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MAINTENANCE TIMING OPTIMIZATION: A CASE OF EAST AFRICA PORTLAND CEMENT COMPANY (EAPCC)

BY

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Declaration

I declare that this thesis is my original work and has never been presented to this institution or to any other institution for examination or for any other purpose.

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Certification

I certify that the above-mentioned student carried out the work detailed in this report under my supervision.

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Abstract

Due to intense global competition and increasing demands from stakeholders, companies are striving to improve and optimize their productivity in order to stay competitive. The performance and competitiveness of manufacturing companies is dependent on the reliability and availability of their production facilities. Therefore, it is the objective of the maintenance department to maximize the machine availability. The use of effective maintenance policies is one of the methods that have been used in other manufacturing organizations. However, the main issue in maintenance policy optimization is in determining the optimal time to carry out a maintenance task. If the task is made too early, the components may not have been utilized to full capacity. If the interval is too long, it reflects too high machine downtime due to unplanned maintenance. The purpose of this research is to determine the optimal time for preventive maintenance that can be utilized at EAPCC in order to minimize the downtime, maximize the availability, minimize the maintenance cost, and maximize the productivity and consequently the profitability of this organization.

In order to achieve the objective of the research, a Root Cause Analysis (RCA) was conducted to determine the most critical plant, system and components. Multi-Criterion-Decision-Making (MCDM) was used to determine the most critical plant. The maintenance KPIs that that were used include availability, downtime and number of failures, Mean Time Between Failures (MTBF) and Mean Time To Repair (MTTR). It was found out that Cement Mill 4, the tuff hopper and the crane were the most critical plants, equipment and component respectively. It was found out that the most optimal PM interval for the critical component is 9 months. To deal with the challenge of high downtime on the critical component, three options were proposed: redesign the tuff hopper, replace the crane and use the tool-box. On the long-term objective, it was found out that replacing the crane and redesigning the tuff hopper have the most attractive Net Present Value (NPV).

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List of Notations and Acronyms

Notation	Meaning
ARM	Age replacement model
BRM	Block replacement model
CDF	Cumulative Density Function
CMMS	Computerized Maintenance Management System
C (T)	Cost function at time, *T*
$\mathbf{C_f}$	Cost of failure replacement
$\mathbf{C_p}$	Cost of preventive replacement
CU	Currency Unit
EAPCC	East Africa Portland Cement Company
F(t)	Cumulative distribution function
f(t)	Probability density function
KPI	Key Performance Indicator
MTBF	The mean time between failures
MTTR	The mean time to repair
PA	Pareto analysis
PDF	Probability Density Function
PM	Preventive maintenance
R(t)	Reliability function
$\mathbf{T_r}$	Failure time
T	Optimal replacement time
TBF	Time between failures
TTR	Time to repair
λ(t)	Failure rate function

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1 CHAPTER ONE: INTRODUCTION

This chapter is divided into four main sections. The first section gives an overview of the research background while the second section discusses the problem delineation: the problem environment and the problem statement of the research. The third section deals with the research objectives and research questions while the fourth section includes the scope, limitation and the delimitation of the study.

1.1 Research background

The manufacturing industry has experienced an unprecedented degree of change in the last three decades, involving drastic changes in management approaches, product and process technologies, customer expectations, supplier attitudes as well as competitive behavior (Ahuja et al., 2006). In today's highly dynamic and rapidly changing environment, the global competition among organizations has led to higher demands on the manufacturing organizations (Miyake and Enkawa, 1999). The global marketplace has witnessed an increased pressure from customers and competitors in manufacturing as well as service sector (Basu, 2001; George, 2002).

The rapidly changing global marketplace calls for improvements in a company's performance by focusing on cost cutting, increasing productivity levels, quality and guaranteeing deliveries in order to meet and exceed customers' needs (Raouf, 1994). Organizations that want to survive in today's highly competitive business environment must address the need for diverse product range with state-of-the-art product features, coupled with high quality, lower costs, and more effective, swifter Research and Development (R&D) (Gotoh, 1991; Hipkin and Cock, 2000). In today's fast-changing marketplace, slow, steady improvements in manufacturing operations do not guarantee sustained profitability or survival of an organization (Oke, 2005). Thus the organizations need to improve at a faster rate than their competitors, if they are to become or remain leaders in the industry.

With increased global competition, attention has been shifted from increasing efficiency by means of economies of scale and internal specialization to meeting market conditions in terms of flexibility, delivery performance and quality (Yamashina, 1995). The changes in the current business environment are characterized by intense competition on the supply side and heightened volatility in customer requirements on the demand side. These changes have left their unmistakable marks on the different facets of the manufacturing organizations (Gomes et al., 2006). To meet the challenges posed by the contemporary competitive environment, the manufacturing organizations must infuse quality and performance improvement initiatives in all aspects of their operations to improve their competitiveness (Ben-Daya and Duffuaa, 1995; Pintelon et al., 2006). In an increasing global economy, cost effective manufacturing has become a necessity to stay competitive.

The nature of production technologies has changed tremendously because of the implementation of advanced manufacturing technologies and Just-In-Time (JIT) manufacturing. However, benefits from these programs have often been limited because of unreliable or inflexible equipment (Tajiri and Gotoh, 1992). Historically, management has devoted much of its effort in improving manufacturing productivity by probing, measuring, reporting and analyzing manufacturing costs. Similar efforts in regard to maintenance function productivity are long overdue.

Maintenance, defined as “a set of all activities aimed at keeping an item in, or restoring it to, the physical state considered necessary for the fulfillment of its designed functions”, has been neglected as a competitive strategy in many manufacturing organizations. These inadequacies of the maintenance practices in the past, have adversely affected the organizational competitiveness thereby reducing the throughput and reliability of production facilities, leading to fast deteriorations in production facilities, lowering equipment availability due to excessive system downtime, lowering production quality, increasing inventory, thereby leading to unreliable delivery performance. This has led to lowering of the profitability of many organizations. Samanta (2004) argues that the return on investment on a piece of equipment can be maximized by optimizing its availability.

In financial terms, maintenance can represent 20 to 40 per cent of the value added to a product as it moves through the plant (Hora, 1987; Eti et al., 2006). Further, a survey of manufacturers found that full-time maintenance personnel as a percentage of plant employees averaged 15.7 per cent of overall staffing in a study involving manufacturing organizations (Dunn, 1988). In refineries, the maintenance and operations departments are often the largest and each may comprise about 30 per cent of total staffing (Dekker, 1996). It has been found that in the UK manufacturing industry, maintenance spending accounts for a significant 12 to 23 per cent of the total factory operating costs (Cross, 1988). Bob reported that wasted energy from poorly maintained compressed air systems cost US industry up to $3.2 billion annually (Bob, 2007). Alsyouf showed in a case study that at least 14% of potential improvement in return on investment are directed to contribution of maintenance functions to lost profit, which is due to unplanned stoppages and bad quality caused by maintenance related problems (Alsyouf, 2006). Blanchard demonstrated that a large percentage (e.g. 70% for some systems) of total life cycle cost for a given system is attributed to operating and maintenance activities (Blanchard, 2004). With sobering figures like these, manufacturers are beginning to realize that maintenance optimization is a strategic factor for success (Yoshida et al., 1990). Thus the effectiveness of maintenance function significantly contributes towards the performance of equipment, production and profitability (Teresko, 1992). Kumar asserts that for maintenance to make its proper contribution to profits, productivity, and quality, it must be recognized as an integral part of the plant production strategy (Kumar et al., 2004).

1.2 Company background

The East African Portland Cement Company (EAPCC) started as a trading company importing cement mainly from England for early construction work in East Africa. It was formed by Blue Circle Industries United Kingdom. The name Portland was given due to the resemblance in color of set cement to the Portland stone that was mined on the Isle of Portland in Dorset, England.

Since 1933, East African Portland Cement Company has been Kenya's leading cement manufacturer in the production of world class cement. For example, Blue Triangle Cement, the flagship brand of EAPCC, is well appreciated all over Kenya as a symbol of quality and reliability. The nation's historical structural icons, such as KICC and Thika Super-Highway have been built using Blue Triangle Cement.

The main keys to success of EAPCC have been quality and responsiveness. It is an ISO 9001: 2008 certified company, a mark of professionalism and high standards in operations. EAPCC is also OHSAS certified (Occupational Health and Safety), a mark of world class standards of safety at the workplace. In 2011, it received recognition from the Computer Society of Kenya for Best ERP Implementation, reflecting the successful automation of operations and processes. EAPCC engages in continuous product improvement as well, pegged on changing market trends, technological advancement and dynamic customer needs and wants. The objective of this is to meet or exceed customer needs. The business model of EAPCC is guided by growth, expansion and sustained profitability.

In the last few years, EAPCC has greatly expanded its production capacity. With the introduction of Mill No. 5 and the embrace of coal energy, the Company can presently produce over 1.3 million tons of cement per annum at reduced cost.

1.3 Problem environment

The cement manufacturing process consists of many simultaneous and continuous operations using some of the largest moving machinery in the manufacturing industry. The main processes undertaken by the company include, mining, raw material preparation, clinker manufacturing, cement milling, cement packing, loading and dispatch among other customer care service functions. Cement products produced include cement building blocks, kerbstones and channels, slabs and fencing posts. The company does geological surveys to establish the quality and quantity of available raw materials and from the data obtained, quarry mining plans are drawn and updated as mining progresses.

The limestone is extracted from the earth's crust by the process of blasting. After blasting limestone boulders are transported to the crushing chit and crushed to the required size. The crushed limestone is then transported through belt conveyer to the stacker-reclaimer section. At the factory, crushed limestone and Kunkur are stacked into blending piles. The stacker-reclaimer is used for pre blending of crushed limestone. Reclaimer picks up the required quality of crushed limestone form the stock pile and feeds into the raw mill hopper through belt conveyor. Material is drawn from the piles by a carefully controlled system that cuts across the stockpile, ensuring blending takes place and a uniform raw material quality is achieved. Gypsum, iron ore and pozzolana are also stored in piles. There are different hoppers for the storing of crushed limestone, iron ore and Alumina ore. The stored raw materials from the hopper are proportioned and fed to roller press and subsequently to mill for fine grinding of required fineness. The output of the mill grinding is stored in raw meal silo.

The mill grinds the raw material to a fine powder and dries it using hot exhaust gases from the kiln, a method that conserves energy and reduces production costs. From the raw mill silo the material is extracted and conveyed to the pre-heater section. The powdered homogenized raw mill from the silo is fed to the kiln passes through pre-heaters where raw mill gets partly calcined and converted into clinker at a temperature of about 1300—1450 degree centigrade in the sintering zone of the kiln. The material is calcined and heated in pre-heater and calcined by utilizing kiln waste gases and additional coal finding. This partially calcined material enters into the kiln where the remaining calcinations and clinkerization takes place in the kiln and clinker is discharged into the cooler. The hot clinker is cooled in the grate cooler where cold atmospheric air is drawn in. The clinker from the kiln is cooled in the cooler section and is transported to the clinker stockpile by deep pan conveyor (DPC) to the clinker stock pile, the clinker is transported to cement mill hopper though Deep Bucket Conveyor (DBC). Clinker, with small quantities of gypsum to control setting time, is ground in cement mills that use steel balls. Using compressed air, the finely ground cement is conveyed into cement storage silos. The cement from the mill is transported to storage silo and from there the cement is conveyed to packing plant and is packed in 50kgs bags by rotary packing machine and then directly loaded into trucks/rail rakes and transported to different locations in the country. Figure 1 below shows a summary of the process of processing cement (Sismondo, 2009).

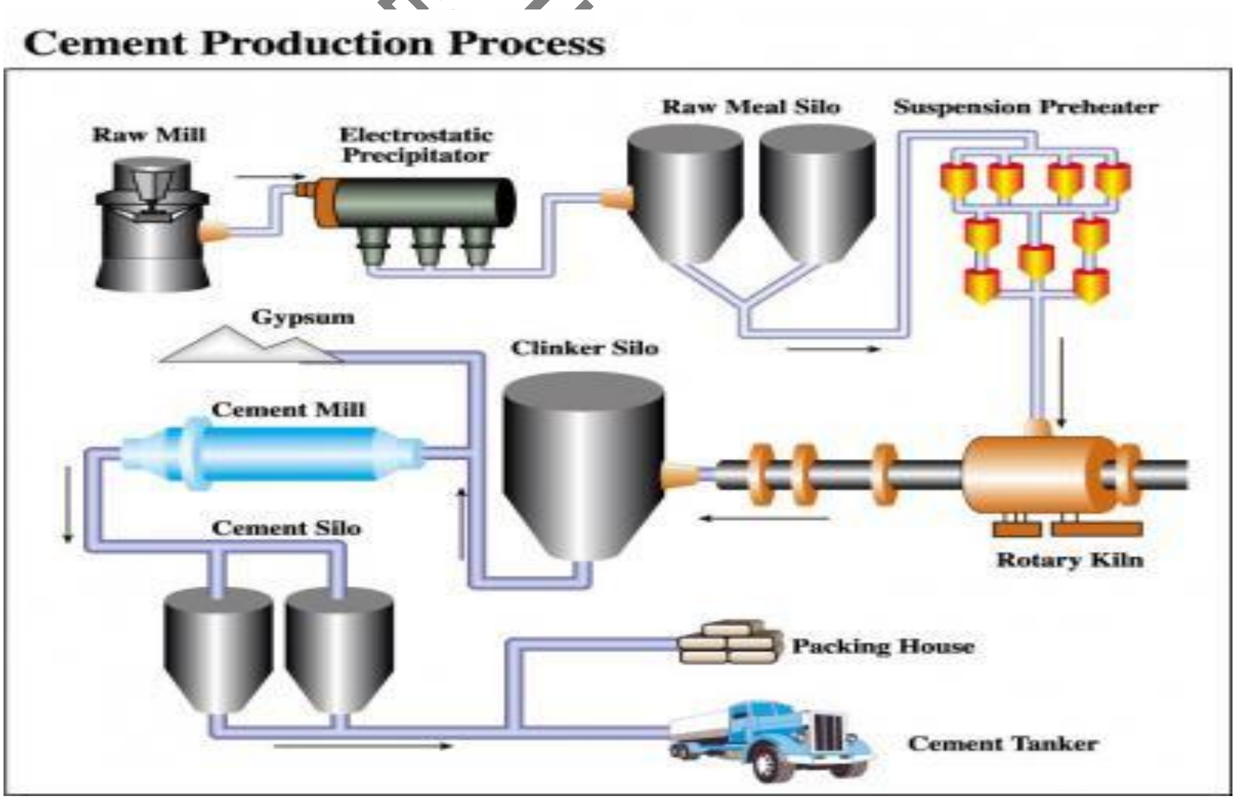


Figure 1-1: The process of cement production

From figure 1 above, we can note that the key plants that make cement a cement processing plant at EAPCC are the raw mill, the crusher, the packers, the cement mills and the kiln. The primary maintenance approach at EAPCC is to do what is necessary to keep the equipment running with maximum production. Some of the key machines and machine elements include motors, bearing lubrication, motor belt replacement, fan blade cleaning, fan wheel balancing, and compressed air system maintenance. Currently at EAPCC, both corrective maintenance (CM) and preventive maintenance are carried out.

