategy to a fully corrective strategy with a number of mixed strategies in-between. Using all the cost data, the outputted optimum replacement ages, and the β and η values found in Section 4.9.1, the model in Figure 3.17 was applied to the pump data. The solution procedure in Section 3.8.2 was followed, resulting in the generation of Figure 4.16. For each pump within the plant, 1000 simulations were run through the model in Figure 3.17, enabling the development of the confidence intervals seen in Figure 4.16.

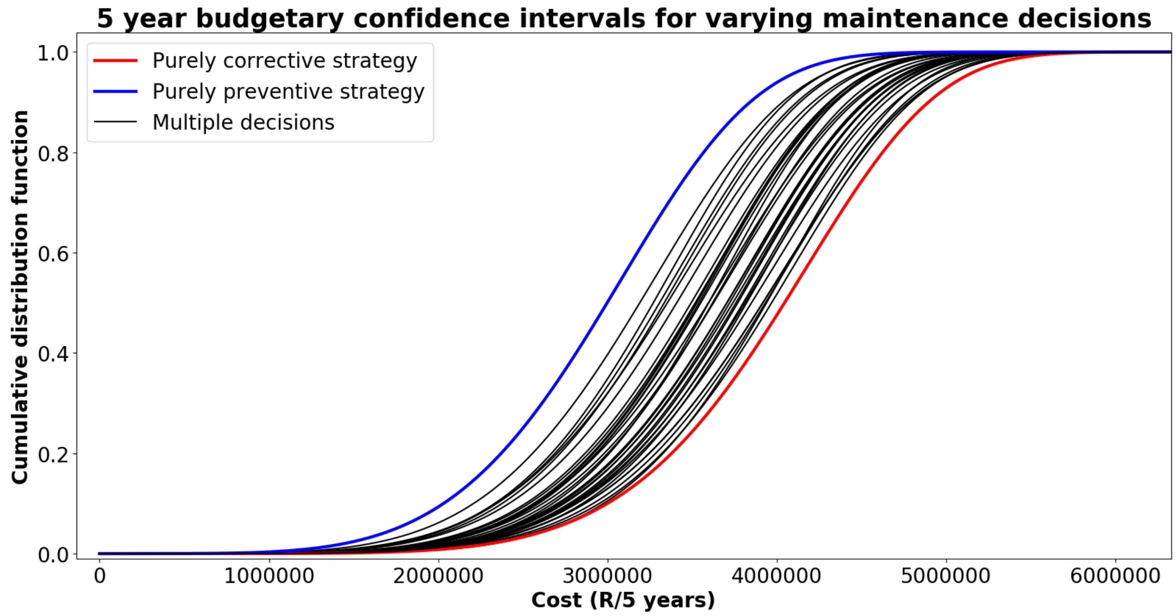

Figure 4.16: Pump 1 five-year budgetary confidence intervals with varying decisions

Figure 4.16 outlines the results of the simulation for pump 1 in the plant for all 32 maintenance decisions looked at over the five-year period. It is evident that a large difference exists in the confidence intervals found for each of the 32 decisions. The two extreme cases of a purely preventive tactic and a purely corrective tactic enclose all the other mixed decisions. A purely preventive maintenance tactic over the five-year period analysed results in the smallest cost interval developed. This suggests that this would be the best tactic to implement for pump 1 to result in the lowest maintenance budget for the period under review. Therefore, from the development of these confidence intervals, it is clear that a certain level of confidence can be chosen for a budget. The higher the confidence chosen, the less the risk of exceeding budget; however, the budgetary requirement for the organisation will be higher. In addition, decisions can be made regarding the type of maintenance action to perform within a certain year by looking at the outcome of the confidence intervals developed for all the decisions within a certain period. Evidently, the most cost-effective decision should be chosen.

The same procedure that was followed for pump 1 was implemented for pumps 2–5. The results of the simulation for all 32 decisions for each pump can be seen in Appendix A. Figures A.1 – A.4 in Appendix A show that the purely preventive maintenance strategy over the five-year period analysed also resulted in the smallest cost interval for each of the pumps from 2 to 5. This suggests that this strategy would be the best approach to implement for all the pumps in the plant to result in the lowest maintenance budget for this period.

To determine whether the information gathered in this section can be used to develop the yearly budget for the pumps, a statistical validation needs to occur. This process determines whether the Weibull distribution can be used to fit the simulated data for the generation of confidence intervals. The K-S test described in Section 3.4 was used for this purpose. The results for each of the five pumps can be seen in Appendix A in Tables A.1 – A.5. It was found that, for each of the 32 decisions for each pump, there was insufficient evidence to reject the null hypothesis, which suggests that the Weibull distribution fits the data with a good enough fit. Thus, with this information available, the yearly budgetary confidence interval for each pump can now be developed.

The application of the model described in Section 3.8 on all five pumps within the plant over a five-year period determined that the preventive maintenance strategy is the best choice to implement for each pump for each year within the period analysed. By extracting only the first year of simulated cost data over the five-year period for each pump, the confidence intervals for the yearly budget for the same period were computed, following the methodology in Section 3.7.4, as seen in Figure 4.17.

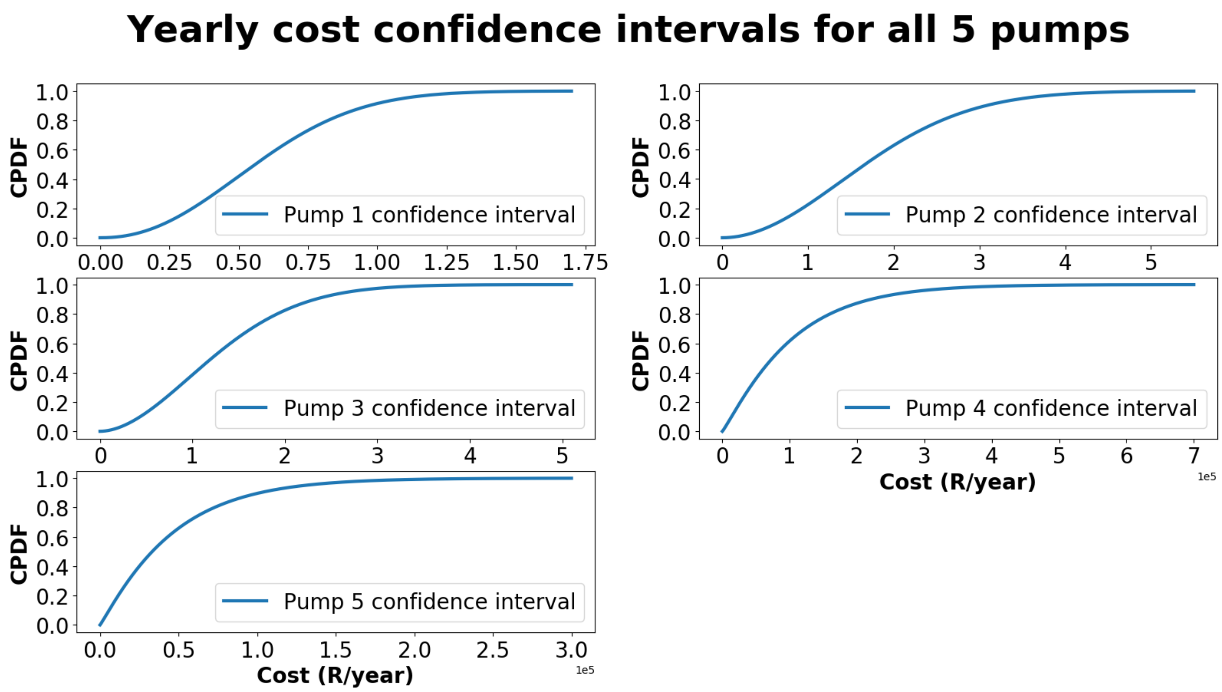

Figure 4.17: Pumps 1–5 yearly cost confidence intervals

Figure 4.17 demonstrates that the analysis results of the general non-repairable systems model for pumps 1–5, as outlined in Table 4.20, can be compared to the confidence intervals for a yearly period for each pump, developed in Figure 4.17. This comparison reveals that the results of the yearly budget developed in Section 4.9.2 only lead to an approximate 50% confidence in the maintenance budget being reached. In terms of the budgetary maintenance requirement of an organisation, this 50% confidence could be regarded as too low with too much uncertainty surrounding the budget. Thus, the development of the confidence intervals for the yearly budget of each pump allows for the choice of a certain level of confidence by an organisation's budgetary department. Increased confidence in the budget results in less uncertainty and risk around it, but this is accompanied by a higher budgetary requirement. For the plant, the choice of an 80% level of confidence as the budgetary requirement for the pumps would result in a budget of R1 503 313.0 per year to maintain all the pumps. This value is 40% greater than the 50% confidence found in Section 4.9.2, but it results in 30% more certainty that the budget will not be exceeded in a specific year. Thus, it is evident that a number of decisions need to be weighed up before a conclusive decision about the budgetary requirement for the pumps can be made. These decisions include selecting either more certainty around the budget at a higher cost, or a lower budget with more risk and uncertainty attached to it.

The final step in the simulation process was to determine whether the Weibull distribution can be used to fit the simulated yearly data for the generation of confidence intervals. For all five pumps, the K-S test determined that there was insufficient evidence to reject the null hypothesis, which means that the Weibull distribution fits the data with a good enough fit. The results of this K-S test for each of the pumps can be seen in Appendix A, Figure A.5. They suggest that this method can be used to generate confidence intervals utilising the non-repairable systems model. The variability in the output of the cost model can be seen in the development of these confidence intervals.

4.9.4 Summary

This section outlined the detailed process that was followed to gain a yearly maintenance budget for the five pumps within the plant. It was found that the optimum preventive maintenance technique to implement was the non-repairable systems model. The output of this model resulted in an average yearly budget of R1 067 971.75. This answer gives a better budgetary requirement than no model being implemented at all, but it only results in a 50% confidence that this budget will be achieved. The simulation model developed in Section 3.8 was implemented on all the pump data to gain more certainty around the budgetary answer found in Section 4.9.2. From this, confidence intervals could be developed around the budget and a certain level of confidence could be chosen.

For all the pumps it was determined that the best maintenance technique to implement over the five-year analysis period was a preventive strategy. The failure strategy resulted in the worst budget being computed. It must be noted that a detailed decision-making process needs to be prescribed when making budgetary decisions using this model. The choice of a higher confidence level results in more certainty and lower risk around the budget, but it also requires a larger budget. Therefore, depending on the particular organisation, different decisions can be made using this tool, dictated by organisational needs.

4.10 Analysis of overhead crane

This section outlines the preventive maintenance methodology that was implemented on the overhead crane in the plant to gain a yearly budgetary requirement for its preventive maintenance. A selection of maintenance data was collected from the Anglo Operating Platform and the time period used for the dataset was from 1 January 2007 – 31 March 2019. As seen in Section 3, general assumptions were made throughout the analysis both as a result of certain factors not being attainable and due to the selection of the optimisation model.