1.4 Problem statement

Scheduling of preventive maintenance at EAPCC has been a big challenge to all the stakeholders in the maintenance department. The current maintenance policy at EAPCC is in such a way that all preventive actions are done on every single machine after a year while corrective actions are done when necessary. However, different machines fail differently. Consequently, for some machines the preventive interval is too short while on others, it is too long. This has led to frequent machine breakdowns, which in turn result in to low availability of different machines. The outcomes of this problem have been ranging from production loss, high production cost, high operation and maintenance (O&M) cost, increase in scrap and rework, inability to meet production deadlines, poor company's reputation and loss of integrity. Consequently, profitability and competitiveness have suffered because the companywide objective of producing over 1.5 million tons of cement per annum is rarely met. This problem has necessitated this research.

1.5 Objectives

1.5.1 Main objective

The main objective of this research is to come up with an optimal PR timing whose objective is to minimize machine breakdown, maximize equipment availability and minimize the cost associated with maintenance.

1.5.2 Specific objectives

i. To identify the critical component that causes major machine breakdown
ii. Determine the optimal time of Preventive Replacement (PR) on the critical components identified in (i) above

iii. Determine the most appropriate maintenance actions to be done on the critical components

1.6 Research questions

To fulfill the above objectives, the following research questions will be addressed:

i. Which machines are critical?
ii. *When* should preventive maintenance be done?
iii. *What* type of maintenance action need to be done?

1.7 Justification

Demand for cement has been increasing in Kenya and East African region. For example, in the year 2012/2013, Kenya's cement consumption rose by 9.67% to 3.4 million tonnes compared to 3.1 million tonnes the year before. This can be attributed to the increase in public transport infrastructure projects, increase in urban housing, Vision 2030 flagship projects and the rapidly growing middle class. With the trillion-shilling Lamu Port Project (LAPSETT) in the underway, the demand of cement is expected to rise in the near future. With such opportunities, the operations at EAPCC must be optimized so that it can compete effectively and efficiently.

In the same period, competition in the market has intensified with new entrants-National Cement and Savannah Cement-and expanded capacities by existing producers such as Bamburi Cement and Athi River Mining. With the expected venture of Dangote Cemeny Company worth $400 Million, the competition is expected to be stiffer. Competition demands that EAPCC must minimize the cost of doing operations so that the profitability of the company can be maximized. Consequently, while launching the financial results of 2012/2013, the management prioritized the following objectives for the 2013/2014 financial year:

i. To return the company to full operation and maximize on its profitability
ii. To Improve productivity and optimize capacity utilization
iii. Invest in Kiln upgrade, new packer and waste heat recovery for own-power generation
iv. Cost containment initiatives, stringent waste management and innovation to help keep costs down
v. Aggressive risk management and value addition initiatives
vi. Employ service delivery innovations to improve customer service turnaround

vii. Minimize accidents and incidence occurrences.

Optimization of PM timing can be used in meeting some of the objectives above. For example, optimization of maintenance policy can lead to a minimization of maintenance costs and increase in the availability. An increase in plant availability can in turn lead to an increase in productivity and consequently, an increase in the revenue. This may lead to optimizing the profitability and hence being competitive.

1.8 Motivation of the study

One of the methods that have been discussed broadly as a strategy in optimization of maintenance is optimizing the PM timing. However, in the manufacturing industry, the application of PM timing is usually based on the recommendation provided by the original equipment manufacturer (OEM). The recommendation based on OEM may not give benefits for the entire machine lifetime because the covariates effects (external factor) of the current machine condition are not taken into account. Labib (2004) stated maintenance that the optimization of PM interval should be based on the real machine condition because the machine may operate in a different environment. This finding was supported by Tam et al. (2006) who suggested that the intervals (time) set by OEM may not be optimal due to the operating conditions that may be very different and the actual outcomes that may not satisfy plant requirements. Therefore, it is necessary to revise or update this interval based on the current machine condition by considering the covariates effect in order to maximize its benefits. The objective of customizing the PM interval in line with the operation conditions at EAPCC is the motivation behind this research.

1.9 Scope and limitations

Due to the time and cost constraints, the proposed model does not take into consideration the covariates effect (external factor) of the current machine condition. These include factors such as technological advancement and weather conditions. Although covariates play an important role in the aging of the machine, including them in the model is not easy. This can be attributed to the fact that the available data at EAPCC is only for machines and not for the external factors.

In addition to that, this research will not cover the effect of maintenance supportability on the determination of optimal maintenance policies. Maintenance supportability includes maintenance procedure, procurement of maintenance tools, spare parts and facilities, logistic administration and documentation.

1.10 Definition of terms

System availability: This is the ability of a system to be in a state to perform a required function under given conditions at a given instant of time or during a given time interval (Neubeck, 2004).

System reliability: This is defined as the ability of a system to perform a required function under given conditions for a given time interval (O'Connor P. D., 2002).

System maintainability: This is the ability of a system under given conditions of use, to be retained in, or restored to, a state in which it can perform a required function, when maintenance is performed under given conditions and using stated procedures and resources (Neubeck, 2004).

MTBF: Mean time between failures is the predicted elapsed time between inherent failures of a system during operation (Jones, 2006)**.**

MTTR: Mean time to repair is a basic measure of the maintainability of repairable items that represents the average time required to repair a failed component or device (Colombo, 1988).

Downtime: This refers to a period of time that a system fails to provide or perform its primary function; it is used to refer to periods when a system is unavailable.

Up time: Time interval during which an item is in an up state.

Maintenance effectiveness: mathematically, maintenance effectiveness can be defined as a ratio between the downtime and the operating time

Maintenance: Combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function.

Failure: Termination of the ability of an item to perform a required function.

Preventive maintenance: Maintenance carried out at predetermined intervals or according to prescribed criteria and intended to reduce the probability of failure or the degradation of the functioning of an item.

Condition based maintenance: Preventive maintenance based on performance and/or parameter monitoring and the subsequent actions.

Corrective maintenance: Maintenance carried out after fault recognition and intended to put an item into a state in which it can perform a required function.

Inspection: Check for conformity by measuring, observing, testing or gauging the relevant characteristics of an item.

Repair: Physical action taken to restore the required function of the faulty item.

1.11 Thesis overview

The overview of this thesis is as follows: Chapter 1 is generally the introduction to the thesis while Chapter two provides a critical literature review of the related subjects. Chapter three is a methodology which deals with data collection research strategy and research approach. In Chapter four, the collected data is analyzed. Chapter five presents the discussion of the results from chapter four while Chapter six addresses the conclusions and recommendations of the future research.

2 CHAPTER TWO: LITERATURE REVIEW

2.1 Overview of maintenance

According to Gilbert (1985), maintenance is defined as a set of all activities aimed at keeping an item in, or restoring it to, the physical state considered necessary for the fulfillment of its designed functions (Gilbert, 1985). However, The Maintenance Engineering Society of Australia (MESA) adopted a wider definition. MESA added activities such as replacement decisions and the design modifications in the scope of maintenance to enhance reliability. Thus, MESA defined maintenance as “all engineering decisions and associated actions necessary and sufficient for the optimization of specified capabilities” (O'Connor P. D., 1991). The scope of maintenance has greatly changed and it now includes equipments’ specification, spare parts acquisition, human resource planning, performance evaluation, operation, improvements, and disposal. According to Tsang, this wide context is what is called physical asset management (PAM) (Tsang, 1973).

The roles of maintenance are also changing with the changes in technology and customers’ needs. Initially, maintenance was seen as just a way of keeping the system running regardless of the associated effectiveness and efficiencies. Many scholars are expanding roles of maintenance in any given manufacturing organization. According to Muchiri, Maintenance has to provide the required reliability, availability, efficiency and capability of production system in accordance to the need of these characteristics (Muchiri P. N., 2009).

2.2 Maintenance policies

A maintenance policy can be defined as a rule of the set of rules describing the triggering mechanism for the different maintenance actions. The maintenance policies considered here are:

i. Failure based maintenance (FBM) - This it is a purely reactive policy where corrective maintenance (CM) is done only when the equipment fails.

ii. Time based or use based maintenance (TBM/UBM) – This is a preventive policy where maintenance is carried out at specified time intervals. For UBM, intervals are measured in working hours while in TBM intervals are in calendar days.

iii. Condition based maintenance (CBM) - This is a predictive policy where PM is carried out whenever a given system parameter or condition approached or reaches a predetermined value or situation.
iv. Opportunity based maintenance
v. Design-out maintenance (DOM)

2.2.1 Failure-based maintenance (FBM)

FBM policy is a pure reactionary policy, where maintenance is performed only when a machine fails. This policy usually requires operating in an emergency mode with the aim of getting the equipment back in service as quickly as possible and in virtually new condition. In this policy, maintenance is carried out after a breakdown.

Breakdown maintenance can be defined as the maintenance which is required when an item has failed or worn out, to bring it back to working order. It is carried out after fault recognition and intended to put an item into a state in which it can perform a required function. This maintenance is often most expensive because worn equipment can damage other parts and cause multiple damage. Corrective maintenance (CM) is probably the most commonly used approach, but it is easy to see its limitations. When equipment fails, it often leads to downtime in production. In most cases this tends to be costly to the business. Also, if the equipment needs to be replaced, the cost of replacing it alone can be substantial. Corrective maintenance is carried out on all items where the consequences of failure or wearing out are not significant and the cost of this maintenance is not greater than preventive maintenance. This type of maintenance can be regarded as unplanned, emergency, breakdown maintenance.

The discussion of the history of maintenance has shown that a fire-fighting maintenance strategy in terms of reactive maintenance leads to unexpected machine breakdowns. Furthermore, the maintenance department is busy most of the time repairing machines. It does not have the time to do maintenance tasks on a regular basis nor does it have the time to improve the maintenance system within the production process. This leads to the fact that preventive maintenance tasks are neglected, resulting in more machine breakdowns. Machine breakdowns exhaust the maintenance department’s capacity to maintain or improve the production system on a regular basis. In the long run, there will be a situation with many unexpected machine breakdowns and an overloaded maintenance department. However, if the consequences to the operation due to the unplanned failure are less than the value added to the operation by changing the component prior to future, run until failure is a viable option.

A key concern for any plant manager is the adequacy of net throughput. When the manufacturing process generates unacceptable throughput, the consequence is an increase in throughput pressure. From past experience the response is to work harder to meet the demand. Working harder involves utilizing existing equipment capacity and labor force more intensively; that can include reworking defective throughput. The unacceptable throughput may include lower than expected gross throughput due to manufacturing equipment speed or power losses that can also bring about throughput pressure. The net result is increased gross throughput requirements, which demands more labor force efforts as well as equipment capacity. When equipment capacity is adequate, by increasing worker efforts, using overtime or adding workers through reassignment, the gross throughput is increased to alleviate throughput pressure. But on the other hand, more utilization of equipment gradually reduces machine reliability and therefore increase machine breakdown rate which consequently increases CM rate. More breakdowns will reduce the available time for production and therefore reduces the net throughput. As the machine reliability falls, on the other hand, process quality will be dropped and therefore acceptable throughput will be dropped which accordingly will reduce the net throughput and therefore to aggravate the problem.

2.2.2 Time based or use based maintenance (TBM/UBM)

In TBM/UBM approach, preventive maintenance (PM) is performed based on traditional use or time usage (Mann et al, 1995). The objective of TBM is to determine the optimum intervals (time) of PM in order to minimize the total cost of failure (reducing failure rate) and machine downtime (production lost). TBM/UBM is usually applied on single or non-repairable component such as machine tool (Jianqiang and Koew, 1997; Bahrami et al, 1998). In addition, TBM/UBM is feasible when the machine or component is in deteriorating state (or other word in increasing failure rate) and the cost of PM is less than the cost of CM (Mann et al, 1995). In relation of this, Mobley (1990) stated that the cost of CM can be in excess of three times of PM. Reasons for this included:

- CM will extend the downtime due to unavailability of components, or labor.
- CM can result in overtime.

- CM is not executed as efficiently as PM.

This type of maintenance policy relies on the estimated probability that the equipment will breakdown or experience deterioration in performance in the specified interval. The preventive work undertaken may include equipment lubrication, cleaning, parts replacement, tightening, and adjustment.

A major obstacle in the effective application of this strategy is determining the optimal replacement/repair time. If the repair is made too early, the components may not have been utilized to full capacity. If the interval is too long the result is an unplanned repair. To complicate matters, most manufacturers recommend preventive maintenance intervals that must be followed to preserve warranty rights. The determination of these intervals by the manufacturer may not be optimum for a particular mining operation, resulting in excessive maintenance costs to the company.

2.2.3 Condition based maintenance (CBM)

Condition-based maintenance (CBM) involves monitoring the condition of mission critical and safety-critical parts in carrying out maintenance whenever necessary to avoid hazards rather than following a fixed schedule.

The concept of CBM was first introduced by the Rio Grande Railway Company in late 1940s and initially it was called “predictive maintenance.” The railway company used CBM techniques to detect coolant, oil, and fuel leaks in the engine by trending changes in temperature and pressure readings. The CBM monitoring techniques served as a great success in terms of reducing the impacts of unplanned failures and identifying when to fix a leak or replenish a coolant or oil sump. The US Army caught on to this idea very early and later on adopted it as a key maintenance strategy for supporting their military equipment.

CBM concepts and applications have emerged in several industries throughout the 1950s, 1960s, and early 1970s. Automotive, aerospace, military, and manufacturing are the main industries where CBM has been embraced and have shown several benefits in both efficiencies and cost savings. Now very large organizations and companies are investing and involved with CBM technology applications including the US Department of Defense (army, air force, navy, and marines) and companies like GM, Honda, GE, Digitech, Honeywell, and others. Advancements in information technology have added accelerated growth in the CBM technology area by enabling network bandwidth, data collection and retrieval, data analysis, and decision support capabilities for large data sets of time series data. The targeted data monitored from a vehicle or any system can give deeper insight on system performance, system health, and root cause of failures, along with forecasting the remaining useful life of the system or a subsystem. This serves as a huge advantage for sustaining the mission critical systems used in aerospace, military, maritime, automotive, manufacturing, and other industry domains. These valuable applications and benefits have pushed CBM as a key capability area to apply to a company's product line – be it automobiles, planes, weapon systems, or other products requiring regular maintenance. These industries are focusing on CBM concepts and maintenance strategies by designing CBM technology enablers into their current and future system architectures.

Figure 2.1 below shows the predictive maintenance cycle

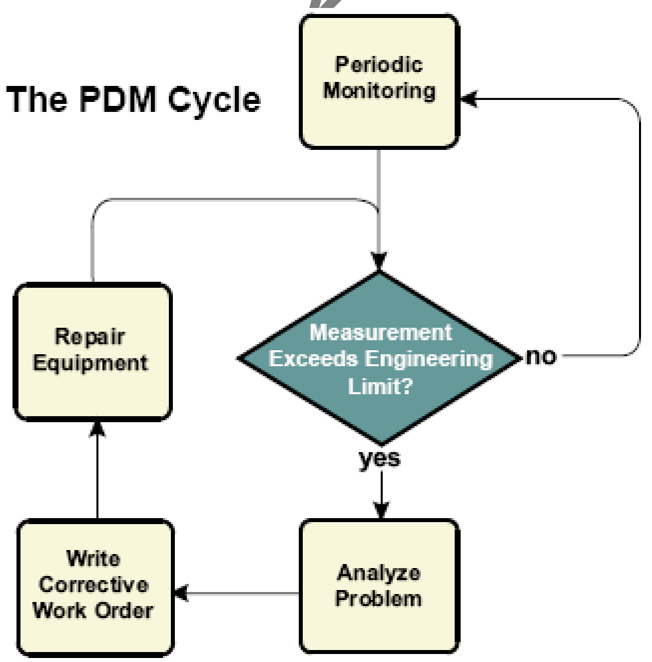


Figure 2-1: Predictive maintenance cycle

As industries move into the future, where machines are unmanned and human monitored as closely as they have been in the past, the need for CBM will increase. Robotic systems, unmanned vehicles, windmill systems, manufacturing systems, and oil pumping systems are just a few system examples that could gain many benefits out of CBM concepts and maintenance strategies. Businesses could save significant money or improve operational efficiencies if they adopt CBM as a maintenance strategy. It may mean reduction in staff, reduction in supply footprint, cost avoidances on second- and third-order failure effects, reduction in downtime, and other benefits applicable to their business domain.

In the past, various attempts have been made to improve maintenance processes. Recently the focus has been shifted toward CBM due to its predictive nature and positive impacts on the supply chain and fleet management. CBM intelligence is centered on the prediction algorithms used for fault prognosis. In the following section, we have addressed some existing efforts toward improvement of fault prediction and CBM.

Lu et al. (2007) investigated a predictive CBM capability to predict a deteriorating system's future condition. The degradation states are modeled as continuous states and fault probability is dependent on random variables. The proposed strategy is centered on the maintenance cost, while prediction accuracy becomes the most important factor.

Specifically when CBM is applied for critical systems it is primarily to detect and predict the fault conditions within very small intervals. According to the authors, a good maintenance system has to have good balance between prediction accuracy and maintenance cost.

Furthermore, Rausch (2008) has investigated a CBM methodology that establishes the relationship between continuous state/time degradation model and CBM systems. This approach is not dynamic as he mentioned in his future research. This has been a center of attention in our proposed system.

Yam et al. (2001) have developed an intelligent decision support system for CBM. This system is based on a recurrent neural network that adds capability parameters to predict future fault conditions. The neural network approaches are efficient, but relatively slow. These approaches also require large set of data for training which turns out to be a big restriction for a real-time application (Yam, 2001).

Chen and Trivedi (2005) used semi-Markov's decision process (SMDP) for optimization of a CBM policy. Chen has proved that optimization over inspection rate as well as maintenance policy is better than that of only over inspection rates. SMDP is well-established approach and good for modeling numerous failure scenarios. On the other hand, it requires a large data set for training and it is not well suited for time-dependent degradations. As a result, it makes SMDP as not very useful for CBM applications, especially for highly critical and time varying types of failures (Chen D. a., 2005).

Barbera et al (1996), proposes a CBM model which assumes that failure rate of the system depend on the variables of the system state and fixed inspection periods. Then the maintenance action is optimized such that the long term costs of maintenance actions and failures are minimized. Later Barbera et al (1999) in developing their previous model, considered a CBM model with fixed inspection periods and exponential failures for a two-unit system. The condition of each unit in equal periods is monitored and after each maintenance action, the state of the system returns to its initial state. In their model, in each inspection interval the failure occurs only once. Also the failure rate depends on the state of the system.

Westberg and Kumar (1997) suggest an approach based on reliability that inspection periods and maintenance thresholds are such estimated that the global cost per unit time is minimized. Grall et al (2002) focus on the analytical modeling of a condition based inspection/replacement policy for a stochastically and continuously deteriorating single unit system. They consider both the replacement threshold and the inspection schedule as decision variables for the problem. They minimize the long run expected cost per unit time by the stationary law for the system state. Amari and McLaughlin (2004)utilized a Markov chain to describe the CBM model for a deterioration system subject to periodic inspection the optimal inspection frequency and maintenance threshold were found to maximize the system availability. Castanier et al (2005) consider a two unit system which can be maintained by good as new preventive or corrective replacements.

Barata et al (2002) uses Monte-Carlo simulation to model the continuously monitored deteriorating systems. They assume that after each maintenance action a random amount of improvement is made on the state of the system which is independent of current system state. Then the optimized thresholds of maintenance are such found that the total expected cost of system be minimized

There are three basic steps used to carry out CBM: data acquisition, data processing, and decision-making. The data acquisition stage of CBM collects the real time data from a plant floor. Based on the overall objective of the production line and the type of machines, various sensors may be used to generate data. Micro-sensors, ultrasonic sensors, and acoustic emission sensors are some of the widely used sensors, which can be designed to generate useful data from a production line. The data collected are categorized into two types: event data and condition data. Event data record the occurrence of events on a plant floor such as machine failures, maintenance actions, overhauls, replacements, etc., while condition data are obtained from the sensors to infer the health of the machines. The data hence acquired are further processed and analyzed either locally or at a central location to be fed into decision support systems (DSS).

Coetzee (2004) identified that CBM is normally suitable when failure rate is dependent on operating condition rather than time. A complete CBM program must include monitoring and diagnostic techniques. These techniques include vibration monitoring, acoustic analysis, motor analysis technique, motor operated valve testing, thermography, tribology, process parameter monitoring, visual inspections and other non-destructive testing techniques.

Vibration analysis is applicable to all mechanical equipment; its profile analysis is a useful tool for predictive maintenance, diagnostics and many other uses. Ultrasonic, just like vibration analysis, is a sub set of noise analysis. The only difference in the two techniques is the frequency band they monitor. On the other hand, tribology is the general term that refers to design and operating dynamics of the bearing-lubrication-rotor support structure of machinery. Two primary techniques are being used for predictive maintenance; these techniques are lubricating oil analysis and wear particle analysis. Lastly, thermography can be used to monitor the condition of the plant machinery, structures and systems. It uses instrumentation design to monitor the emission of infrared energy to determine operating conditions.

2.2.4 Opportunity based maintenance (OBM)

In opportunity maintenance (OM), the preventive maintenance (PM) is done only or mainly when failures force the system to stop. Opportunistic maintenance basically refers to the scheme in which preventive maintenance is carried out at opportunities, either by choice or based on the physical condition of the system.

The policy is most useful and most easily applied to systems which run continuously and have a high cost rate of down-time. A very complex series system, consisting of thousands of items subject to failure, will usually have a failure every few hundred hours even when PM is applied, whereas the optimal intervals for PM are mostly measured in thousands of hours. There may, however, be a critical size of system, as measured by the total expected failure down time, below which the opportunities can never be adequate.

An advantage of this opportunistic maintenance is that corrective repair combined with preventive repair can be used to save set-up costs. Note that by combining both types of repair, one may not know in advance which repair actions should be taken, and thus sacrifices the plannable feature of preventive maintenance. However, there are many situations in which opportunistic maintenance is effective. For example, when corrective repair on some components requires dismantling of the entire system, a corrective repair on these components combined with preventive repair on other or neighboring components might be worthwhile. Another instance is when a certain corrective repair on failed components can be delayed until the next scheduled preventive maintenance.

OBM has been first studied in Radner and Jorgenson 1963, and in McCall 1963. Since then, many extensions of opportunistic maintenance have been introduced and studied in the literature. Berg (1976) studies a system with two identical components with exponential distributed lifetimes, for which the non-failed component as well as the failed component are both replaced by a new one if the age of the non-failed component exceeds a threshold. Zheng and Fard (1991) examine an opportunistic maintenance policy based on failure rate tolerance for a system with k different types of components. These and other opportunistic maintenance models have been summarized in Dekker, van der Schouten and Wildeman (1997) and in Wang (2002). All these models, however, address the optimization issues for components operating independently.

2.2.5 Design-out maintenance (DOM)

Design-out maintenance (DOM) is a proactive policy, in which focus lies on improving the design of the installation with the objectives of lowering the mean time to repair (MTTR) or increasing the mean time between failures (MTBF). Some of the important concepts that are considered during DOM include ergonomics, systems reliability, economics, modularity and standardization.

2.3 Maintenance policies optimization models

A maintenance model is defined as mathematical model which aims to find the optimum balance between the costs and benefits of maintenance while taking all kinds of constraints into account (Scarf, 1997). There are plenty of maintenance optimization models in the academic literature, but not all of them have potential for successful application. It is important to identify the models that are applicable to practical problems. Also a lot of optimization techniques exist to solve the generation and maintenance scheduling problems. Unfortunately, not all of them are suitable for practical problems.

Dekker performed a review on the maintenance optimization models, and pointed out that that there is a significant gap between maintenance theory and practice (Dekker R. , 1996). The author also pointed out that the successful application of maintenance optimization is not obvious, and that many models have been developed for math purposes only. Mathematical analysis and techniques, rather than solutions to solve real problems, have been central in many papers on maintenance optimization models. Furthermore, Dekker pointed out that industries are not interested in publications (Dekker R. , 1996).

To have academics study industrial problems, they have to be exposed to the real industrial problems and be rewarded if they solve them. Scarf also performed a review on the development of mathematical models in maintenance (Scarf, 1997), and he also pointed out that mathematical models in maintenance should consider the applicability in real industry, not just the academic interests.

2.3.1 Preventive Maintenance models

PM is a process of making decisions regarding when is the best time the machine should be replaced in order to minimize the failure frequency, maximize equipment reliability, maximize the equipment availability and minimize failure cost (Bahrami-Ghasrchami et al., 2000). The PM strategy involves performing preventive tasks such as repair, replacement or inspection at pre-determined interval (Gertsbakh, 2000). This interval is based on scientific approach such as PM optimization. The aim of PM's strategy is to reduce the failure rate of the machine or component, thus the machine downtime and maintenance (repair or replacement) costs can be reduced.