4.10.1 Dataset analysis

The data collected from the Anglo Operating Platform for the overhead crane was only in the form of historical cost data since historical failure data was not attainable. This historical cost data only recorded the cost of materials and resources used during the specific analysis period. The cost of labour and production losses due to maintenance actions on the overhead crane were not taken into account. The historical maintenance cost data was collected in yearly periods. For each year, the total sum spent on different maintenance activities on the overhead crane was recorded. There were 35 different maintenance-related activities documented for the overhead crane each year, along with the cost surrounding each of these activities. In the time period analysed, 13 historical cost data points were recorded for each of the different maintenance activities, one for each year in the period between 2007 and 2019.

The next step in the analysis process was to determine the best maintenance optimisation technique to be applied to the overhead crane dataset to result in a yearly budgetary requirement for an organisation. It is clear from Figure 3.1 that none of the historical failure data models could be used to analyse the dataset since no historical failure data was attainable. Either the forecasting model or the LCC analysis remained to be used. Since the data collected was in the form of maintenance cost data for different sub-systems within the total overall overhead crane system, the forecasting model was selected for use.

4.10.2 Preventive maintenance model implementation

As stated above, for the given set of historical cost data available and using Figure 3.1, it was found that the forecasting model was the best optimisation technique to apply to the set of overhead crane data. Section 3.11 outlines all the mathematics behind the use of this model. The forecasting model has a choice of three different models that can be implemented on historical cost data, namely the single, double and triple exponential smoothing models. For each model, different requirements are needed within the failure data to enable the application of the model to a specific set of data. These requirements include whether a trend and seasonality are present within the dataset. For the 35 sets of cost data related to the overhead crane, it was assumed that both a trend and seasonality were present within the datasets. This assumption was validated by plotting each set of cost data over its period in which the trend and seasonality could be seen. This validation process was performed on each of the 35 sets of cost data related to the overhead crane system. For all the datasets, it was found that a trend and seasonality were present. Figure 4.18 outlines this validation process for one of the 35 sets of cost data.

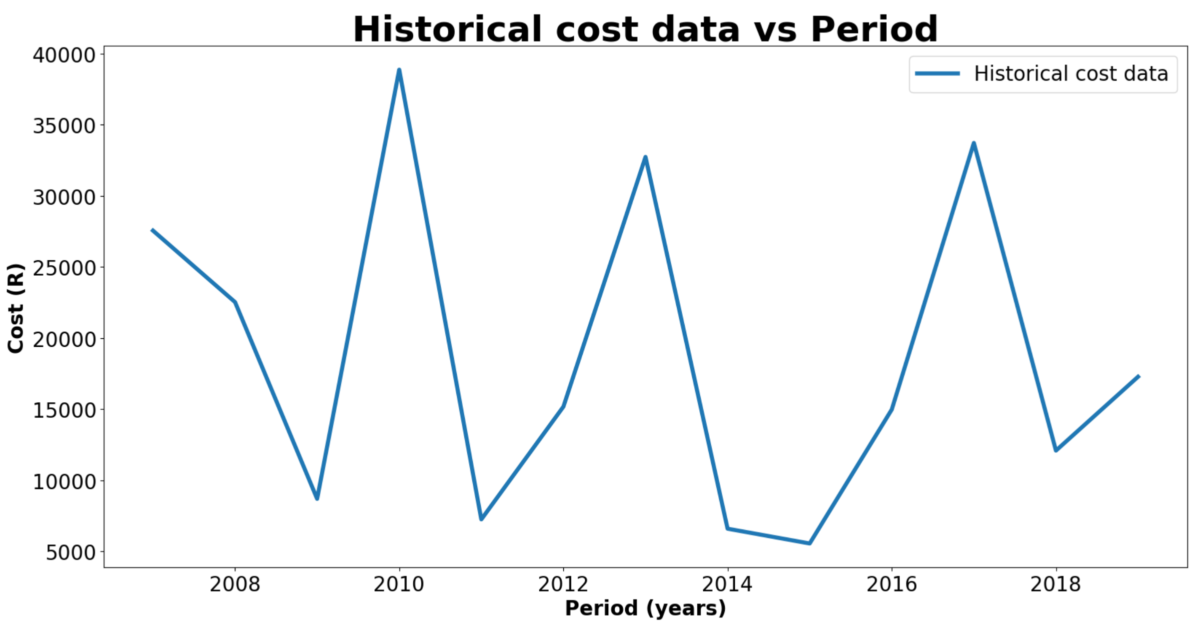

Figure 4.18: Seasonality and trend validation

Figure 4.18 shows that a trend is present in the dataset, as well as three clear seasons. Therefore, it can be concluded that the triple exponential smoothing forecasting model will be used to analyse all 35 sets of cost data for the overhead crane system.

4.10.3 Budgetary calculation for the overhead crane

This section outlines the methodology that was followed to calculate the yearly budgetary requirement for the maintenance of the overhead crane in the plant. Section 4.10.2 found that the best optimisation technique to apply to the given dataset is the triple exponential smoothing forecasting method. This method is described in detail in Section 3.11. From Section 3.11 it can be seen that three equations needed to be solved for the triple exponential forecasting model to be implemented. These included the smoothing equation (Equation 3.82), the trend equation (Equation 3.83) and the seasonality equation (Equation 3.84). For each equation, a constant must be solved that is dependent on all the other equations. These constants were solved using an optimisation algorithm, as discussed in Section 3.11.2. This optimised the MSE error function to gain the best values for the constants. Before the optimisation algorithm for the computation of the constants could be implemented, the seasonality index for each set of data needed to be determined. Section 3.11.3 was applied for each dataset to establish this index.

The triple exponential forecasting model was implemented on each of the 35 datasets for the overhead crane system. A 15-year forecast was presented to show what the trend and seasonality effects would be on the maintenance budget in successive years. The sum of each of the 35 forecasted datasets was calculated to gain one overall yearly budget for the overhead crane. The actual cost data was compared to the forecasted data to ascertain whether this forecasting method could be accepted as a way to determine this yearly maintenance budget. The overall results of the implementation of this forecasting method on the overhead crane data can be seen in Figure 4.19.

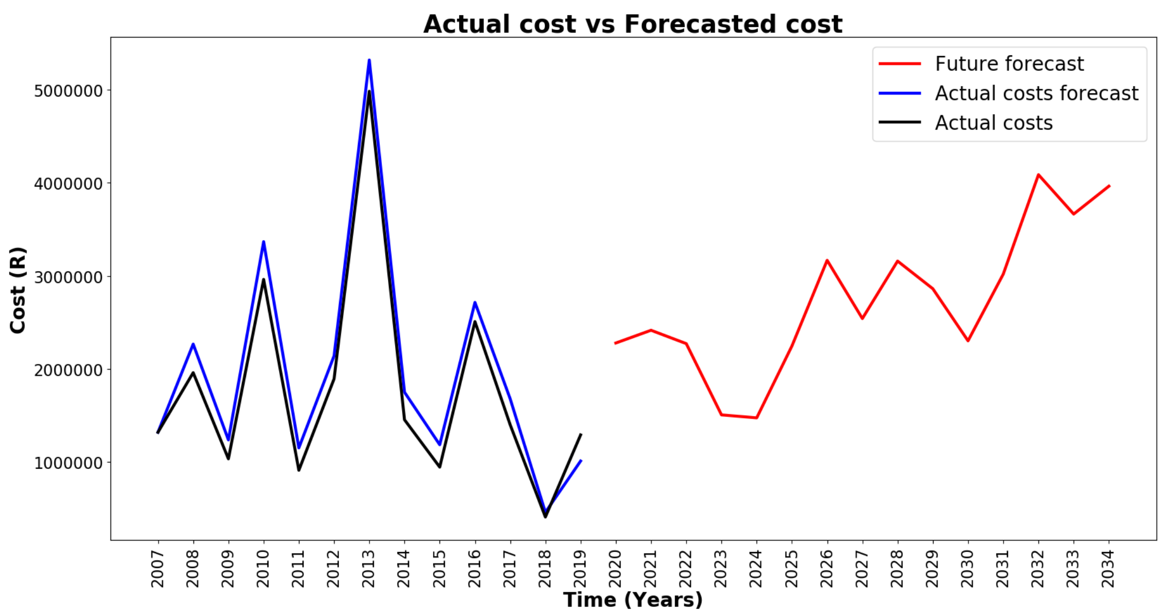

Figure 4.19: Overhead crane cost forecast

Figure 4.19 outlines the total actual maintenance costs found in the following ways: by summing all 35 datasets over their respective periods; from the forecast of the total actual costs; and from a 15-year future forecast of the overhead crane's maintenance costs. From Figure 4.19 and by applying Equation 3.91, it was established that the MAPE of the forecast resulted in a value of 15.67%. Table 3.9 shows that this forecast resulted in a 'good' outcome, which suggests that the method of determining the yearly budget for the overhead crane can be used with reasonable certainty and gives a better estimate than not budgeting at all. For the succeeding year of 2020, the yearly budgetary requirement to maintain the overhead crane was found to be R2 277 212.36. This is the budgetary estimate established by using this forecasting technique. It needs to be set aside in the year 2020 to maintain the overhead crane in the plant.

4.10.4 Summary

This section has outlined the preventive maintenance optimisation technique that was implemented on the set of overhead crane data within the plant. The triple exponential smoothing forecasting model was found to be the best model to use on the 35 sets of maintenance cost data relating to the overhead crane. By implementing this model with its relevant optimisation algorithms, it was found that the succeeding year of 2020 needs to budget for a yearly cost of R2 277 212.36. The accuracy around this forecast was established as 15.67%, which was labelled 'good' according to Table 3.9. This suggests that the budget gives a good estimate of the probable maintenance-related costs in 2020. Since a forecast is being used to determine the budget for a succeeding year, there will always be uncertainty around the outcome. However, the uncertainly around this budget is better than a complete guess or not budgeting at all. The actual budget for 2020 can be compared to the forecasted budget for 2020 in terms of the accuracy of the model. In addition, as the years progress, more historical data can be added to the forecasting model to result in a more accurate outcome. Finally, the budget computed in this section can be included in an organisation's overall budgetary requirement for a yearly period. If the findings are followed, an organisation will be less likely to exceed the budget for an annual period due to the implementation of this preventive maintenance optimisation technique.

4.11 Analysis of pump 6

This section outlines the preventive maintenance methodology that was implemented on pump 6, the final element in the plant for analysis, to gain a yearly budgetary requirement for its preventive maintenance. Data was collected from the Anglo Operating Platform. The time period used for the dataset was from 1 July 2016 – 31 August 2018. As seen in Section 3, general assumptions were made throughout the analysis both as a result of certain factors not being attainable and due to the selection of the optimisation model.