Alternatively, PM can be seen as the care and servicing by personnel for the purpose of maintaining equipment and facilities in satisfactory operating condition by providing for systematic inspection, detection and correction of incipient failures either before they occur or before they develop into major defects. This type of maintenance has many different variations and is subject to various researches to determine the best and most efficient way to maintain equipment. Recent studies have shown that Preventive maintenance is effective in preventing age related failures of the equipment.

Preventive Maintenance (PM) first developed at General Electric. PM is undertaken in advance of the interruption of production and major breakdown and strives to keep production flow continuously running. It is defined as the planned maintenance of plants and equipment in order to prevent or minimize breakdowns and depreciation rates. It is the procedure adopted in most of the companies to maintain desirable and reliable operating conditions of equipment and machinery. One drawback of PM policy is that some components may be over maintained, i.e. replaced prematurely. In the literature, two basic PR models that are widely discussed are the Block Replacement Model (BRM) and the Age Replacement Model (ARM) (Savsar, 2006).

2.3.1.1 The Age Replacement Model (ARM)

In ARM, a component is always replaced according to its age, *T* or failure, whichever occurs first, where *T* is constant (Barlow and Hunter, 1960). In fact, ARM is more practical and has more benefits as compared to BRM. For example Jiang et al (2006) shows that the cost saving by using PR based on ARM is higher compared with BRM. This is because PR by using BRM performs more PR actions (more than needed), which reflects to high maintenance cost and production lost. According to Jiang *et al.* (2006) age replacement model is more useful in practical application and it gives more benefit in terms of cost saving. In literature, the applications of these models are widely reported. One of them is from Huang *et al.* (1995) that applied age replacement model in order to minimize the cost of failure for a case of drilling tools replacement problem.

The general mathematical form of ARM developed by Barlow and Hunter (1960) is presented in the equation below

$$C(T) = \frac{C_f F(T) + C_P R(T)}{\int_0^T R(t)\,dt}$$

The main objective of this model is to determine the optimum time *T* by minimizing the cost function *C* (*T*).However, the equation above neglects the time to perform a repair. Pintelon (2006) included the time to perform a maintenance activity such as repair in the equation 1 above. Therefore, the adjusted cost minimization model is as shown in equation (2) below

$$E[cost] = \frac{C_f * F(T) + C_p * R(T)}{\int_0^T t dF(t) + t_r * F(T) + (T + t_m) * (1 - F(T)}$$

Where C (T) is the cost function, C_p is the cost of preventive maintenance, C_f is the cost of corrective maintenance, F (T) is the cumulative failure distribution function, R (T) is the reliability function, T is the optimum time of replacement, t_r is the time required to perform CM and t_m is the time required to perform PM.

Pintelon (2006) went ahead and suggested ways of solving the integral part in the equation 2 above. For a Weibull distribution, the equation can be approximated with the Taylor's series as shown in equation 3 below (Pintelon L. , 2006)

$$\int_0^T t dF(t) = \frac{\beta}{\tau}\sum_{k=1}^{\infty}(-1)^k\left\{\frac{(u^{\beta})^{k+1}}{k!}\right\}$$

2.3.1.2 Block replacement model

In BRM, a component is replaced at constant intervals or time irrespective of the age of the component while failure replacements are done whenever necessary (Barlow and Proschan, 1965). However, BRM is not a popular model for real application. This can be attributed to the fact that BRM exist in complicated form and practically it is difficult to apply. Moreover, according to Bahrami et al (2000), BRM has the undesirable characteristic that relatively good components are replaced more frequently than required. Consequently, it leads to high maintenance cost and increase in downtime.

Equation (3) is the general mathematical form of BRM given by Barlow et al. (1965).

$$C(T) = \frac{C_p + C_f M(T)}{T}$$

Where M (T) is the expected number of failures per any given time

Glasser (1969) stated that the main obstacle to solve BRM is the determination of the expected number of failures M (T). Therefore, Bahrami-Ghasrchami et al. (2000) proposed a more simplified BRM as shown in Equation (2.5) below.

$$C(T) = \frac{C_p + C_F F(T)}{T}$$

According to Bahrami-Ghasrchami et al. (2000), the expected number of failures is approximately equal to the cumulative density function of the distribution in question.

2.3.1.3 Applications of BRM and ARM

In the literature, the application of the BRM and ARM models in solving various PM problems is widely reported. For instance, Jiang et al. (2006) considered ARM and BRM in a study on the effect of the optimal replacement policy in terms of the relationship between preventive effect and cost saving. Nakagawa and Mizutani (2009) modified ARM and BRM for the replacement policy of finite time span cases, with the motivation that the working times of most units are finite in actual fields. Huang et al. (1995) proposed a standard solution of ARM in order to minimize the replacement cost of failure in the case of a replacement drilling tool. Jianqiang and Keow (1997) went ahead and modified the ARM used in a computer-integrated manufacturing environment. From the model, they determined the optimum time of tool replacement in order to minimize failure and production cost. Another important research in the area of PM optimization was done by Lai and Chen (2006), who applied the principle of ARM in developing a periodic replacement policy for a two-unit system with a failure rate interaction between units. The aim of this policy is to determine the optimal time of periodic replacement that minimizes the cost per unit time. This work was redone by Chien and Sheu (2006), who extended the optimal replacement policy based on ARM with a minimal repair of the system subject to shocks. The aim of this policy is to determine the optimal pair of minimal repair and replacement that minimizes the long-run expected cost per unit time.

In another paper, Chien et al. (2006) proposed a generalized replacement policy based on the ARM principle by considering two types of failure, namely, type I and type II. The basis of this policy is that a system is replaced at the *n*th type I failure or first type II failure, or at age *T*, whichever occurs first. Failures are random in nature. Consequently, Kenné et al. (2007) applied ARM in formulating an analytical model for the PM policy in a production environment subject to random machine breakdowns.

One of the challenges in implementing the PM models is associated with the complexities in solving mathematical problems. Bahrami-Ghasrchami et al. (2000) proposed a new perspective of BRM to reduce the complexities in solving the model, which is applicableon a machine tool in the crankshaft line at a car engine manufacturing company.

The assumption that after a PM activity, the machine becomes as good as new (AGAN) was used in optimizing PM for a very long time. However, Abdel-Hameed (2006) proposed an imperfect maintenance policy based on BRM in order to decide whether to repair or replace a device at failure depending on its age at failure.

2.3.2 Inspection models

Inspection is a process of identifying the current state of the machine by detecting the hidden failure or sign that may lead to major damage and it is usually applies on complex system (Jardine, 1973). Hence, preventive actions such as minor modification, minor repair, minor replacement and/or cleaning can be taken before the major failure occurs (Hauge et al, 2002). Examples of inspection activities are physical records (checking) and condition monitoring techniques such as vibration, noise, radiation, oil and temperature tests. The benefit of inspection is to prevent the machine from major failure (Bahrami et al, 1998). Many inspection models have been proposed to determine the optimum time to carry out the inspection and the earliest basic model was introduced by Barlow et al (1963). Following the introduction by Barlow, various inspection models have been developed and modified based on various case study problems.

For example, inspection model is widely applied on emergency and storage equipment or system. For instance, Jardine (1973) proposed an optimal inspection model on the equipment that is used in emergency condition such as fire extinguisher and alarm system. The benefit of this model is to determine the optimum time of inspection in order to maximize the availability of these equipment that used in emergency condition. Ito and Nakagawa (1995) suggested an optimal inspection model for storage system such as weapon equipment. The objective of this model is to determine the optimum time of inspection to maximize the reliability of this storage system.

In other cases, inspection model also has also been applied for the case of randomly failing or randomly shocks system. For instance, Mathew and Kennedy (2002) developed an optimal inspection model based on failure due to random shock load. The objective of this model is to reduce failure frequency as well as to minimize the failure cost. Chelbi and Ait-Kadi (1999) and (1995); Hariga (1996) developed and proposed an inspection model for determining the optimal inspection time for a system subjected to random failure. The objective of this model (inspection model) is to minimize the cost of preventive and corrective action. Chelbi and Ait-Kadi (2000) proposed the inspection models for the case of randomly failing system, which the objective is to maximize the system availability.

2.3.3 Cost models

The area of cost optimization in maintenance has been heavily researched. Salonen and Deleryd (2011) modeled the costs of poor maintenance by studying the cost effects of quality in both preventive and corrective maintenance. Tam and Price (2008) developed an investment model for maintenance, which minimizes the sum of three cost categories: the costs of maintenance resources, the costs of planned downtime, and the costs of quantified risks. Oke (2005), on the other hand, has developed a profitability model for internal maintenance departments of industrial companies. Thus the perspective of Oke's model is that of a customer company. In addition, the cost categories are not specified in that model.

Traditional cost models assume that lost production dominates the downtime cost and neglect discontinuities due to stock-piles exhaustion and lost raw material. These models assume constant production rates and unit prices, and then downtime costs rise linearly with maintenance service time (Jardine A. T., 2006). Vorster and De la Garza segregate different sources for the consequential costs and propose a non-linear time-dependency of downtime and intervention costs (Vorster M. D., 1990).

Analytical results to quantify downtime costs are generally difficult to obtain. For example, Roman and Daneshmend use simulation to study the effect of contractors on service level in open-pit mines (Roman, 2000). Quintana and Ortiz consider simulation for resource assignment in a maintenance shop (Quintana, 2002). Cor (1998) uses a similar strategy to quantify the time and economic impacts of operational changes. These changes may include alterations to the sequence of work, to the design, or non-stationary conditions. As a consequence, they may influence the quantity and type of resources required to perform the works, and logically, on equipment idle time and usage. A supplementary strategy considers the use of past information: Edwards and Yisa (2001) use regression analysis to predict the expected downtime cost rate for tracked hydraulic excavators in opencast mining industry (D.J. Edwards, 2001).

Vorster and Sears propose what they call failure cost profiles which measure the expected cost per unit time in terms of the duration of the downtime interval. For a fixed repair time, they introduce a cost-related criterion that also takes into account the relative productivity of multifunctional equipment. By doing so, they are able to decide replacement and task assignments for a fleet of similar equipment (Vorster M. S., 1987).

The customer-service provider relationships management has been modeled for example by Hui and Tsang (2006). However, their model focuses solely on the perspective of the customer. Komonen (2002) has developed a cost model for industrial maintenance. This model is very academic by nature and focuses on finding economies of scale in industrial maintenance business by using regression analysis. Also in this case, the perspective is that of a Service-based company. Models that integrate qualitative and quantitative perspectives exist in maintenance performance measurement. For example Alsyouf (2006) has developed a model which illustrates the impact of maintenance actions on the return on investment.

2.3.4 Integrated models

As it can be noted from the above examples, maintenance optimization requires the intersection of more than one objective function. In practice, the application of PR model has been modified and extended based on BRM or ARM in order to solve many maintenance problems and it is usually applies to non-repairable component. Jianqiang and Keow (1997) modified the ARM that applied in computer-integrated manufacturing environment. From the model they determined the optimum time of tool replacement in order to minimize the failure, maximize the availability and minimize the production cost.

Lapa et al. (2006) presented a model for preventive maintenance planning based on reliability and cost (Lapa, 2006). Xing et al. (2011) presented a model based on analysis of the reliability of weapons system under the conditions of variable maintenance period. In this paper an optimization model was established on the basis of relationship between the preventive maintenance cost and the corrective maintenance cost of equipment maintenance period (Xing, 2011).

Aghezzaf et al (2007) proposed an integrated production and preventive maintenance planning model. The main objective of this model was to determine an integrated production and maintenance plan with the objective of minimizing the expected total production and maintenance costs over a finite planning horizon. The model takes into account the fact that the production system may fail randomly. In addition to that, the proposed model takes explicitly into consideration the reliability parameters of the system. Considering the reliability parameters, PM cost is entered as a function of failure rate in the model (Aghezzaf, Jamali, & Ait-Kadi, 2007).

Sharma *et al.* investigated the optimal system maintenance policy that may be the one which either minimizes system maintenance cost rate or maximizes the system reliability measures (Sharma, 2011). Chen investigated a developed procedure to find the sequence that minimizes the total setup time and to minimize the completion time with maintenance schedule in a manufacturing system (Chen W.-J. , 2010).

2.4 Failure time modeling

2.4.1 Fitting of failure and repair data

Fitting of failure and repair data to the suited distribution is a key element in maintenance optimization and simulation. This is because it can help highlight problems such as poor quality parts and improper repairs. Additionally, knowing the probability of failure of components based on data collected from equipment provides a basis for planning of component replacement intervals. Thus, the decision as to when to repair or replace components can be made by the owner using actual data instead of having to rely on manufacturer's recommendations which tend to be too conservative.

In some articles on deterioration modeling, expert judgment has been used to estimate (some of) the parameters of a stochastic process. For example, Wang *et al*. (2000) model the hazard rate of water pumps in the presence of preventive maintenance (PM) as a gamma process. In the absence of PM the mean of the gamma process is taken as the hazard rate of the Weibull distribution. The scale parameter of this distribution is estimated by expert judgment. The method of maximum likelihood is applied to estimate the other parameters, such as the scale parameter of the gamma process itself and the parameters that model the effect of PM on the hazard rate.

In order to fit a Brownian motion or a gamma process to inspection data, statistical methods for the parameter estimation are required. The parameters μ, σ and q of the gamma process can be estimated by maximizing the likelihood function of the independent increments of deterioration (cinlar *et al.*, 1977) with respect to μ, σ and q. This likelihood function can be extended from a single component to multiple components by considering m independent components.

A recent paper by Pandey *et al.* (2007) shows that the implications of the type of deterioration model to both the implied lifetime as well as the replacement policy of engineering structures can be considerable. According to the authors, the gamma process appears to be more versatile than a random variable model for stationary deterioration processes.

The use of probability distribution to represent failures and repairs was proposed by Vineyard et al. (1996). Separate data were included for the mechanical, hydraulic, electrical, electronic, software and human failures as well as repairs. The data were fitted to appropriate probability distributions. Their study indicated that the time between failures follows a Weibull distribution and the time to repair follow lognormal distribution. The conclusion of the above research was that electronic components were the least likely to fail but the mechanical failures resulted in the highest downtime. Another conclusion of the study was that the contribution of human failures, i.e. failures due to human errors was the most significant contributor to the total failure categories indicating that the increased complexity of the flexible manufacturing systems might lead to more human errors.

Wang et al (1998) proposed a failure probabilistic model for CNC lathes. Their analysis included field failure data collected over a period of two years on approximately 80 CNC lathes in China. The data were fit to a probability distribution using the rating matrix approach. The results of the above study showed that the lognormal and Weibull were the most appropriate for describing time between failure data and time to repair respectively. Also it was identified that the electrical and electronic components contributed the most towards failure of CNC lathes.

Yazhou et al (1993) conducted a research very similar to the one mentioned above. Field failure data of 24 Chinese CNC machine tools were studied over a period of one year. The failure data were fit to both Weibull and exponential in order to determine the best fit to represent the underlying failure distribution. The data were also fitted on a Weibull paper. The fitted plots were evaluated for goodness-of-fit by correlation analysis. The analysis of the linear correlation has been found to be more significant for the exponential distribution. From the findings of data analysis, the study concluded that the failure pattern of machining centers best fits the exponential distribution as compared to the Weibull distribution.

Liu et al (2010) analyzed the field failure data from 14 horizontal machining centers (HMC) over one year collected from an engine machining plant in China. They used generalized linear mixed model for analyzing the field failure data from the HMCs. From the findings, the Weibull distribution is best fitted for the analysis of failure data for the HMCs. Dai et al (2003) applied a type I censor likelihood function to make the fitting of Weibull distribution of time between failures of machining center. They also used Hollander's goodness of fit tests to prove that the time between MC failures follows a Weibull distribution. However, the authors failed to clearly clarify the type of machining center analyzed and also failed to mention whether the failure data corresponded to a single failure mode or mixed failures.

Some researchers have suggested that before fitting failure data to a certain distribution, it is important to remove the statistical outliers from the data so as to improve the distributional fit. The Boxplot technique is a useful graphical procedure to identify the outliers present in the data. A boxplot is graphical measure of variability. Devore (2007) lists the prominent features that Boxplots measure as measure of central tendency, measure of dispersion, measure of skewness, kurtosis, and identification of outliers. By definition for the Boxplot any observation further than 1.5 standard deviations from the inter-quartile range is a mild outlier. An outlier is extreme if it is more than 3 standard deviations from the inter-quartile range, and it is mild otherwise. MINITAB is the most common computer package used in the identification of outliers. Unfortunately, MINITAB does not differentiate mild outliers from extreme outliers (Devore, 2007). While analyzing the failure data of manufacturing cells, Balaji (2011) conducted The Goodness of fit test by first removing both the mild and extreme outliers from the time between failure data and the results. The author went ahead to estimate the Weibull parameters of transfer lines using mentioned maximum likelihood estimation (MLE) procedure (Balaji, 2011). Kumar agrees with the author by asserting that the estimation of reliability distribution parameters can be achieved using techniques such as maximum likelihood method (Kumar S. , 2008).

Kumar performed a review on the application of proportional hazard model in reliability analysis before 1995 (Kumar D. , 1995). This method has been applied to compare the hazard rates of various types of values operating under different conditions in a nuclear power plant. Jardine and his coworkers applied the proportional hazard method for precise reliability prediction using oil analysis for aircraft engine (Jardine A. A., 1987).

While analyzing time to repair, Balaji used the same procedure highlighted above in eliminating statistical outliers. In order to find a theoretical distribution for the time to repair data, the author suggested another approach. The approach entails comparing the Skewness (the third standardized central moment) and Kurtosis (fourth standardized central moment) from the sample data to the skewness and kurtosis of known theoretical distributions.

Seyed (2012) while analyzing the failure data of a shearer machine concluded that the failure rate analysis shows that the failure rates of the hydraulic, haulage and electrical systems were decreasing, meanwhile, the failure rates of the water system, cutting arms and cable system were increasing. The failure data fir the haulage and hydraulic system best fitted the Weibull distribution while that of the water system and electrical system best fitted the gamma and lognormal distribution respectively (Seyed, 2012).

The possibility of a single machine's failure data following more than one distribution has also been researched extensively. The reliability distributions after a maintenance activity are usually different from those used before the maintenance activity. For example, Dascalu argued that the distribution function would change due to corrective maintenance. The author proposed an approach for reliability modeling using a semi-Markov chain model with a Weibull with Monte Carlo distribution (Dascalu, 2000). The author concluded that a different reliability distribution is assumed each time a corrective maintenance is performed. In addition to that, Chan and Shaw suggest that failure rate is reduced after each preventive maintenance action, and the degree of reduction of failure rate depends on the system age and the number of preventive maintenances (Chan, 2000).

Kumar (2008), while analyzing railways' failure data, suggested the Weibull distribution should be used (Kumar S. , 2008). The author attributed this to the fact that the Weibull distribution it has the ability to provide reasonably accurate failure analysis and prediction with small sample size. Another important reason to use this distribution is because the Weibull distribution is often used to represent the problems related to mechanical component such as aging, wear and degradation. Furthermore, the Weibull distribution has no specific characteristic shape and depending upon the values of the parameters in its reliability functions, it can adapt shape of many distributions. This Great adaptability of Weibull distribution results in accurate failure analysis and prediction. The author used Weibull ++6 (Reliasoft, 2006) software in the estimation of the shape and scale parameters (Kumar S. , 2008).

Michael (2000), while analyzing failure and repair data for flexible manufacturing systems (FMS) concluded that the Weibull distribution was found to be the best fit for all the equipment failure types with the exception of electrical failures which were found to be best represented with a lognormal distribution. The author also used a chi-square goodness-of-fit test was used to test the fit of MTBF and MTTR (for each failure type) to theoretical distributions (Michael Vineyard, 2000).

In many studies, the Weibull distribution is used even before testing the data. For example, Chan modeled the reliability distributions of heavy-duty gas turbines and their parts using the Weibull distributions. The author attributes the popularity of this distribution to the fact that it can be used to describe both increased failure rate and decreased failure rate as random variables. The other reason is that a logarithmic transformation of the Weibull random variable produces a random variable that belongs to the "location-scale" which has several good features for statistical analysis (Gertsbakh, 2000). However, Muchiri argues that the Weibull distribution is best suited for modeling failure data with an increasing failure rate (Muchiri N. P., 2010). Cristiano on the other hand asserts that the Weibull distribution is commonly used because of its characteristics of easily adapting to the data and its direct relation with the physical state of the equipment (Cristiano, 2006). Nakagawa and Nakamura (2007) also used the Weibull distribution in the analysis of failure data (Nakagawa T. N., 2007). Tam et al (2006) applied the Weibull distribution to model the lifetime of multi-component system in order to determine the optimal maintenance interval While Farrero et al (2002) used the Weibull model for failure data analysis on production system in order to determine the optimum time of replacement stocks. Nakagawa (2007) argues that the Weibull distribution is often used to represent the problems related to mechanical component aging, wear and degradation (Nakagawa T. N., 2007).

Further literature reveals that many researchers agree with the assumption that the failure times have a Weibull distribution and the repair times have a lognormal distribution (Abernethy, 2000) (Wiseman M., 2001). Wiseman asserts that about 85–95% of all failure data are adequately described with a Weibull distribution (Wiseman M., 2001). The reasons are that the Weibull distribution has the ability to provide reasonably accurate failure analysis with a small sample size, that it has no specific characteristic shape, and that, depending upon the values of the parameters; it can adapt the shape of many distributions. It is also known that the lognormal distribution is widely used to model repair times. In addition to that, the author asserts that about 85–95% of all repair times are adequately described by a lognormal distribution. This is due to the skewness of the lognormal distribution, with a long tail to the right; provide a fitting

representation of the repair situation. In a typical repair situation, most repairs are completed in a small time interval, but in some cases repairs can take a much longer time (Wiseman M., 2001).
Sometimes, the use of two-parameter Weibull distribution is used in modeling failure data. Liu et al. (2010), while presenting a preventive maintenance policy that was formulated using a fuzzy reliability framework used two-parameter Weibull distribution in the modeling of failure data (Liu, 2010).

Once the parameters have been fitted to the candidate model(s) it is necessary to determine how well they fit the data. Tests that are commonly applied to data include the Chi Square test, the Kolmogorov-Smirnov test (K-S) and the Darling-Anderson test. The Chi Square test involves comparing the number of data that fal1 into selected classes with the number that would be expected to fall in those classes from the assumed distribution while the Kolmogorov-Smirnov test uses a comparison of the ranked value of the data with what the expected value of the ranks would be from the assumed distribution. Sayed (2012) asserts that The Kolmogorov–Smirnov (K-S) test is the best classical used for the validation and selection of the best-fit distribution. Other than the above statistical tests, Mann, Schafer and Singpurwalla [1974] developed a goodness of fit test for the Weibull distribution.

Many researchers have set some prerequisite in parameter estimation. They all conclude that before determining which distribution is the best for the available data, one must perform a trend analysis and serial correlation test to determine whether the data are independent and identically distributed (iid) or not (Ascher and Feingold, 1984; Klefsjo¨ and Kumar, 1992; Modarres, 2006; Birolini, 2007). Some authors have also used The Laplace trend test and an autocorrelation test for trend and serial correlation testing (J.I. Ansell and M.J. Phillips, 1994).

Regarding to results of the trend analysis, if the assumption that the data is identically distributed is not valid, then classical statistical techniques for reliability analysis may not be appropriate; therefore, a non-stationary model such as non-homogeneous Poisson process (NHPP) must be fitted (Kumar and Klefsjo¨, 1992; Ascher and Feingold, 1984). The presence of no trend and no serial correlation in failure data reveals that the data is independent and identically distributed (iid) and therefore the classical statistical techniques are the best way for reliability modeling.

However, it is not a must to fit failure and repair data in their respective distributions before conducting reliability and availability modeling. Amarjit (2011) used quality control and SPC charts in the analysis of failure and repair data. Data for mean downtime (MDT) and mean time to repair (MTTR) were used to evaluate the stability and capability of the repair processes for each pipe type. The analysis was completed through the use of control charts, operating characteristic (OC) curves, and process capability indices (Amarjit Singh, 2011).

In addition to that, some researchers assert that the use of probability theory in modeling failure and repair data does not give accurate results. For example, Juang (2008) proposed a new method to compute optimal values of MTBF and MTTR based on GA. A knowledge-based interactive decision support system was developed to assist the designers' set up and to store component parameters during the intact design process of repairable series-parallel system (Juang, 2008).

2.4.2 Other distributions

Other than the Weibull, exponential, normal and lognormal distributions, the triangular distribution is also used in the analysis of repair data. Muchiri, while analyzing the repair data of a chemical industry, used the triangular distribution. He attributed this to the fact that the standard deviation was very high (Muchiri N. P., 2010). The Exponential distribution model is used to model the failure time with constant failure rate. This model is one of the important models for modeling the failure time of electric and electronic component or system (Ebeling, 1997). For instance, Tong et al (2002) applied the exponential distribution for assessing performance of lifetime (failure rate) index of electronic component. The failure and repair data of load haul dumper (LHD) was modeled by Samanta (2004) using the exponential distribution (B. Samanta, 2004). Therefore, the Failure rates and repair rates for all the subsystems of the LHD are constant over time and statistically independent.

Ebeling (1997) asserts that The Normal and Lognormal distributions models are widely used to model the failure time with increasing failure rate for fatigue and wear-out phenomena (Ebeling, 1997). In many cases, these distributions are used in modeling the failure time of the cutting tool. For example, Chelbi and Kadi (1999) used the Normal distribution to model the failure time of cutting tools. On the other hand, Jianqiang and Keow (1997) used the Lognormal distribution to fit the failure time of the cutting tool for the purposed of determination the best replacement interval.

2.4.3 Statistical techniques

2.4.3.1 Introduction

Developing certain statistical concepts is a prerequisite for performing maintenance activities. This section deals with essential reliability functions that affect maintenance decisions.

Distributions can be either discrete or continuous. Discrete distributions are used when the parameter being examined can only assume a number of discrete values. Examples of discrete distributions are Binomial, polynomial and Poisson distributions (Pintelon L. , 2006).

On the other hand, continuous distributions are used when the parameters being investigated can assume any infinite number of values. Examples of continuous distributions are the exponential, normal, lognormal, gamma, Chi and Weibull distribution (Pintelon L. , 2006).

The statistical distributions that were used in the subsequent distribution in the modeling of failure and repair data include the Weibull, normal, lognormal, gamma and the exponential distribution.

2.4.3.2 The Weibull distribution

The Weibull distribution is named after Waloddi Weibull. In general, it models data by a function of the following form (Stephens, 2004):

$$f(t) = \frac{\beta}{\eta}\left(\frac{t-\gamma}{\eta}\right)^{\beta-1} \exp\left(-\left(\frac{t-\gamma}{\eta}\right)^{\beta}\right)$$

The three parameters of a Weibull distribution are β (the shape parameter), γ (the location parameter) and η (the scale parameter).