4.11.1 Failure data analysis

The data collected for pump 6 was historical failure data recorded over a certain period. For each failure point recorded, an associated cost of failure was also recorded. The historical failure data was recorded in days and 13 data points were documented for the pump in the time period examined.

Failure data and cost data were attainable for pump 6 within the plant. Figure 3.1 indicates that the next step in the analysis process was to perform a trend test on the data to determine which maintenance technique should be applied for the balance of the analysis. Using the Laplace trend test, a value of $L = -1.26$ was found. This resulted in the failure data lying in the 'grey' area of Figure 3.5. This shows that another trend test needed to be performed in order to validate whether a trend is present within the dataset. The test chosen was the Lewis-Robinson test. The results of this test still showed that the failure data was lying within the 'grey' area of Figure 3.5. Therefore, to gain a definite answer regarding the trend within the dataset, the data for pump 6 was plotted against itself. Visually, it was found that the dataset did not possess any trends. Thus, it could be assumed that no trends were present in the dataset for pump 6.

With the available historical data and the outcome of the trend test, it could be determined from Figure 3.1 that the best maintenance optimisation model to implement for further analysis of pump 6 was the non-repairable systems model. This model is outlined in depth in Section 3.6. The underlying equation for this model is Equation 3.37, which allows for an optimum maintenance strategy to be developed by minimising the cost function, resulting in the computation of an optimum replacement age with an associated cost. Equation 3.37 shows that the two driving factors behind the implementation of this equation are $R(t_p)$ and $f(t)$. These are the reliability and probability density functions, respectively, of the Weibull distribution. Section 3.6 indicates that, to calculate these two functions, the Weibull parameters β and η need to be determined. Following the methodology in Section 3.6.2, and applying the maximum likelihood method, β and η were computed for pump 6, as seen in Table 4.22.

Table 4.22: Pump 6 Weibull parameters

Parameter	Value
β	1.26
η (days)	262.88

Using the parameters in Table 4.22, the reliability and probability density functions for pump 6 were computed, as follows:

$$R(t) = e^{-\left(\frac{t}{262.88}\right)^{1.26}}$$

$$f(t) = \frac{1.26}{262.88}\left(\frac{t}{262.88}\right)^{1.26-1} e^{-\left(\frac{t}{262.88}\right)^{1.26}}$$

Before $R(t_p)$ and $f(t)$ can be used conclusively in the non-repairable systems model, it first needs to be determined whether the results of the Weibull distribution fit the set of pump failure data with a good enough fit. As discussed in Section 3.4, the K-S test is used to test the fit of the actual data to the modelled Weibull distribution. Following the methodology for the K-S test in Section 3.4, the critical value of pump 6 within the plant was found to be 0.361 at a confidence interval of 95% where $\alpha = 0.05$. Figure 4.20 was computed by plotting the cumulative distribution function in Equation 3.31 over the empirical distribution function in Equation 3.6 for pump 6.

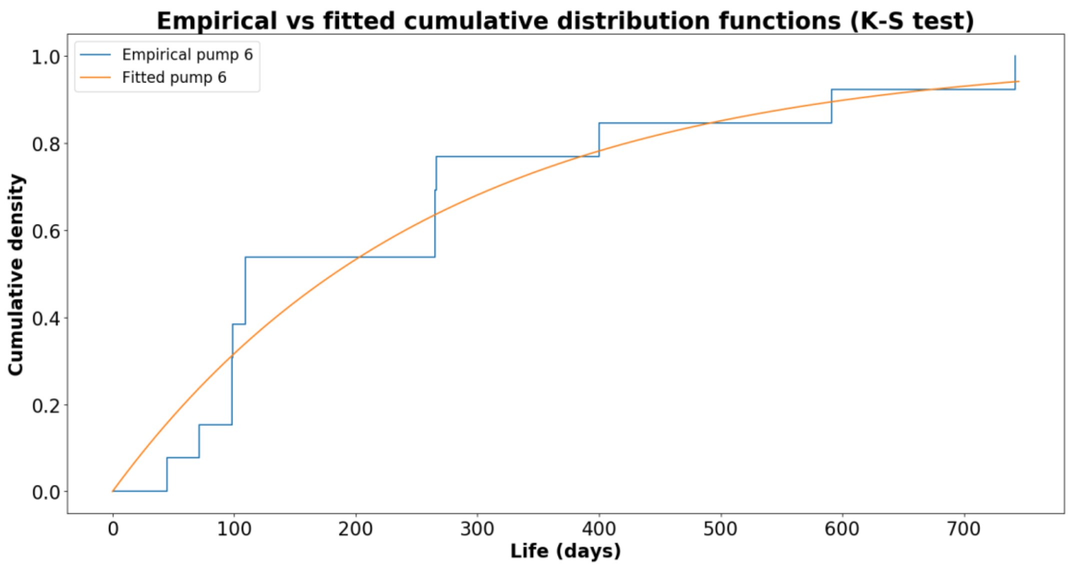

Figure 4.20: K-S test

Using Figure 4.20, the test statistic D_n was computed as 0.20. Thus, it can be seen that $D_n < c_n$, which suggests there is insufficient evidence to reject the null hypothesis. This means that the Weibull distribution fits the data with a good enough fit.

4.11.2 Budgetary calculation for pump 6

In Section 4.11.1 it was found that the best maintenance optimisation technique to implement on the set of pump data was the non-repairable systems analysis. The use of this optimisation technique on the pump failure data was verified in Section 4.11.1 and by utilising the K-S test. The next step in the overall analysis process was to determine an overall budgetary requirement for the maintenance of pump 6 within the plant. Since the non-repairable systems model is being implemented, Equation 3.37 is the underlying equation of this cost optimisation process (Section 3.6). The equation shows that two of the unknowns have already been computed, namely $R(t_p)$ and $f(t)$, as seen in Section 4.11.1. The last two unknowns that make up the equation are the cost of prevention and the cost of failure. As stated above, the data for the cost of a failure action was documented on the Anglo Operating Platform for each failure point recorded for the pump. This data was extracted for the pump and averaged out, resulting in a cost of failure being determined for the pump. The preventive maintenance cost for the pump was not attainable as it had never been recorded. The true cost of a machine breakdown can be reasonably estimated to lie between 4–15 times the maintenance cost (Soccio, 2016). Thus, taking a value between this interval, it was assumed that the cost of preventive maintenance would be 10 times less than that of a failure action. Using this assumption, the fixed costs associated with this non-repairable systems model were found for pump 6, as seen in Table 4.23.

Table 4.23: Pump 6 associated costs

Failure cost C_f	**Preventive cost C_p**
R113 983	R11 398

The cost information in Table 4.23 and the Weibull parameters computed in Table 4.22 allow Equation 3.37 to be applied to the pump 6 failure data. This resulted in the development of Figure 4.21.

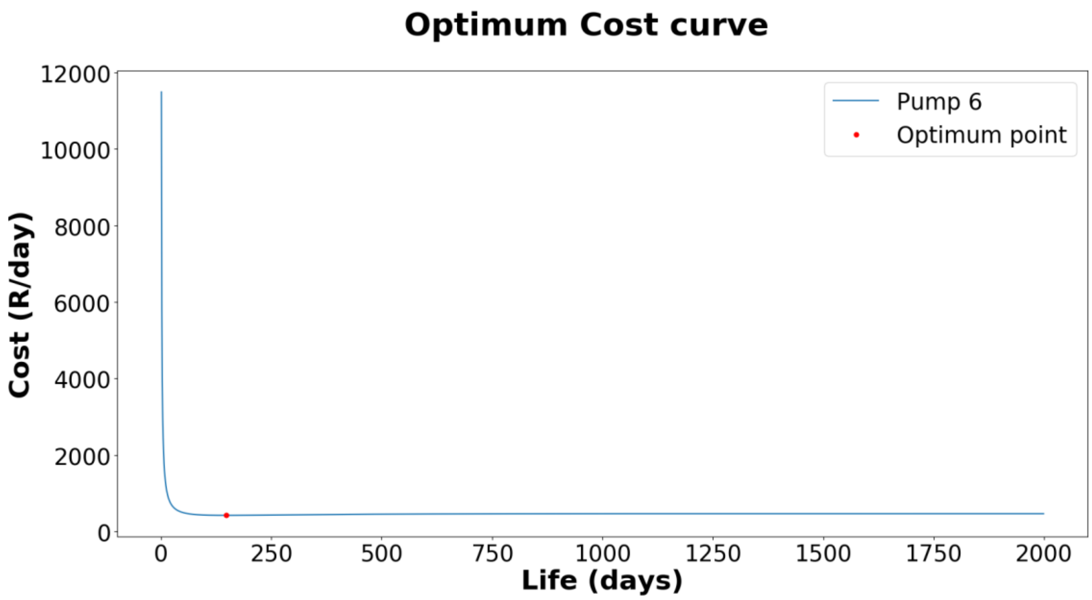

Figure 4.21: Pump 6 optimum cost curve

Figure 4.21 shows the cost curve of pump 6 following the non-repairable systems analysis. It can be seen that no clear optimum point exists to practise preventive maintenance as the graph has no definite dip. However, an optimum replacement point can be found at 148 days and at a cost of R422 per day. To determine whether this optimum replacement point needs to be strictly followed, the run to failure cost was also computed. It was found to be R466 per day. The increase from the optimum replacement cost to the run to failure cost was found to be only 10%. In terms of an overall maintenance strategy, this cost increase can be seen as insubstantial, which suggests that it would be more worthwhile to let pump 6 run to failure than to actively partake in preventive maintenance. The reason is that, in the long run, downtime and setup costs for the implementation of the preventive maintenance activities could result in costing more than just letting the pump run to failure and replacing it at failure. If an organisation regarded the 10% cost increase as too large, a 5% increase in the optimum replacement cost could be found. This would result in a replacement interval of between 78–362 days, indicating that the pump could be replaced anywhere in this interval and result in only a 5% cost increase. Clearly this replacement interval is large, which shows the insensitivity around the optimum replacement age. Taking the run to failure cost into account, the yearly budgetary requirement to maintain pump 6 under this strategy was computed as R170 090.

4.11.3 Summary

This section has outlined the optimum preventive maintenance strategy for implementation on pump 6 within the plant. This should ensure the lowest possible maintenance costs, which can be incorporated into a yearly budgetary requirement for the maintenance of the entire plant. It was found that the non-repairable systems analysis would be the best maintenance technique to implement due to the available data and the results of the trend tests. This approach found that the optimum age to perform preventive maintenance is every 148 days, with an associated cost of R422 per day. It was also determined that the cost curve generated was extremely insensitive to the extension of the replacement age whereas, if the pump was replaced at failure, it would only result in a 10% cost increase. This indicates that it is imperative to consider the implementation of maintenance actions and the outcome if they were not to be applied. In some scenarios, it could be regarded as more worthwhile not to implement preventive maintenance as its effect would be insubstantial. Therefore, it is essential to weigh up all scenarios before making a conclusive decision about the implementation of specific maintenance action.