As the name suggests, the shape parameter determines the shape of the distribution. When $\beta<1$, the Weibull distribution has a hyperbolic shape. When $\beta=1$, the distribution becomes an exponential function. When $\beta>1$, it is an unimodal function where skewness changes from left to right as the value of β increases (Abernethy, 1996).

Location parameter is normally provided by the manufacturer. By definition, the probability density function of the Weibull distribution is zero for $t<\gamma$. That is, there is no risk of failure before γ, which is therefore termed as the location parameter or the failure-free period of the distribution (Stephens, 2004).

On the other hand, the hazard rate, ***h (t),*** of the Weibull distribution is of the following form (Abernethy, 1996):

$$h(t) = \frac{\beta}{\eta}\left(\frac{t-\gamma}{\eta}\right)^{\beta-1}$$

The mean time between failures (MTBF) is the average time we expect components to fail; it is the mean time we expect a component to perform its designed function after the time of installation. However, MTBF is only applicable to systems with repairable components. The meantime between failures finds its application in preventive and predictive maintenance planning. For the case of a Weibull distribution, the MTBF is given by

$$MTBF = \eta\Gamma\left(1+\frac{1}{\beta}\right)$$

2.4.3.3 The exponential distribution

In probability theory and statistics, the exponential distribution is a continuous probability distribution that describes the time between events independently and at a constant average rate.

The exponential distribution is the simplest and most widely used reliability distribution. Systems whose failures follow the exponential distribution exhibit a constant failure rate. One implication of this is that, for systems operating in the constant failure rate region of their life cycle, planned preventative maintenance does not enhance the reliability of the system. The exponential distribution is the only continuous memory random (Barlow R. a., 1965).

The PDF for an exponential distribution is given by the equation shown below (Ciinlar, 1977)

$$f(t) = \lambda e^{-\lambda t}$$

On the other hand, the CDF for an exponential distribution is given by the following equation (Marsaglia, 2004):

$$F(t) = 1 - e^{-\lambda t}$$

Where λ is the hazard rate or the failure rate

2.4.3.4 The normal distribution

In probability theory, the normal (or Gaussian) distribution is a very commonly occurring continuous distribution that tells the probability of a number in some context falling between any two real numbers. Normal distributions are extremely important in statistics and are often used in the natural and social sciences for real-valued random variables whose distributions are not known (Spiegel, 1992).

The normal distribution is immensely useful because of the central limit theorem, which states that, under mild conditions, the mean of many random variables independently drawn from the same distribution is distributed approximately normally, irrespective of the form of the original distribution: physical quantities that are expected to be the sum of many independent processes (such as measurement errors) often have a distribution very close to the normal (Marsaglia, 2004).

The PDF of the normal distribution is given by the following equation

$$f(t) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(t-\mu)^2}{2\sigma^2}}$$

Where μ and σ represents the sample mean and the standard deviation respectively

2.4.3.5 The lognormal distribution

The lognormal distribution is a probability distribution whose logarithm has a normal distribution. It is sometimes called the Galton distribution. The lognormal distribution is applicable when the quantity of interest must be positive, since log(*x*) exists only when *x* is positive (E. Limpert, 2001).

The probability density function (PDF) of the lognormal distribution is given by the equation below (Aitchison, 1957)

$$f(t) = \frac{1}{t\sigma\sqrt{2\pi}} e^{\frac{-(\ln t-\mu)^2}{2\sigma^2}}$$

On the other hand, the cumulative density function (CDF) of the lognormal distribution is given by the equation below (Aitchison, 1957)

$$F(t) = \Phi(\frac{in\ t - \mu}{\sigma})$$

Where F (t) is the CDF, f (t) is the PDF, σ is the standard deviation and μ is the sample mean.

2.5 Analysis approaches

2.5.1 Multi-Criteria Decision Making (MCDM)

One of the most popular approaches for conflict management is Multi-Criteria Decision Making (MCDM). Multi-criteria optimization is the process of determining the best feasible solution according to the established criteria (representing different effects). Multi-criteria analysis (MCA) deals essentially with complex decisions that involve a large amount of information, a number of alternative outcomes and criteria to assess these outcomes. MCA techniques can be used to identify a single preferred option, to rank options, to short-list a number of options for further investigation, or simply to distinguish acceptable from unacceptable alternatives.

Practical problems are often characterized by several incommensurable and conflicting (competing) criteria, and there may be no solution satisfying all the criteria simultaneously. Therefore, the solution is a set of non-inferior solutions, or a compromise solution according to the decision maker's preferences. A compromise solution for a problem with conflicting criteria can help the decision makers to reach a final decision. The compromise solution is a feasible solution which is closest to the ideal, and a compromise means an agreement established by mutual concessions (Opricovic and Tzeng, 2004).

A performance matrix or consequence table is considered to be a standard feature of MCA. Each row describes an option and each column the performance of the options against each criterion. Criteria are established with respect to objectives or the overall objective of the exercise. Individual performance assessments may be expressed as numerical or "bullet point" scores or colour coding may be used. The performance matrix may constitute the final product of an analysis, or a further assessment of the extent to which objectives are met by the matrix entries may be required.

2.5.2 Root Cause Analysis

Wilson et al. (1993) have defined the Root Cause Analysis as an analytic tool that can be used to perform a comprehensive, system-based review of critical incidents. It includes the identification of the root and contributory factors, determination of risk reduction strategies, and development of action plans along with measurement strategies to evaluate the effectiveness of the plans. Dew (1991) and Sproull (2001) state that identifying and eliminating root causes of any problem is of utmost importance.

Root Cause Analysis (RCA) is a technique that conducts a full-blown analysis to identify the latent root causes of 'Why' any undesirable event occurred. It identifies necessary steps to eliminate the event in its entirety and prevent reoccurrence. RCA finds and corrects the causes of a problem, hence it is used where solutions are sought to stop problems from happening again. RCA is typically used as a reactive method of identifying event(s) causes, revealing problems and solving them. Analysis is done *after* an event has occurred. Insights in RCA may make it useful as a preemptive method. In that event, RCA can be used to *forecast* or predict probable events even *before* they occur.

Root Cause Analysis (RCA) was firstly originated within the nuclear industry when accidents and incidents investigators discovered the need to go beyond the 'what' happened to accommodate a far wider scope of 'why' it happened, thus providing spacer room for real organizational learning. RCA thus facilitated an important way-out of the shortages in abnormal occurrence investigations which were usually terminated in the past without the 'real' cause of the mal performance, technical or human, being determined.

According to Duggett (2004) several root cause analysis tools have emerged from the literature as generic standards for identifying root causes. Some of them are the Why-Why Analysis, Multi-Vari Analysis, Cause-and-Effect Diagram (CED), the Interrelationship Diagram (ID), and the Current Reality Tree (CRT). He has added that the Why-Why analysis is the most simplistic root cause analysis tool where as current reality tree is used for possible failures of a system and it is commonly used in the design stages of a project and works well to identify causal relationships.

2.6 Financial tools

2.6.1 Net present value analysis (NPV)

NPV is used is finance to represent the sum of the present values (PVs) of the individual cash flows of the same entity (Nitzan & Bichler, 2009). In other words, it can be described as the "difference amount" between the sums of discounted: cash inflows and cash outflows. It compares the present value of money today to the present value of money in the future, taking inflation and returns into account (Khan, 2003).

NPV compares the value of a dollar today to the value of that same dollar in the future, taking inflation and returns into account. If the NPV of a prospective project is positive, it should be accepted. However, if NPV is negative, the project should probably be rejected because cash flows will also be negative. On the other hand, an NPV of zero indicates that the investment would neither gain nor lose value for the firm (Lin & Nagalingam, 2000).

In maintenance, NPV has been used severally used in determining the most optimal solution. Muchiri (2010), while analyzing the different alternatives in a chemical plant used the NPV. In the analysis, the yearly cash flow was calculated as the sum of the yearly maintenance cost savings (from avoided failures) and incremental contribution from additional production output. The incremental contribution is calculated as the product of variable margin and production output increase.

The NPV was calculated as shown by the equation below:

$$NPV = -I + \sum_{t=1}^{t} \{(S + A)\frac{1}{(1+i)^t}\}$$

Where I is the investment, A is the additional production revenue, S is the maintenance saving, (i) is the interest rate and t is the time of the analysis.

2.6.2 Simple payback analysis

Simple payback measures the time it takes for the energy savings to payback the initial cost of the project. Usually, it is calculated by dividing the capital investment by the estimated energy saving; as shown by the equation below.

$$Payback = \frac{Capital\ investment}{Energy\ saving}$$

This measure is effective for establishing the time period required to recover your initial investment. It is simple to calculate but does not consider three very important factors:

i. Energy savings continue for the life of the equipment or project life - payback does not take into account the life of the equipment.
ii. A safe dollar is worth more than a risky one - payback does not allow comparison of the option with other investments
iii. A dollar today is worth more than a dollar tomorrow – simple payback does not take the time value of money into account.

The advantages of the simple payback analysis include:

i. Simple to calculate.
ii. Easy to understand and explain.
iii. Provides a rough indicator of the associated risk based on project length.

However, the disadvantages of simple payback include:

i. Too simplistic a measure on which to base decision.
ii. Does not take the life of the investment into account.
iii. Does not allow a comparison with other types of investments
iv. Does not take the time value of money into account.

2.7 Conclusion

From the literature review, it can be concluded that Maintenance decision makers are usually faced by the following two important questions:

i. *When* should maintenance be done?

This determines the maintenance interval. Some of the maintenance intervals that are considered by the maintenance decision makers include:

- CM Time - Failure occurs at random times and thus cannot be predicted. Thus, corrective maintenance is done at random times.
- PM time - This can be scheduled / planned maintenance activities and thus they are deterministic. PM time can also be determined by the condition of the equipment according to the results of inspections and degradation or operation

control. Thus random PM can be carried out based on condition monitoring. PM timing can also be influenced by other factors like production schedules where PM is carried out during change-over.

- Condition monitoring time is normally planned and therefore it is deterministic.

ii. What type of maintenance policy needs to be done?

This determines the choice of the maintenance policies that trigger the maintenance actions. The maintenance policies considered in this section are:

- *Failure based maintenance (FBM)* - This it is a purely reactive policy where corrective maintenance (CM) is done only when the equipment fails.
- *Time based or use based maintenance (TBM/UBM)* – This is a preventive policy where maintenance is carried out at specified time intervals. For UBM, intervals are measured in working hours while in TBM intervals are in calendar days.
- *Condition based maintenance (CBM)* - This is a predictive policy where PM is carried out whenever a given system parameter or condition approaches

There are so many distributions that can be used to model both failure and repair data. However, from the literature survey, it can be noted that the Weibull distribution best fits modeling of failure data while the lognormal distribution best suits the modeling of repair data.

3 CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Introduction

This chapter highlights the various methods and procedures that were adopted in conducting the study in order to answer the research questions and meet the research objectives. It is divided into the research design and experimental design.

3.2 Research design

This thesis employs a case study approach. To meet the research objectives and answer the research questions, this research employed a mixture of different types of research. First of all, this research work can be classified as an exploratory study, where information was collected using literature and direct interviews to find out the relationship between the difference maintenance Key Performance Indicators (KPIs) at EAPCC. In addition to that, this research can be classified as a deductive research, where literature was used to identify theories and the theoretical framework of preventive maintenance (Stuart, 1962)

This research also adopted quantitative, correlation and descriptive research designs to achieve the research objectives and provide answers to the research questions. To answer the first research question, quantitative research design was used; whereby statistical tools were used to process maintenance data into information that was used decision-making (selection of the critical components). Furthermore, quantitative design was used to answer the second research question whereby classical the ARM model was used in identifying the optimal PM interval. Descriptive research design was employed in answering the third research question. Descriptive studies usually determine the frequency determining the occurrence of something or the relationship existing between two or more variables (Creswell, 2012). In this case, the relationship between production, downtime and cost was used in the financial evaluation of the suggested maintenance actions to be performed on the most critical component.

Finally, this research can be seen as a longitudinal study. This is because all the data used in this case has been collected for a very long period (36 months).

3.3 Data collection techniques

To understand the maintenance environment at EAPCC, direct personal interviews (PI) were frequently administered to the key personnel in the maintenance department. PI method involves presentation of oral-verbal stimuli and reply in terms of oral-verbal responses. Some of the information that was gathered by this technique of data collection include nature of failures, challenges facing the maintenance department and suggestions of solutions to challenges facing the maintenance department.