4.12 Case study summary

So far in Section 4, the model developed in Section 3 has been demonstrated on a contrived plant consisting of a number of different components and systems. Varying data has been attainable for the different elements within the plant. The model outlined in Figure 3.1 has been implemented on the plant to find a budgetary requirement for each section. All the challenges put forward in the problem statement have been addressed. The final challenge to address is to combine all the separate budgetary requirements into one concise budget that can be used by the finance department of an organisation to make decisions about the yearly maintenance budget of a plant.

4.12.1 Overall budgetary requirement

Figure 4.1 shows that the plant consisted of a number of different components and systems, including a dump truck, conveyor systems, an overhead crane and a selection of pumps. As described throughout Sections 4.4 – 4.1, different types of datasets were available for the different elements within the plant from the Anglo Operating Platform. No set preventive maintenance optimisation method could be used to analyse all the different datasets due to variability within the datasets themselves. The model developed in Section 3 was implemented on the plant and the process outlined in Figure 3.1 was followed. The yearly budgetary requirement to maintain all the different elements within the plant was determined using a selected optimisation model. Table 4.24 shows the relevant optimisation model for each element, found through the implementation of the methodology in Figure 3.1, and its accompanying yearly budgetary requirement.

Table 4.24: Individual budgetary breakdown

Component/system	Model applied	Yearly budgetary requirement
Dump truck	Life cycle costing model	R5 815 182.00
Conveyor 1	Repairable systems model	R196 871.00
Conveyor 2	Block replacement model	R6 069 065.00
Conveyor 3	Grouping model	R7 074 586.00
Overhead crane	Forecasting model	R2 277 212.00
Pumps 1–5	Non-repairable systems model	R1 067 971.00
Pump 6	Run to failure model	R169 725.00

Table 4.24 indicates that an optimum maintenance cost for each separate system/component within the plant has been computed. This is the average cost that should be budgeted for the succeeding year in order to maintain the plant according to this optimum policy. Figure 4.22 was developed to demonstrate the distribution of the different models within the plant and how the output of each optimisation model affected the total overall budgetary requirement of the plant.

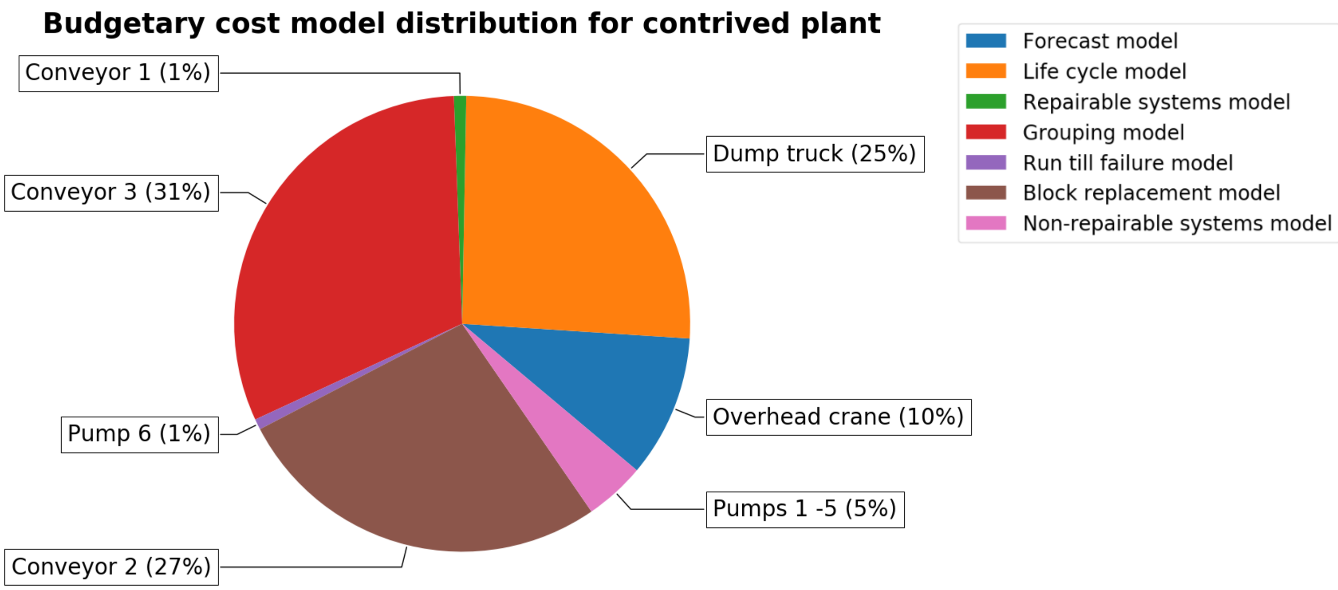

Figure 4.22: Budgetary distribution within the plant

Figure 4.22 illustrates the distribution of each individual cost model in the overall budgetary requirement. It shows a clear separation between the different models and a substantially greater contribution by certain models compared to other models. The reason is the cost information obtained from the Anglo Operating Platform in which some elements in the plant have greater failure costs associated with them than others. This results in the maintenance costs of these elements being significantly higher than some of the other elements. Figure 4.22 gives a strong visual representation of the percentage of the overall budget needed to maintain the specific elements within the plant, thereby allowing the budgetary department of an organisation to see exactly where their budget is being spent and on what.

Section 3 demonstrated that the output of certain models throughout the analysis resulted in average costs being computed for the yearly budget for specific elements within the plant. These models included the block replacement model implemented on conveyor 2 and the non-repairable systems model implemented on pumps 1–5. Thus, in terms of a budgetary requirement, an average budget could result in too much uncertainty and risk as there is only a 50% chance of this budget being reached. Figure 4.23 was developed to show the confidence levels around the overall yearly maintenance budget to maintain the entire plant.

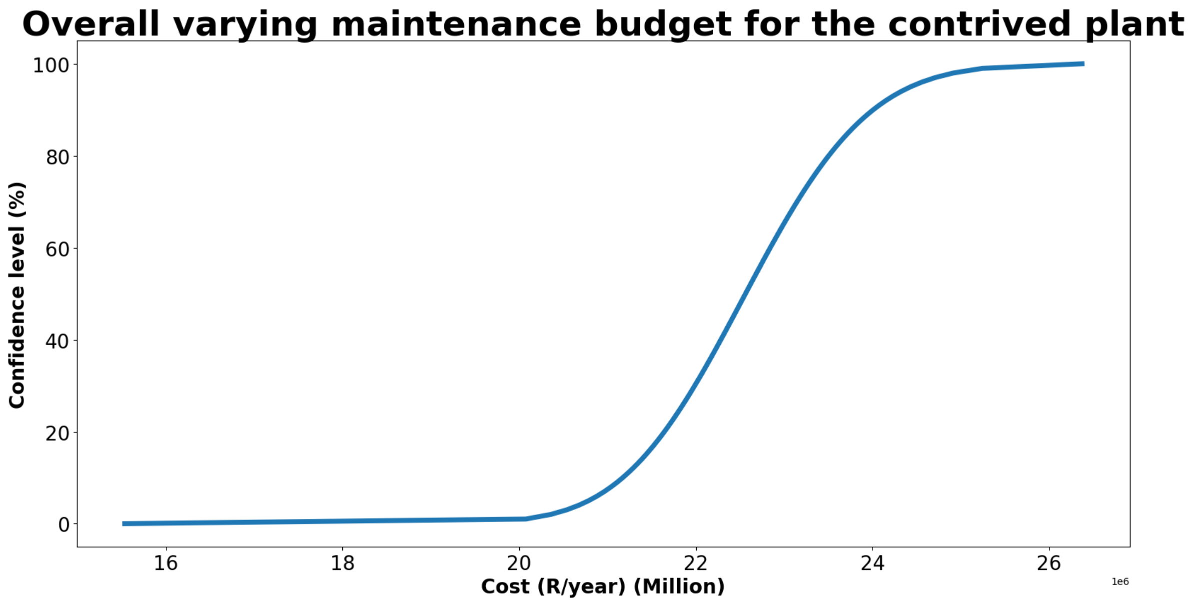

Figure 4.23: Overall varying maintenance budget for the plant

Figure 4.23 indicates clear confidence levels surrounding the overall maintenance budget for the plant. It shows that, at a confidence of 50%, the resultant budget is identical to the average budget obtained using the standard models – without the implementation of the two simulation models in Sections 3.7, 3.8 and 3.10.2. This validates that these general maintenance optimisation models do output the average cost of a maintenance action for a certain period. However, extended modelling needs to occur to create more certainty around the outcome of the general models. The implementation of the models developed by the author in Sections 3.7, 3.8 and 3.10.2 enables confidence around the budget to be computed, allowing more certainty and less risk to be outputted for a budget. This is evident in Figure 4.23 in which a certain level of confidence can be chosen for the overall budgetary requirement for the plant. A higher level of confidence will result in less uncertainty and less risk around the budget, but it will also require a larger budget to maintain the plant within a specific yearly period. Thus, the development of this overall budgetary maintenance model allows maintenance departments to make various decisions about the budget they are willing to put aside each year. The risk and uncertainty surrounding this budget can be obtained by using a figure such as Figure 4.23 that will guide the department to make the best decision in terms of the yearly maintenance budget of an organisation.

4.12.2 Case study summary

From the detailed scope of research presented in Section 1 and the literature study presented in Section 2, it can be noted that a definite gap exists in the literature. This gap relates to the availability of an overall maintenance model that is generic to a number of variable scenarios, in which the output of a budgetary requirement lies at its forefront. Section 3 presented a proposed overall maintenance methodology that incorporated a large variety of individual maintenance models. This principle was applied to the case study presented in Section 4.

The case study utilised a contrived mining plant comprised of a variety of different systems and components. Available data was collected from the Anglo Operating Platform to form the basis of the entire analysis. Due to the variety of data collected, the overall maintenance model outlined in Figure 3.1 was exercised to its full potential since every element in the overall model was illustrated in the case study.

It is evident that the overall maintenance model effectively produces one overall budgetary requirement for a plant, presenting the results in a relatively simplified manner for the complex problem at hand. This enables the results to be easily understood by a budgetary decision maker. However, the final budgetary requirement can also be completely misunderstood. This suggests that the overall maintenance model developed needs to be completely understood by an organisation before its implementation to ensure it is utilised to its full potential.

By implementing the overall maintenance model, it was found that each element within the plant required the application of a different individual model. The model enabled the computation of an individual maintenance plan for each element, consisting of an optimum replacement age and an associated cost. Through the various elements present within the plant and the nature of the data analysed, the generic use of the model developed could be illustrated to demonstrate that it is not confined to one specific scenario. The use of all the individual failure models within the overall model were validated using goodness of fit tests in which it was found that the null hypothesis could not be rejected.

The final overall budgetary requirement for the plant being analysed in this research was developed by incorporating all the individual cost requirements found by utilising the model presented in Figure 3.1. The implementation of Monte-Carlo simulations in the maintenance model allowed certainty around the budget to be determined, resulting in the mitigation of risk. In the evaluation of the final budgetary decision tool, it was concluded that the implementation of such a maintenance model into an organisation will result in a total plant optimised cost for the preventive maintenance of the plant. Such a tool could result in significant cost reductions due to its variability, ease of use and application.

5 Conclusion and recommendations

5.1 Conclusion

An extensive literature study was presented in Section 2 that reviewed the overall thought process and view on plant asset management as a whole. The latest advanced modelling methods and techniques were investigated, and the benefits related to an overall maintenance model were extracted and examined. It was determined that a substantial amount of literature is available on all the individual maintenance models that have been developed over the years and that cost optimisation could be applied to a number of these models. A large gap in the literature in terms of maintenance optimisation was observed in one area. This was in the field of an overall maintenance optimisation model that could be implemented in a variety of unique scenarios to develop one comprehensive budgetary requirement for an organisation as the main output. To ascertain how to develop such an extensive model for application to multiple situations, Sections 2 and 3 presented an exhaustive review on a significant number of the individual maintenance models that already exist. The individual models were then critically analysed, allowing for their implementation into an overall model. In-depth modifications to the existing models were applied and additional models were developed to enable the overall maintenance model to be as generic as possible.

This dissertation proposes an integrated overall maintenance optimisation methodology with the capabilities to be implemented into a wide variety of plants and resulting in the development of an all-inclusive budgetary requirement for the preventive maintenance of a specific plant for a given period. The model developed incorporates a number of maintenance methodologies that have already been tried and tested. These include non-repairable systems analysis, repairable systems analysis, block replacement models and optimum maintenance grouping methodologies. The four maintenance techniques considered all deal with in-depth statistical analysis that requires the acquisition of failure data in order to implement the models. All these models are based on analysing the failure characteristics of a certain piece of machinery or equipment. The output is the optimisation of a cost function that results in the optimum cost and age of replacement of the element under scrutiny. In terms of the outcome of an overall budgetary maintenance model, considering these four models alone would result in a methodology that could only be used on elements in a plant with failure data attached to them. To address this issue and to develop a more general maintenance model, two other modelling techniques were investigated: a forecasting technique and a life cycle modelling methodology. These two methods were considered because, in any organisational setting, the one piece of data that is rarely not attainable is the cost data spent on a specific action. This can range from failure cost data to replacement cost data. Thus, it was concluded that the development of a model which could incorporate all these different types of data, based on availability, would be more beneficial than simply neglecting this aspect altogether.

It was established that significant modifications could be made to the already developed maintenance models found in the literature by introducing a simulation methodology that quantifies the risk around the cost outputs of the models. This was implemented on both the non-repairable systems model and the block replacement model.. This methodology utilised Monte-Carlo simulations to construct confidence intervals around the outputted cost. Instead of just an average cost being budgeted for a certain period, the significance was that a confidence around a budget could be chosen, increasing certainty and reducing risk.

To illustrate the actual functioning of the overall maintenance methodology developed in this dissertation, a case study was presented. It made use of a contrived plant comprised of a number of different systems and components with varying types of available data attached to them. The data was gathered from the Anglo Operating Platform from a number of different mines. The elements within the plant were chosen directly based on attainable data and to illustrate the functioning of all the sub-models within the complete maintenance model developed. The use of the case study validated the maintenance methodology that was developed in terms of its potential effectiveness in establishing an overall preventive maintenance budgetary requirement for a plant with a variety of data inputs.

The research presented in this dissertation led to the development of an overall preventive maintenance model that met all the aims and outcomes initially stated. The model developed can be used in a diverse range of scenarios and situations, resulting in the final outcome of one comprehensive budgetary decision that can be put forward to management. A novel simulation method was implemented on a number of the sub-maintenance models in order to create certainty around the outcomes. Historical failure and cost data were necessary for the implementation of this model, and the model's effectiveness was validated using the case study. It was found that the outcome resulted in an effective decision-making tool with significant potential for implementation in a variety of organisations in search of optimal budgetary requirements.

5.2 Recommendations

As stated in Section 5.1, the overall maintenance model developed in this research resulted in an effective decision-making tool for use in establishing an annual budgetary requirement for an organisation. In any research, areas exist in which future improvements can occur. This section outlines all these areas.

1. The model developed is a general maintenance model that can be applied to a number of different industries in which varying systems and components occur. This study considered equipment from the mining sector only. To validate the model further, it would be beneficial to implement it in a variety of different sectors and in an actual plant environment. The output of the model could then be compared to a current maintenance strategy and conclusions could be drawn.

2. One area that the overall maintenance methodology does not presently consider is condition-based maintenance. This section of maintenance could be incorporated into the current model to make it even more general and open.

3. In the grouping model developed in Section 3.9, the optimum strategy devised was based on considering the optimum replacement times of all the components involved and optimising the replacement interval. A more detailed model on the topic of opportunistic maintenance could be developed using genetic algorithms.

4. Monte-Carlo simulations could be implemented into the repairable systems analysis, resulting in the development of an output that is not just an average but rather has confidence intervals surrounding it.

5. As with any model built on historical data, the quality of the data plays an integral role in the accuracy of the outcome. The data collected in this research allowed the expression of all the fundamental processes. To further improve the results, future studies could be performed with better data integrity that should lead to improved results.

6. Unfortunately due to time constraints the industry surveys could not be completed. Future industry surveys could be implemented into a number of different organisation to prove the validity of the model.

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Appendix A Case study result curves

Appendix A presents the results of the case study outlined in Section 4.9.

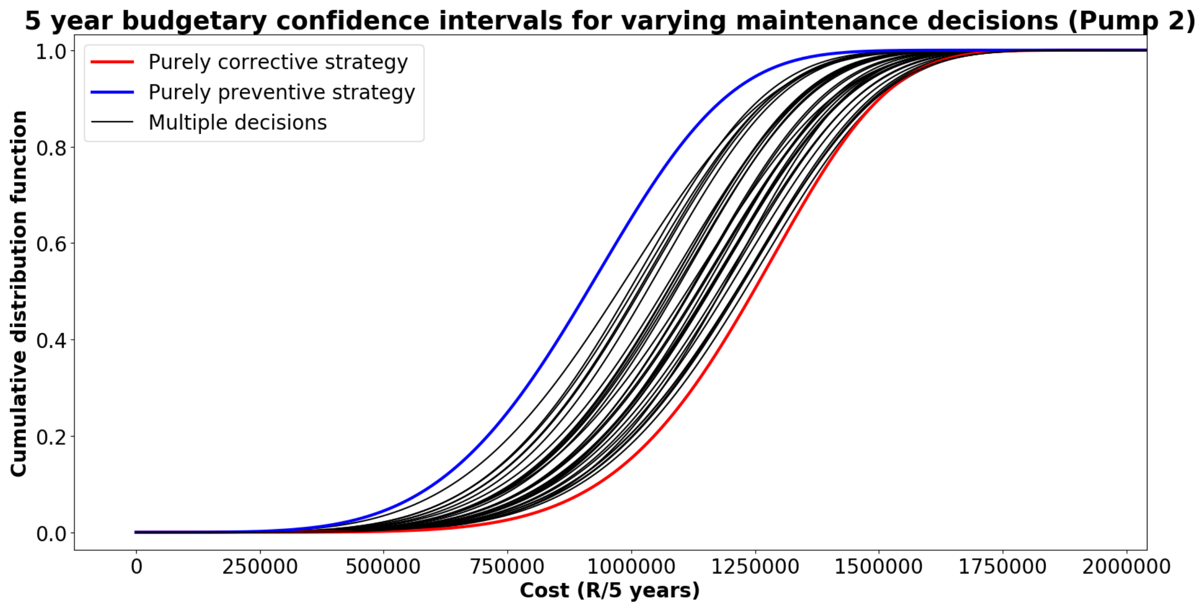

Figure A.0.1: Pump 2 five-year budgetary confidence intervals with varying decisions

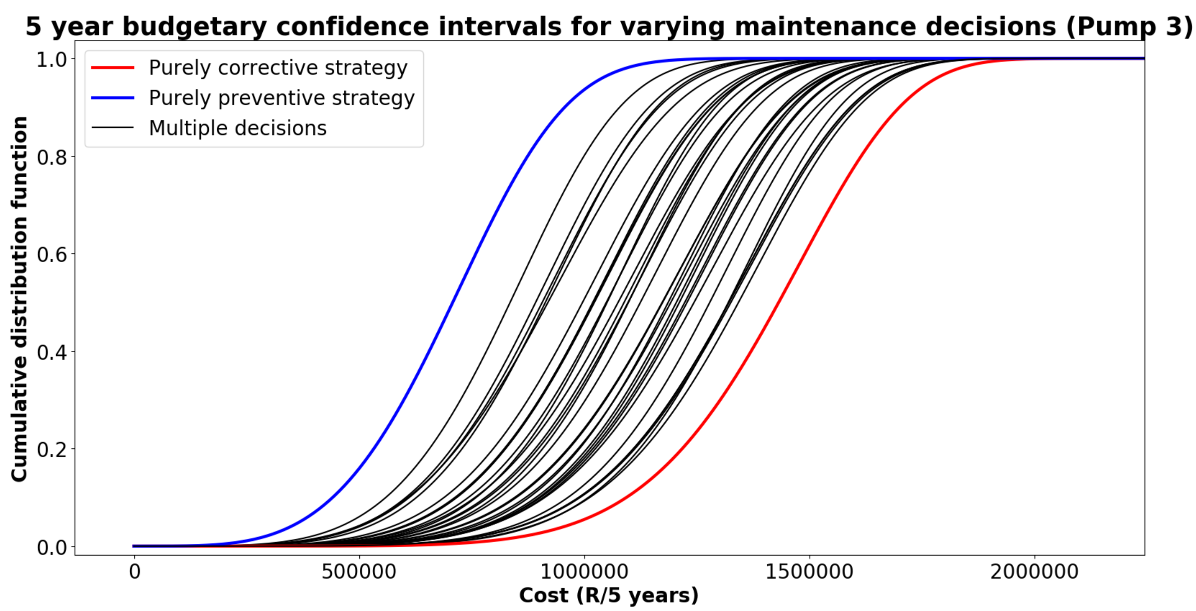

Figure A.0.2: Pump 3 five-year budgetary confidence intervals with varying decisions