To answer all the three research questions, secondary data from the maintenance database at EAPCC was used. The database consisted of two main data levels:

i. daily operation and production reports (were recorded by shift supervisors)
ii. mechanical maintenance reports (were recorded by mechanical supervisors and repair man)

The data collected and analyzed from the maintenance department included:

- Causes and quantification of production losses (outages)
- Production output
- Availability
- Maintenance Cost data
- Maintenance data - PM & CM interventions
- Failure data
- Repair data
- Root cause analysis data (for failures)

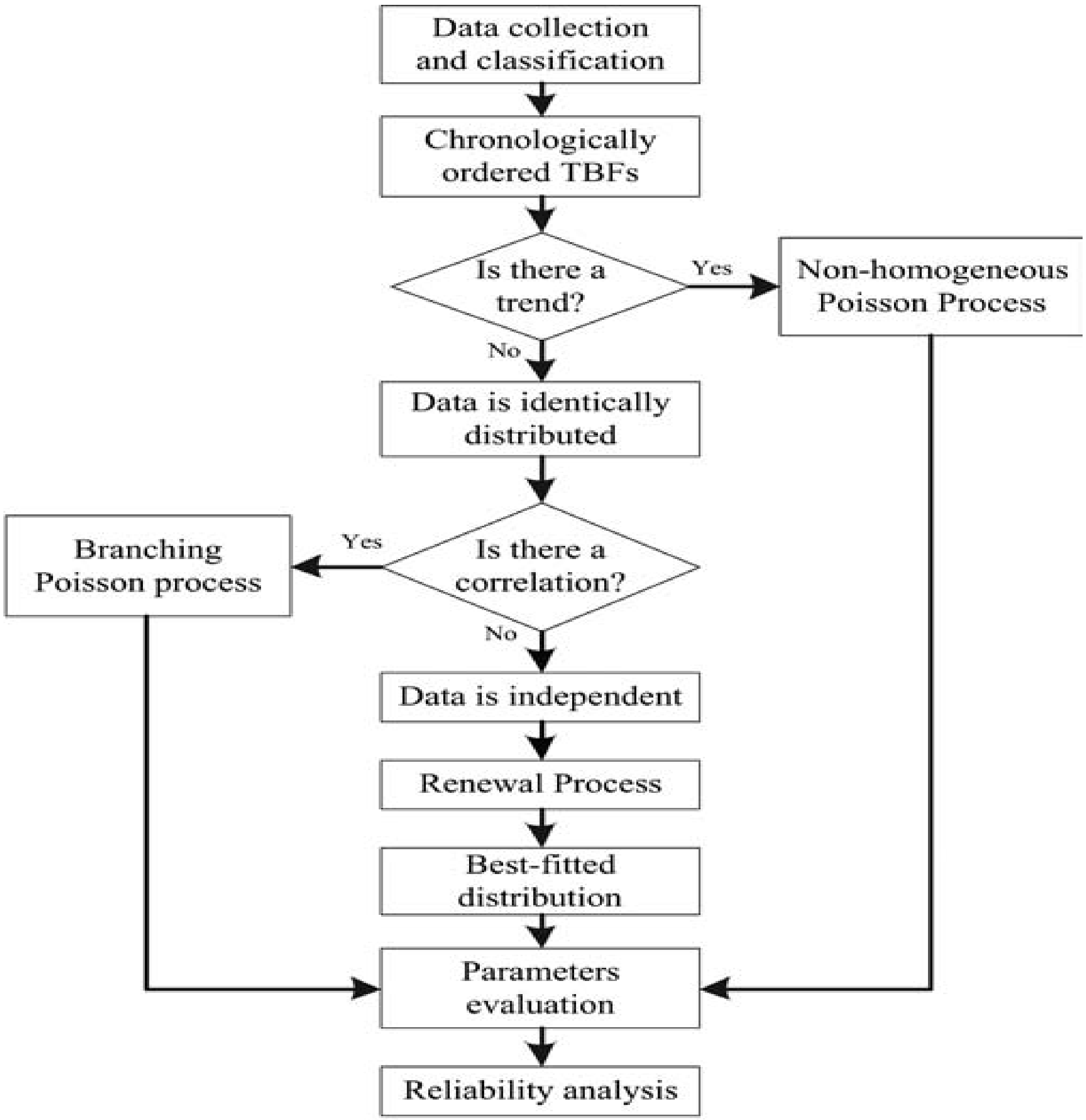
3.4 Data analysis techniques

To answer the first research question, a root cause analysis (RCA) was conducted. In order to determine the most critical plant, equipment and component Pareto analysis (PA) was used as a tool of RCA. Furthermore, multi criterion decision making (MCDM) was used in the selection of the key plant. With this method, each maintenance KPI was considered to be a selection criterion. The maintenance KPIs that were used include availability, MTTR, MTBF, downtime and the number of stoppages. In addition to that measures of central tendency such as the mean were used in the identification of the most critical plants and machines. The measures of dispersion such as skewness, kurtosis, standard deviation and variance were also used.

To answer the second research question, the failure and repair data from the database were used. Failure data was assumed to follow a Weibull distribution while repair data was assumed to follow the lognormal distribution. *EasyFit* computer package was used in the determination of the distributions' parameters. The data analysis procedure used in this study was adopted from Kumar (1990) as shown in the figure 3.1 below.

To answer the third research question, a scenario analysis was performed. The net present value (NPV) analysis was used in the determination of the most economical alternative. Furthermore, a regression analysis was performed with an objective of determining the relationship between production and downtime on the most critical component.

Tables, pie charts and bar graphs plotted using EXCEL were used to present the data due to their strong visual representation of data. This is because they enable ease in the understand ability, analysis and interpretation of the results.



Source: Kumar (1990)

Figure 3-1: The data analysis procedure

3.5 Summary of chapter three

It is vital to opt for an appropriate research design, philosophy, approach, strategy and method as these are the base at which the whole study rests on. The success or failure of the research solely depends on selecting an appropriate research method and pertinent research tools; they should be in compliance with the subject matter. By picking a wrong research method or tool, a researcher can easily end up not meeting the research objectives and answering the research questions. Table 3.1 below summarizes the methodologies used per research question

Table 3-1: A summary of the research methodology used in this study

Research methodology	Research questions		
	Research question 1	**Research question 2**	**Research question 3**
Research design	Case study approach		
	Quantitative, correlation, longitudinal and descriptive	quantitative, Longitudinal, correlation, and descriptive	quantitative, correlation, exploratory, longitudinal
Data collection	CMMS data	CMMS data	CMMS data
Type of data	Availability, time to repair, time between failures, downtime and number of stoppages	Availability, O&M cost data, time to repair, time between failures, downtime and no. of stoppages	Production, cost and downtime data
Data analysis tools and methods	Pareto analysis, Multi-Criterion Decision Making and measure of central tendency	Anderson-Darling test, distribution analysis, classical ARM model and measure of central tendency	Sensitivity analysis, regression analysis and NPV analysis
Computer packages used	EXCEL	EXCEL and EasyFit	EXCEL

4 CHAPTER FOUR: DATA ANALYSIS AND RESULTS

4.1 Introduction

In this chapter, the data collected is analyzed in order to determine the critical components and the most optimal PR timing. The critical plants, machines and components were identified using Pareto analysis and both the measures of dispersion and measures of central tendency. The maintenance KPIs that will be used in the identification of the critical machines includes availability, downtime, MTTR, MTBF and Overall Equipment Effectiveness (OEE).

The data collected and analyzed from both production and maintenance departments included:

- Causes and quantification of production losses (outages)
- Maintenance data - PM & CM interventions
- Failure data per equipment and per component
- Repair data
- Root cause analysis data (for failures)

4.2 Identification of critical plant

4.2.1 Availability criterion

At EAPCC, the target-availability is 93%. However, this target is rarely met. Figure 4.1 below shows the average availability of each production plant as compared to the target for three years (from June 2010 to May 2013).

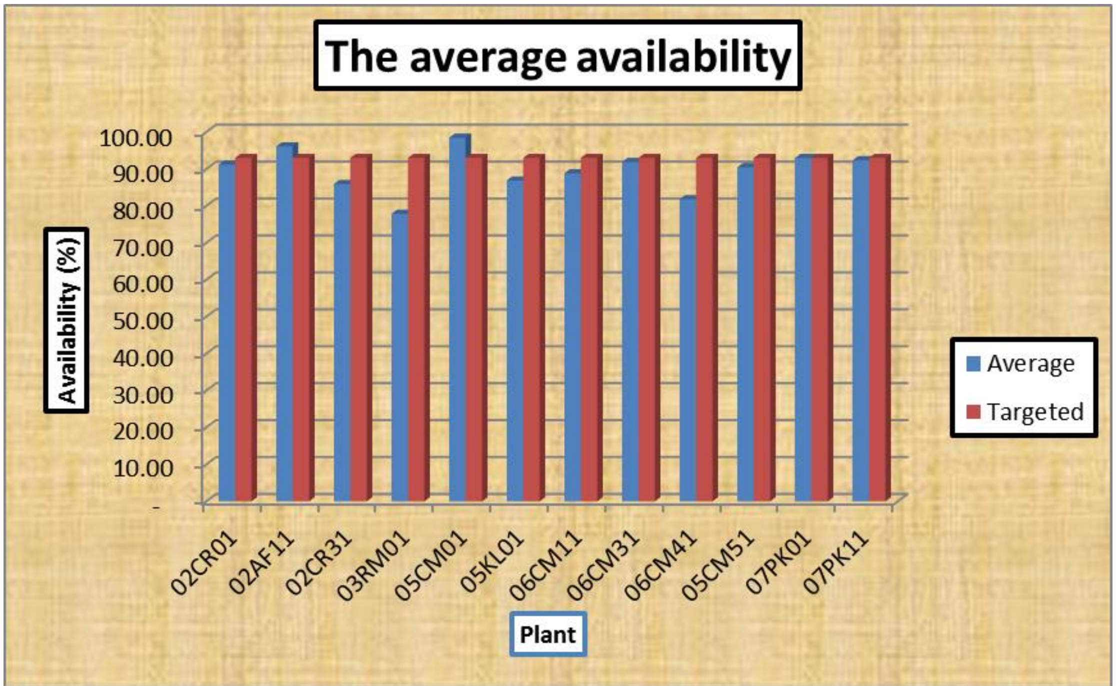


Figure 4-1: The average availability for the different production lines

From figure 4.1 above, we can note that the Raw mill (03RM01) and cement mill 4 (06CM04) are the most affected by the problem of low availability with the average availability of 87% and 81% respectively. It can further be noted that the monthly availability of most of the plants is below the organization target of 93%. With the exception of cement mill 1 and the crusher, which have the average availabilities of 96.12% and 98.47% respectively, the average availability for the other plants for the last 36 months is below the targeted value. This can be attributed to a of number reasons: High number of breakdowns and failures, Short mean time between stoppages (MTBS), Long mean time to repair (MTTR), Low maintenance effectiveness and unavailability of critical spare parts. For example, the raw mill has a highest contribution for the total stoppages (with 39.6%). This is followed by coal mill, cement mill 3 and cement mill 4 with total contribution to the number of stoppages of 13.36%, 12.89% and 12.82% respectively. Furthermore, it can be noted that there is no consistence pattern in the availability patterns for the different plants. This can be attributed to the randomness of failures that occur at EAPCC.

4.2.2 The number of stoppages criterion

The number of stoppages per year in each plant is very high. Table 4.1 below shows a summary of the average annual number of stoppages per plant for a period from June 2010 to May 2013 (36 months).

Table 4-1: The average annual number of stoppages for the last three years

Plant	No of stoppages	% Contribution
Kiln	198	3.760684
Coal Mill	868	16.48623
Raw Mill	1918	36.42925
Mill 1	221	4.197531
Mill 3	78	1.481481
Mill 4	731	13.88414
Mill 5	680	12.91548
Packer 1	277	5.261159
Packer 2	294	5.584046
Total	5265	100

From table 4.1 above, we can note that the raw mill has a highest contribution to the number of stoppages (with 36.4%). This is followed by coal mill, cement mill 4 and cement mill 5 with total contribution to the number of stoppages of 16.4%, 13.3% and 12.5% respectively.

The increase in the number of stoppages has led to an increase in the number of stop hours in the above four mentioned plants. Table 4.2 below shows a summary of the average annual stop hours per plant for the last three years.

Table 4-2: A summary of the average annual downtime for the different plants

Plant	Average annual downtime	% Contribution
Kiln	2750.2	8.273493
Coal Mill	3068.1	9.229839

Raw Mill	3952.2	11.8895
Mill 1	6237.8	18.76532
Mill 3	8262.4	24.85598
Mill 4	3703.8	11.14223
Mill 5	2085.6	6.274161
Packer 1	1551.4	4.667114
Packer 2	1629.6	4.902365
Total	33241.1	100

Basing on the downtime, the most critical plants are the Cement Mill 3, Cement Mill 1, Cement Mill 4 and the Raw Mill. It is interesting to note that even though the raw mill has the highest number of stoppages per year (1918), its average annual downtime (3952 hours) is much less as compared to the Cement Mill 3 (8262 hours), cement mill 1 (6237 hours) and cement mill 4 (3701 hours). Perhaps this can be attributed to a shorter mean time to repair (MTTR) for the raw mill as compared to the other plants. Similarly, the kiln has the highest downtime with less number of stoppages because each stoppage requires more time for a maintenance action. On average, Cement Mill 3 has a downtime of 677.46 hours per month. Out of the total 720 hours per month, Cement Mill 3 has only 42.54 hours for production. It can be noted that 94% of the total time per month is actually downtime.

The downtime tabulated in table 4.2 above can be attributed to different factors. These factors are grouped into various categories: production, engineering, mechanical, electrical, instrumentation, administration, KPLC, IT, sales, idling of machines, project and works. Table 4.3 below shows a summary of the different downtime ownership for a period of between June 2010 and May 2013 (36 months) at EAPCC.