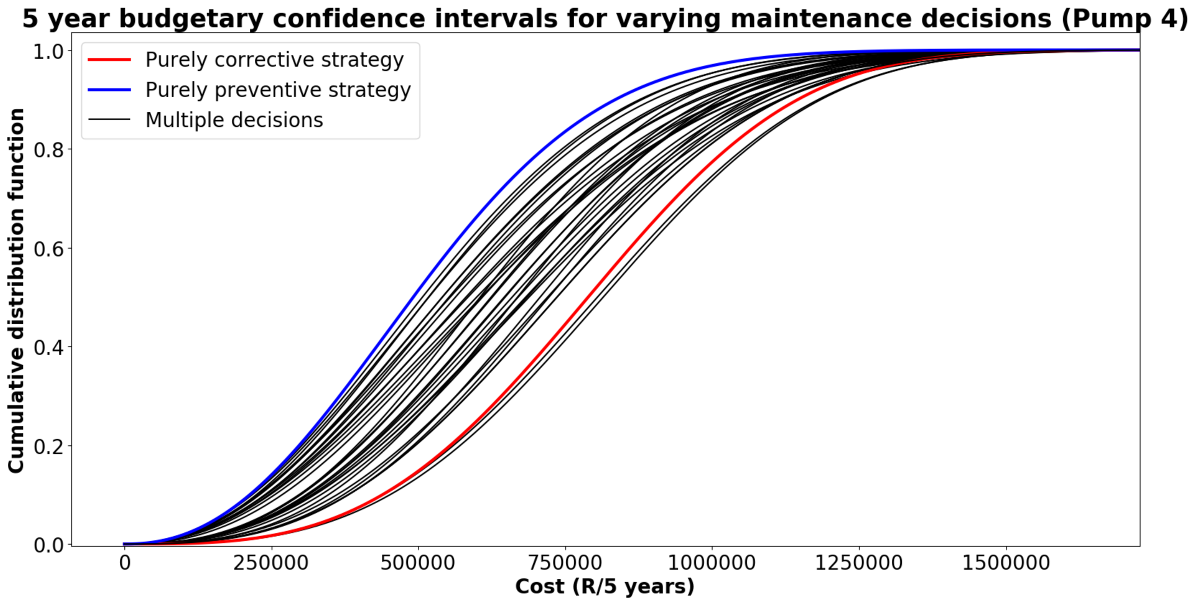

Figure A.0.3: Pump 4 five-year budgetary confidence intervals with varying decisions

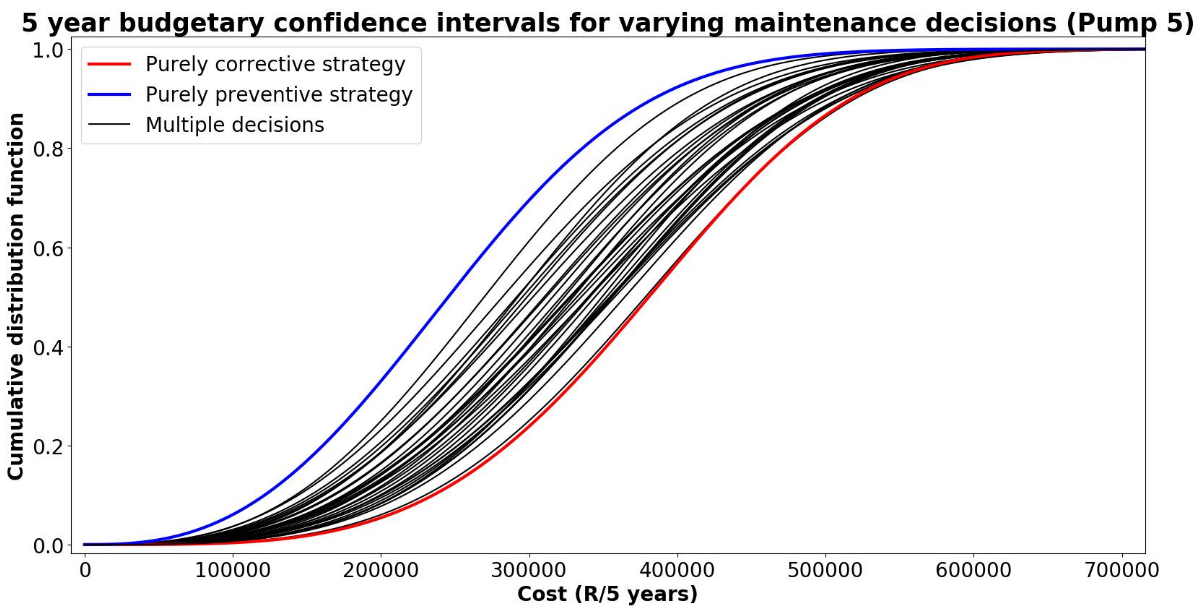

Figure A.0.4: Pump 5 five-year budgetary confidence intervals with varying decisions

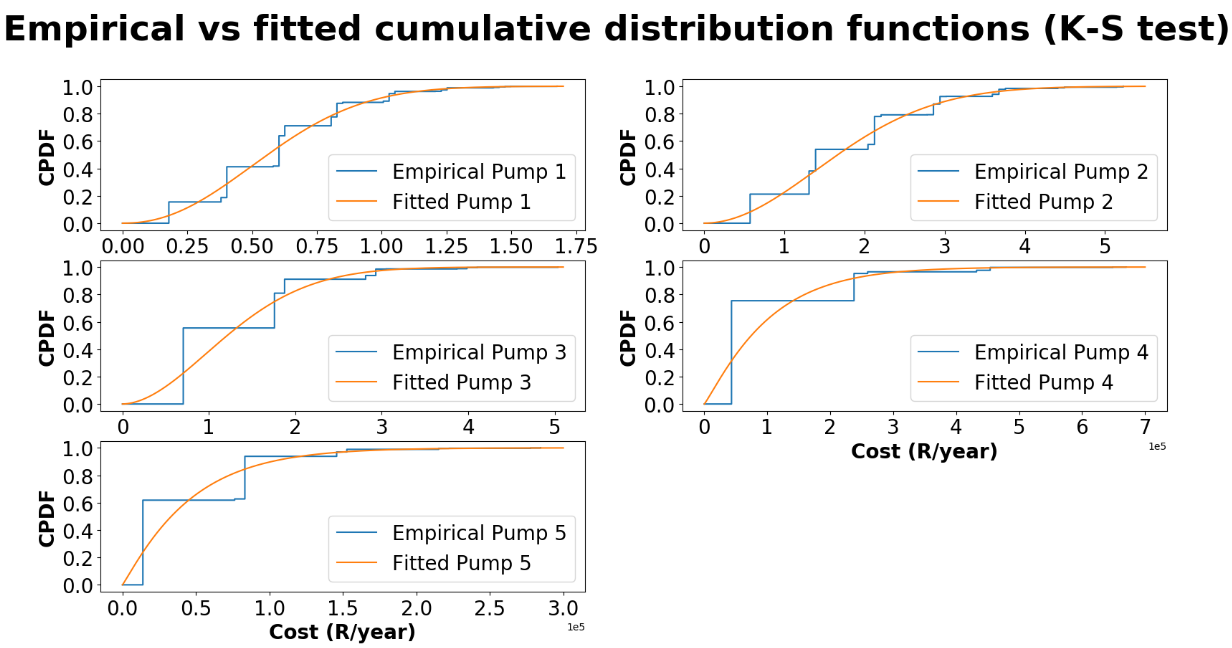

Figure A.0.5: K-S test for yearly budgetary confidence intervals

Table A.1: Pump 1 K-S test results

Strategy	***Strategy vector***	***Number of events***	D_n	c_n
Strategy 1	$B = (0,0,0,0,0)$	19	0.119	0.301
Strategy 2	$B = (0,0,0,0,1)$	84	0.111	0.148
Strategy 3	$B = (0,0,0,1,0)$	91	0.107	0.143
Strategy 4	$B = (0,0,0,1,1)$	99	0.078	0.137
Strategy 5	$B = (0,0,1,0,0)$	77	0.081	0.155
Strategy 6	$B = (0,0,1,0,1)$	107	0.087	0.131
Strategy 7	$B = (0,0,1,1,0)$	107	0.089	0.131
Strategy 8	$B = (0,0,1,1,1)$	110	0.075	0.130
Strategy 9	$B = (0,1,0,0,0)$	91	0.087	0.143
Strategy 10	$B = (0,1,0,0,1)$	103	0.083	0.134
Strategy 11	$B = (0,1,0,1,0)$	103	0.081	0.134
Strategy 12	$B = (0,1,0,1,1)$	110	0.090	0.130
Strategy 13	$B = (0,1,1,0,0)$	99	0.081	0.137
Strategy 14	$B = (0,1,1,0,1)$	120	0.080	0.124
Strategy 15	$B = (0,1,1,1,0)$	113	0.078	0.128
Strategy 16	$B = (0,1,1,1,1)$	108	0.085	0.131
Strategy 17	$B = (1,0,0,0,0)$	68	0.105	0.165
Strategy 18	$B = (1,0,0,0,1)$	104	0.068	0.133
Strategy 19	$B = (1,0,0,1,0)$	102	0.089	0.135
Strategy 20	$B = (1,0,0,1,1)$	106	0.065	0.132
Strategy 21	$B = (1,0,1,0,0)$	97	0.100	0.138
Strategy 22	$B = (1,0,1,0,1)$	115	0.076	0.127
Strategy 23	$B = (1,0,1,1,0)$	107	0.083	0.131
Strategy 24	$B = (1,0,1,1,1)$	113	0.074	0.128
Strategy 25	$B = (1,1,0,0,0)$	99	0.096	0.137
Strategy 26	$B = (1,1,0,0,1)$	103	0.089	0.134
Strategy 27	$B = (1,1,0,1,0)$	108	0.099	0.131
Strategy 28	$B = (1,1,0,1,1)$	117	0.082	0.126
Strategy 29	$B = (1,1,1,0,0)$	107	0.081	0.131
Strategy 30	$B = (1,1,1,0,1)$	105	0.087	0.133
Strategy 31	$B = (1,1,1,1,0)$	108	0.082	0.131
Strategy 32	$B = (1,1,1,1,1)$	95	0.085	0.140

Table A.2: Pump 2 K-S test results

Strategy	*Strategy vector*	*Number of events*	D_n	c_n
Strategy 1	$B = (0,0,0,0,0)$	16	0.127	0.327
Strategy 2	$B = (0,0,0,0,1)$	65	0.100	0.169
Strategy 3	$B = (0,0,0,1,0)$	63	0.103	0.171
Strategy 4	$B = (0,0,0,1,1)$	79	0.087	0.153
Strategy 5	$B = (0,0,1,0,0)$	61	0.109	0.174
Strategy 6	$B = (0,0,1,0,1)$	78	0.097	0.154
Strategy 7	$B = (0,0,1,1,0)$	76	0.089	0.156
Strategy 8	$B = (0,0,1,1,1)$	82	0.088	0.151
Strategy 9	$B = (0,1,0,0,0)$	64	0.106	0.170
Strategy 10	$B = (0,1,0,0,1)$	83	0.094	0.149
Strategy 11	$B = (0,1,0,1,0)$	87	0.099	0.146
Strategy 12	$B = (0,1,0,1,1)$	79	0.090	0.153
Strategy 13	$B = (0,1,1,0,0)$	82	0.081	0.150
Strategy 14	$B = (0,1,1,0,1)$	87	0.094	0.146
Strategy 15	$B = (0,1,1,1,0)$	83	0.078	0.149
Strategy 16	$B = (0,1,1,1,1)$	80	0.097	0.152
Strategy 17	$B = (1,0,0,0,0)$	56	0.097	0.182
Strategy 18	$B = (1,0,0,0,1)$	77	0.092	0.155
Strategy 19	$B = (1,0,0,1,0)$	75	0.095	0.157
Strategy 20	$B = (1,0,0,1,1)$	84	0.091	0.148
Strategy 21	$B = (1,0,1,0,0)$	77	0.088	0.155
Strategy 22	$B = (1,0,1,0,1)$	85	0.073	0.148
Strategy 23	$B = (1,0,1,1,0)$	80	0.081	0.152
Strategy 24	$B = (1,0,1,1,1)$	80	0.075	0.152
Strategy 25	$B = (1,1,0,0,0)$	73	0.094	0.159
Strategy 26	$B = (1,1,0,0,1)$	79	0.092	0.153
Strategy 27	$B = (1,1,0,1,0)$	81	0.092	0.151
Strategy 28	$B = (1,1,0,1,1)$	84	0.087	0.148
Strategy 29	$B = (1,1,1,0,0)$	77	0.073	0.155
Strategy 30	$B = (1,1,1,0,1)$	79	0.089	0.153
Strategy 31	$B = (1,1,1,1,0)$	80	0.088	0.152
Strategy 32	$B = (1,1,1,1,1)$	66	0.088	0.167

Table A.3: Pump 3 K-S test results

Strategy	***Strategy vector***	***Number of events***	D_n	c_n
Strategy 1	$B = (0,0,0,0,0)$	12	0.140	0.375
Strategy 2	$B = (0,0,0,0,1)$	43	0.135	0.207
Strategy 3	$B = (0,0,0,1,0)$	47	0.118	0.198
Strategy 4	$B = (0,0,0,1,1)$	43	0.136	0.207
Strategy 5	$B = (0,0,1,0,0)$	49	0.139	0.194
Strategy 6	$B = (0,0,1,0,1)$	52	0.129	0.189
Strategy 7	$B = (0,0,1,1,0)$	46	0.135	0.201
Strategy 8	$B = (0,0,1,1,1)$	42	0.120	0.210
Strategy 9	$B = (0,1,0,0,0)$	46	0.131	0.201
Strategy 10	$B = (0,1,0,0,1)$	52	0.118	0.189
Strategy 11	$B = (0,1,0,1,0)$	56	0.125	0.182
Strategy 12	$B = (0,1,0,1,1)$	50	0.121	0.192
Strategy 13	$B = (0,1,1,0,0)$	50	0.126	0.192
Strategy 14	$B = (0,1,1,0,1)$	51	0.120	0.190
Strategy 15	$B = (0,1,1,1,0)$	47	0.123	0.198
Strategy 16	$B = (0,1,1,1,1)$	47	0.123	0.198
Strategy 17	$B = (1,0,0,0,0)$	34	0.144	0.233
Strategy 18	$B = (1,0,0,0,1)$	41	0.139	0.212
Strategy 19	$B = (1,0,0,1,0)$	48	0.125	0.196
Strategy 20	$B = (1,0,0,1,1)$	48	0.115	0.196
Strategy 21	$B = (1,0,1,0,0)$	46	0.119	0.201
Strategy 22	$B = (1,0,1,0,1)$	56	0.129	0.182
Strategy 23	$B = (1,0,1,1,0)$	47	0.130	0.198
Strategy 24	$B = (1,0,1,1,1)$	46	0.120	0.201
Strategy 25	$B = (1,1,0,0,0)$	43	0.121	0.207
Strategy 26	$B = (1,1,0,0,1)$	52	0.131	0.189
Strategy 27	$B = (1,1,0,1,0)$	53	0.108	0.187
Strategy 28	$B = (1,1,0,1,1)$	51	0.125	0.190
Strategy 29	$B = (1,1,1,0,0)$	40	0.128	0.215
Strategy 30	$B = (1,1,1,0,1)$	48	0.123	0.196
Strategy 31	$B = (1,1,1,1,0)$	38	0.120	0.221
Strategy 32	$B = (1,1,1,1,1)$	29	0.116	0.253

Table A.4: Pump 4 K-S test results

Strategy	***Strategy vector***	***Number of events***	D_n	c_n
Strategy 1	$B = (0,0,0,0,0)$	9	0.163	0.430
Strategy 2	$B = (0,0,0,0,1)$	26	0.140	0.259
Strategy 3	$B = (0,0,0,1,0)$	25	0.124	0.264
Strategy 4	$B = (0,0,0,1,1)$	33	0.122	0.231
Strategy 5	$B = (0,0,1,0,0)$	24	0.158	0.269
Strategy 6	$B = (0,0,1,0,1)$	32	0.111	0.234
Strategy 7	$B = (0,0,1,1,0)$	32	0.134	0.234
Strategy 8	$B = (0,0,1,1,1)$	26	0.131	0.259
Strategy 9	$B = (0,1,0,0,0)$	20	0.131	0.294
Strategy 10	$B = (0,1,0,0,1)$	33	0.118	0.231
Strategy 11	$B = (0,1,0,1,0)$	32	0.115	0.234
Strategy 12	$B = (0,1,0,1,1)$	26	0.116	0.259
Strategy 13	$B = (0,1,1,0,0)$	27	0.145	0.254
Strategy 14	$B = (0,1,1,0,1)$	33	0.115	0.231
Strategy 15	$B = (0,1,1,1,0)$	25	0.135	0.264
Strategy 16	$B = (0,1,1,1,1)$	29	0.155	0.246
Strategy 17	$B = (1,0,0,0,0)$	21	0.181	0.287
Strategy 18	$B = (1,0,0,0,1)$	28	0.141	0.250
Strategy 19	$B = (1,0,0,1,0)$	33	0.120	0.231
Strategy 20	$B = (1,0,0,1,1)$	30	0.134	0.242
Strategy 21	$B = (1,0,1,0,0)$	27	0.115	0.254
Strategy 22	$B = (1,0,1,0,1)$	26	0.118	0.259
Strategy 23	$B = (1,0,1,1,0)$	31	0.118	0.238
Strategy 24	$B = (1,0,1,1,1)$	23	0.163	0.275
Strategy 25	$B = (1,1,0,0,0)$	21	0.166	0.287
Strategy 26	$B = (1,1,0,0,1)$	24	0.128	0.269
Strategy 27	$B = (1,1,0,1,0)$	24	0.115	0.269
Strategy 28	$B = (1,1,0,1,1)$	23	0.125	0.275
Strategy 29	$B = (1,1,1,0,0)$	21	0.155	0.287
Strategy 30	$B = (1,1,1,0,1)$	26	0.138	0.259
Strategy 31	$B = (1,1,1,1,0)$	21	0.146	0.287
Strategy 32	$B = (1,1,1,1,1)$	18	0.186	0.309

Table A.5: Pump 5 K-S test results

Strategy	***Strategy vector***	***Number of events***	D_n	c_n
Strategy 1	$B = (0,0,0,0,0)$	10	0.165	0.409
Strategy 2	$B = (0,0,0,0,1)$	28	0.121	0.250
Strategy 3	$B = (0,0,0,1,0)$	27	0.115	0.254
Strategy 4	$B = (0,0,0,1,1)$	32	0.120	0.234
Strategy 5	$B = (0,0,1,0,0)$	26	0.122	0.259
Strategy 6	$B = (0,0,1,0,1)$	33	0.102	0.231
Strategy 7	$B = (0,0,1,1,0)$	37	0.111	0.218
Strategy 8	$B = (0,0,1,1,1)$	35	0.112	0.224
Strategy 9	$B = (0,1,0,0,0)$	25	0.123	0.264
Strategy 10	$B = (0,1,0,0,1)$	35	0.095	0.264
Strategy 11	$B = (0,1,0,1,0)$	34	0.089	0.227
Strategy 12	$B = (0,1,0,1,1)$	34	0.092	0.227
Strategy 13	$B = (0,1,1,0,0)$	31	0.118	0.238
Strategy 14	$B = (0,1,1,0,1)$	32	0.096	0.234
Strategy 15	$B = (0,1,1,1,0)$	35	0.099	0.224
Strategy 16	$B = (0,1,1,1,1)$	34	0.092	0.227
Strategy 17	$B = (1,0,0,0,0)$	19	0.156	0.301
Strategy 18	$B = (1,0,0,0,1)$	28	0.122	0.250
Strategy 19	$B = (1,0,0,1,0)$	32	0.135	0.234
Strategy 20	$B = (1,0,0,1,1)$	32	0.127	0.234
Strategy 21	$B = (1,0,1,0,0)$	28	0.110	0.250
Strategy 22	$B = (1,0,1,0,1)$	36	0.101	0.221
Strategy 23	$B = (1,0,1,1,0)$	33	0.102	0.231
Strategy 24	$B = (1,0,1,1,1)$	31	0.103	0.238
Strategy 25	$B = (1,1,0,0,0)$	25	0.151	0.264
Strategy 26	$B = (1,1,0,0,1)$	32	0.126	0.234
Strategy 27	$B = (1,1,0,1,0)$	30	0.120	0.242
Strategy 28	$B = (1,1,0,1,1)$	34	0.115	0.227
Strategy 29	$B = (1,1,1,0,0)$	29	0.161	0.246
Strategy 30	$B = (1,1,1,0,1)$	31	0.107	0.238
Strategy 31	$B = (1,1,1,1,0)$	30	0.133	0.242
Strategy 32	$B = (1,1,1,1,1)$	29	0.126	0.246

Appendix B Barringer's LCC analysis step process

Appendix B outlines a step process used by Barringer and Weber (1996) for a total life cycle cost (LCC) analysis of a system in order to reach the best decisions on which alternative solution to implement in different organisations.

Step 1: Define the problem that requires LCC

To perform a detailed and accurate life cycle cost analysis, the problem at hand needs to be well developed with an in-depth understanding of what the project entails, including all its intricate details. This necessitates acquiring all possible information about the project and having a sound awareness of important sources from whom/which the information can be obtained.

The reason for performing the LCC analysis needs to be known and all the alternative methods and techniques need to have been considered. The outcome of the LCC analysis is to reach a conclusion about what alternative is best for the current system. This is what needs to be achieved at the end of an LCC analysis (Barringer & Weber, 1996).

Step 2: Look at all alternative solutions with costs involved

An LCC analysis would not be regarded as a complete and accurate analysis of an item or system unless it compared different solutions to a problem. This means that various alternative methods need to be examined to ensure that the best possible solution is implemented for a system.

In terms of maintenance optimisation for a system, three different methods will be considered, namely 'run to failure', 'time-based maintenance' and 'condition-based maintenance'. The cost-optimisation models in Sections 3.2 and 3.3 will be implemented in the LCC analysis and all the alternatives will be compared to ensure that the best and most economical solution is chosen for the system (Barringer & Weber, 1996).

Step 3: Develop a cost breakdown structure

A cost breakdown structure is a method of separating all the costs involved in a system from acquisition to disposal in order to understand exactly which costs can and will affect the decisions made about the system. A variety of different costs are involved in the lifetime of a mechanical system. These can be divided into acquisition and sustaining costs (Barringer & Weber, 1996).

Figure B.1 outlines the costs that can be found in different mechanical systems. Depending on the system at hand, not all the costs in Figure B.1 will be associated with a specific system. Extra costs could also be involved.

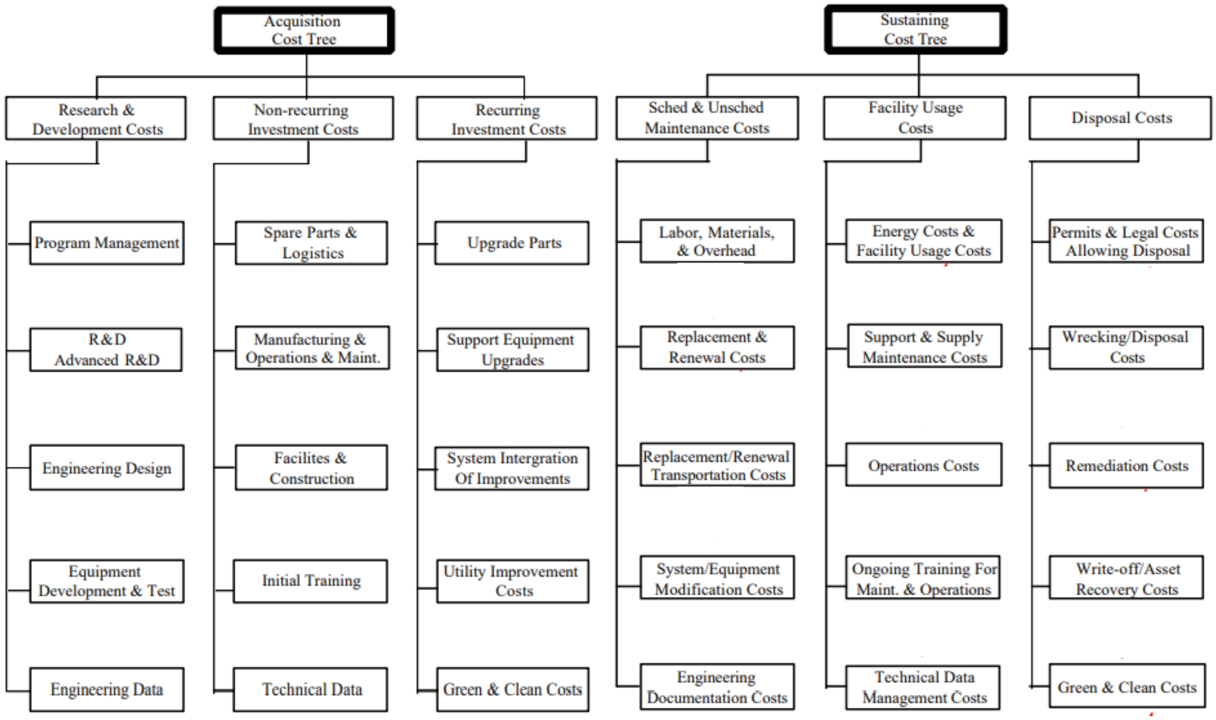

Figure B.1: Cost breakdown structure, adapted from Barringer and Weber (1996)

Step 4: Develop an analytical cost-optimisation model

This is one of the most important processes in the whole LCC analysis since it is the tool that will be used to determine which alternative method related to maintenance is best suited for a certain system. The model needs to look at the net present value (NPV) of the system over a certain time period. This NPV will be compared to the alternatives, resulting in a final decision being made.

All the cost information based on Sections 3.2 and 3.3 needs to be inputted into the model, and the time value of money also needs to be taken into account. The present value of the system per time interval can be computed for various time intervals, and an optimum can be found based on initial constraints. The NPV of a system will allow a capital decision to be made. Maintenance optimisation will be at the forefront of this decision since it is one of the greatest contributors towards the NPV (Barringer & Weber, 1996).

Step 5: Develop breakeven charts for all alternative options

A breakeven chart is used to allow for a visual representation of the alternative methods that could be implemented into a system over a certain life period. This chart allows one to see which alternatives pay back quickly with big returns. Therefore, the chart allows the most desirable alternative to be chosen for a system with a visual comparison to the other alternatives (Barringer & Weber, 1996).

Step 6: Develop Pareto charts for cost contributors within the system

The Pareto chart is a tool that enables all the main cost contributors for each alternative to be itemised and identified. This allows a more careful analysis of these cost contributors. Significant attention needs to be given to trying to reduce their cost contribution. The Pareto chart can also be used to identify the highest cost-contributing components within a system, thus allowing for time to be spent on the items that will be most detrimental to a company if failure occurs (Barringer & Weber, 1996).

Step 7: Perform a sensitivity analysis

The sensitivity analysis allows one to ascertain the level of sensitivity of a specific system in terms of replacement and performing certain maintenance actions at other than the optimum time. Reliability, maintainability, availability and NVP costs are all examined to determine the sensitivity. The effectiveness of a system is often used in this analysis because it assesses reliability, maintainability and availability. This is then plotted against the NPV value and time, allowing the sensitivity of the different alternatives to be seen over a time period (Barringer & Weber, 1996).

Step 8: Study risks of components

This section of the LCC analysis considers the main cost contributors and a number of the failure data criteria when making a decision. These include the reliability, mean time between failures (MTBF), availability, maintainability and survivor functions. The reason is that sometimes a high cost-contributing element has desirable failure occurrences. This means that, even though it may have a high cost, it has a low probability of failing. Thus it can be surmised that, preferably, more time should be spent on items that fail more regularly since these regular failures could add up to more cost than one high cost item failure (Barringer & Weber, 1996).

The data found using the models in Sections 3.2 and 3.3 will be used for this analysis.

Step 9: Make a decision based on cost impact

This is the final step in the LCC analysis. It involves deciding about which alternative to implement, based on all the previous steps. All the data and models need to be considered to ensure that the correct decision for the system is made. This process is imperative as the decision will be carried forward for the rest of the maintenance optimisation process (Barringer & Weber, 1996).

Appendix C Failure data for Caterpillar 789 180 ton haul truck

Table C.1: Failure data for Caterpillar 789 180 ton haul truck

Failure number	Value	Failure number	Value	Failure number	Value
1	78	***28***	555	***55***	214
2	80	***29***	245	***56***	98
3	173	***30***	20	***57***	45
4	50	***31***	4	***58***	96
5	142	***32***	36	***59***	180
6	97	***33***	412	***60***	118
7	44	***34***	497	***61***	8
8	1 141	***35***	308	***62***	66
9	12	***36***	394	***63***	62
10	251	***37***	532	***64***	231
11	1 185	***38***	243	***65***	215
12	1 236	***39***	165	***66***	179
13	236	***40***	107	***67***	26
14	236	***41***	663	***68***	1
15	177	***42***	58	***69***	25
16	62	***43***	155	***70***	85
17	78	***44***	250	***71***	82
18	433	***45***	77	***72***	106
19	689	***46***	21	***73***	159
20	44	***47***	58	***74***	16
21	233	***48***	10	***75***	191
22	1 322	***49***	64	***76***	268
23	2	***50***	70	***77***	15
24	488	***51***	41	***78***	209
25	511	***52***	453	***79***	2
26	86	***53***	14	***80***	32
27	1 176	***54***	258	***81***	22

Failure number	Value	Failure number	Value	Failure number	Value
82	99	***98***	70	***114***	83
83	38	***99***	70	***115***	41
84	62	***100***	6	***116***	18
85	13	***101***	12	***117***	43
86	10	***102***	30	***118***	61
87	15	***103***	28	***119***	56
88	1	***104***	42	***120***	105
89	18	***105***	72	***121***	45
90	34	***106***	16	***122***	2
91	19	***107***	136	***123***	23
92	2	***108***	53	***124***	1
93	135	***109***	442	***125***	1
94	15	***110***	1	***126***	12
95	17	***111***	1	***127***	3
96	215	***112***	264	***128***	28
97	39	***113***	762		

Appendix D Conveyor 3 set-up cost calculations

Appendix D outlines the methodology that was followed in order to gain the setup cost for a failure action on conveyor 3. This cost is one of the main inputs into the model, which was used to analyse the failure data for conveyor 3.

The historical failure data for the conveyor was obtained from the Anglo Operating Platform for the Sishen mine in the Northern Cape, South Africa. As stated in Section 4.8, although failure data from the Anglo Operating Platform was attainable for the conveyor set, historical cost data was not. In order to acquire historical cost data, the 2017 Sishen mine annual dissertation was consulted. Data on the performance and output of the mine was obtained, which allowed for a setup cost to be determined. The calculations for the setup cost follow.

From the 2017 Sishen mine annual dissertation, it was found that 31.1 million tons of iron ore were produced in 2017 with a unit cost of R287/ton. It was assumed that two main conveyors led into the production plant and that the average downtime to fix a failure action on a conveyor was one hour.

Using all this information, Equations D.1 – D.3 could be followed, which enabled the computation of the setup cost.

Using Equation D.1, the hourly production of the plant could be computed.

$$\text{Hourly production} = \frac{\text{Yearly production}}{365 \times 24} \tag{D.1}$$

$$\text{Hourly production} = \frac{31.1 \times 10^6}{365 \times 24} = 3550.23 \text{ tons per hour}$$

Using Equation D.2, the hourly production per conveyor could be computed.

$$\text{Hourly production/conveyor} = \frac{\text{Hourly production}}{2} \tag{D.2}$$

$$\text{Hourly production/conveyor} = \frac{3550.23}{2} = 1775.11 \text{ tons/hour/conveyor}$$

Therefore, from Equations D.1 and D.2, the downtime setup cost due to a failure action could be computed using Equation D.3.

$$\text{Downtime setup cost} = \text{Hourly production/conveyor} \times \text{ unit cost per ton} \tag{D.3}$$

$$\text{Downtime setup cost} = 1775.11 \times 287 = \text{R}509\ 457.8$$

Thus, from Equations D.1 – D.3, the setup cost per failure action was computed as R509 457.8/per hour under the current assumptions.