Table 4-3: The summary of the annual downtime ownership for the last three years

Downtime ownership	Kiln	Coal Mill	Raw Mill	Mill 1	Mill 3	Mill 4	Mill 5	Packer 1	Packer 2	Total
Production	699.8	1844	1118	1288	5576.8	954.7	478.3	115.3	105.9	12180.8
Engineering	0	0	206.5	146	68.7	328.8	562.5	582	644.5	2539
Mechanical	727.6	74.7	1243	761.6	95.9	886.2	271.4	47	70.9	4178.3
Electrical	231.5	86.4	275.7	135.3	122.7	421	82.3	9.1	29	1393
Projects	0	1.6	11.9	0	0	4.7	0	0	0	18.2
Admin	12.4	5.4	0	0	0	4.8	28.7	0	0	51.3
KPLC	107.7	79.2	99.6	31.7	0	65.2	121.5	28.3	28.2	561.4
Works	971.2	976	995.8	0	0	0	28.9	0	0	2971.9
MOB	0	0	0	0	0	0	1.5	0	0	1.5
Sales	0	0	0	3875	2,382	1038	510.5	604.7	637.6	9047.8
Instrumentation	0	0	0	0	0	0	0	0	0	0
IT	0	0	0	0	0	0	0	53	49.5	102.5
Idle	0	0	0	0	0	0	0	112	64	176

To investigate the performance dynamics that lead to downtime, further analysis on the root cause was carried out and Figure 4.2 below drawn. From figure 4.2 below, we can note that during the last three years, production contributed 37% of the total downtime in all the plants while sales contributed 27% of the downtime. Downtime due to production was high on all the mills (cement mills, coal mill and the raw mill) while downtime due to sales was high on the cement mills and the packaging plant. It is also interesting to note that instrumentation did not contribute anything towards the high number of downtime in any plant during the last 36 months. Mechanical and electrical had a downtime contribution of 13% and 4% respectively while engineering had a downtime contribution of 8%.

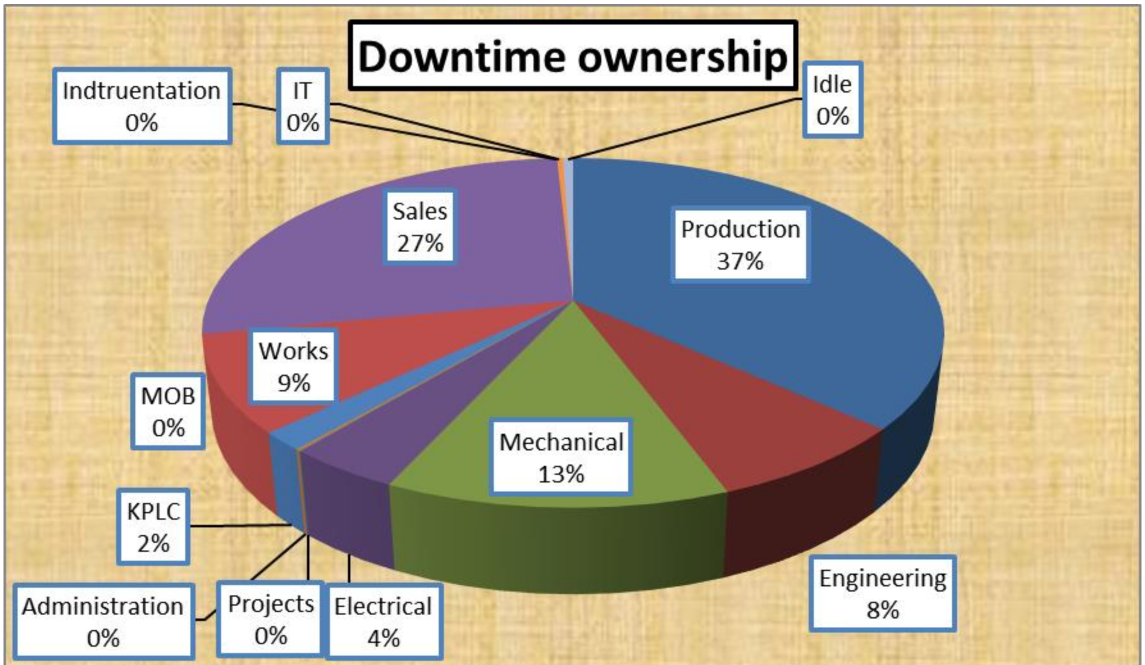


Figure 4-2: The downtime ownership

Of all the downtime ownership, only four categories are directly related to the maintenance department: mechanical, electrical, engineering and production. Figure 4.3 below shows a summary of the downtime ownership that is directly related to the maintenance department.

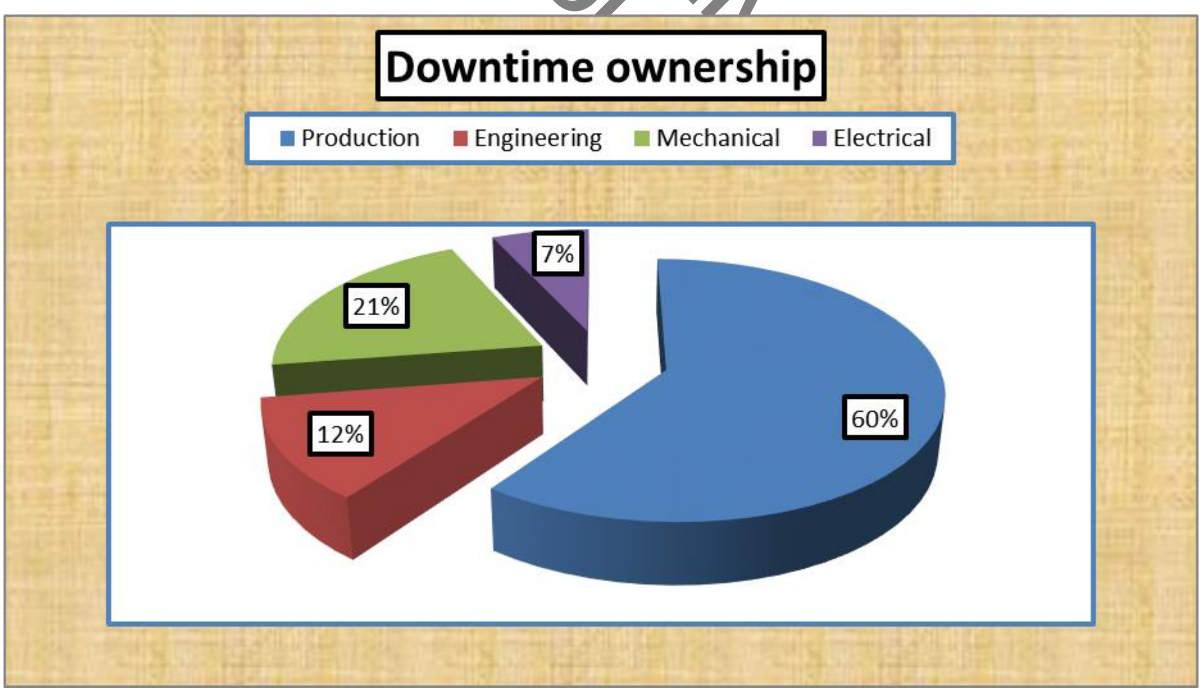


Figure 4-3: Downtime ownership directly related to the maintenance department

By considering downtime ownership directly related to the maintenance department, it is worth noting that production has a contribution of 60% while mechanical, engineering and electrical have contributions of 21%, 12% and 7% respectively. A Pareto analysis reveals that only two factors contribute 81% of the total downtime due to maintenance.

4.2.3 Mean time between failures (MTBF) criterion

For mechanical, electrical, production and engineering failures, further analysis was carried out to determine their effect per plant. Using the 3 years failure data, the MTBF for the different plants was calculated and tabulated as shown in Table 4.4 below.

Table 4-4: The relevant descriptive statistics for the MTBF (in hours) of the different plants

Descriptive	*Raw mill*	*Kiln*	*Mill 1*	*Mill 3*	*Mill 4*	*Mill 5*	*Packer 1*	*Packer 2*
Mean	5.2785	57.5666	19.6989	7.9670	11.1088	27.7654	87.3911	37.5914
Std Error	1.2431	15.4875	2.9421	2.9439	1.9086	5.7056	50.6349	12.0207
Median	3.9418	52.3111	15.7066	6.5571	9.3001	30.0421	26.6916	27.1227
Std Dev	4.12291	51.3665	9.7579	9.7640	6.3302	18.9234	167.937	39.8683
Variance	16.9983	2638.52	95.2180	95.3371	40.0719	358.096	28202.9	1589.48
Kurtosis	3.0137	7.4207	-0.9094	7.4701	1.0080	-2.1442	9.7840	5.6335
Skewness	1.8279	2.5402	0.6898	2.5298	1.2991	0.0459	3.0748	2.1749
Range	13.415	184.27	26.6306	35.4	20.17297	43.96857	583	144.5

Using the information in table 4.4 above, we can note that the raw mill is the plant that adversely suffers from the problem of shorter MTBF (with an average monthly MTBF of 5.2 hours). In essence, this means that the raw mill stops every 5.2 hours. It is followed by cement mill 3 and cement mill 4 with average MTBF of 7.9 and 11.1 hours respectively. The kiln and packer 1 are the only plants that have maximized there MTBF. However, their average MTBF is lower than the targeted value of at least 120 hours.

4.2.4 Mean time to repair (MTTR) criterion

Similarly, the repair data for the mechanical, electrical, production and engineering failures were further analysis to determine the MTTR per plant. Using the 3 years failure data, the MTTR for the different plants was calculated and tabulated as shown in Table 4.5 below

Table 4-5: The descriptive statistics for MTTR for the last 36 months

Descriptive	***Raw mill***	***Kiln***	***Mill 1***	***Mill 3***	***Mill 4***	***Mill 5***	***Packer 1***	***Packer 2***
Mean	2.146	15.154	12.373	23.216	14.344	2.361	2.229	1.956
Std error	1.080	5.254	3.903	15.909	1.017	0.541	0.757	0.629
Deviation	3.583	17.428	12.945	52.766	3.373	1.797	2.513	2.086
Variance	12.844	303.754	167.597	2784.262	11.379	3.229	6.316	4.355
Kurtosis	2.909	2.492	0.986	9.607	0.783	-1.483	-0.384	-0.895
Skewness	1.982	1.675	1.497	3.046	1.238	0.356	1.074	0.963
Range	10.677	56.098	36.778	178.45	10.660	4.830	7.066	5.530

Basing on the information in table 4.5 above, the most critical plants are Cement Mill 3, The Kiln, Cement Mill 4 and Cement Mill 1. An analysis of MTTR shows that mill 3 is most affected by the problem of long MTTR. Averagely, every failure on mill 3 takes 23.16 hours to be restored back to normal. This is followed by the kiln and Cement Mill 4 at the average of 15.154 and 14.344 hours respectively. Even though the raw mill has the highest number of stoppages per month, it is interesting to note that each stoppage takes an average of 2.14 hours to be restored back to normal operation. For maximum availability, the MTTR must be as kept to the minimum as possible.

4.2.5 Multi-Criteria Decision Making (MCDM)

Weights were given to each of the above factors affecting the selection of critical equipment by experts from the maintenance department at EAPCC. Then the criticality of each piece of equipment is decided on the basis of the sum of the weights. The ratings of 1 to 9 were used; 9 representing a high while 1 representing a low. Using the different ratings/weightings, the sum of the weights is as shown in table 4.6 below

Table 4-6: The sum of the weighed factors for the different plants

Plant	Availability	No of stoppages	Downtime	Total	Ranking
Kiln	6	2	4	12	6
Coal Mill	7	9	5	21	3
Raw Mill	9	8	6	23	2
Mill 1	3	3	7	13	5
Mill 3	4	1	3	8	7
Mill 4	8	7	9	24	1
Mill 5	5	6	8	19	4
Packer 1	2	4	2	8	7
Packer 2	1	5	1	7	9

From table 4.6 above, the most critical plant is Cement Mill 4 followed by the Raw Mill. After performing a MCDM, Cement Mill 4 was settled as the most critical equipment. Consequently, in the subsequent section, Cement Mill 4 was analyzed.

4.3 Identification of the critical components

After identifying the most critical plant, the next step was to identify the most critical component on the most critical plant. Cement Mill 4 is made up of a number of components and sub-components. Some of the key components that make up the Cement Mill 4 are summarized as shown in table 4.7 below.

Table 4-7: The key components that make Cement Mill 4

Code	Name of component
HP41	Clinker Hopper
WF 41	Clinker weigh feeder
HP 43	Tuff hopper
FN 41	Motor
PL 41	Cement pipeline
CM 41	Chamber

PC 41	Pneumatic pump
FN 42	Motor
DV 42	Diverter
WF 42	gypsum weigh feeder
WF 43	tuff weigh feeder
BC 41	Belt conveyor
BF 42	V-belts
BW 41	Filter

One of the major problems of Cement Mill 4 is the high downtime. The annual downtime ownership (in hours) for Cement Mill 4 for the last three years is as shown in Table 4.8 below.

Table 4-8: The annual downtime ownership (in hours) on Cement Mill 4

Downtime ownership	2010/2011	2011/2012	2012/2013	Total	% contribution
Production	503.6	2398.7	954.7	3,857.00	37.56696
Engineering	409.7	283.6	328.8	1,022.10	9.955196
Mechanical	301.7	549.3	886.2	1,737.20	16.92023
Electrical	169.7	496.8	421	1,087.50	10.59219
Project	1.3	36.8	4.7	42.8	0.41687
Sales	486.7	630.8	1038.4	2,155.90	20.99834
KPLC	71.8	62.5	65.2	199.5	1.943119
Works	43.8	0	0	43.8	0.42661
MOB	2.3	0.9	0	3.2	0.031168
ADM	0	113.2	4.8	118	1.149313
Total	**1990.6**	**4572.6**	**3703.8**	**10267**	**100**

From table 4.8 above, it can be noted that electrical, mechanical, production and sales have the highest contributions to the total downtime on Cement Mill 4. Together, the four factors contribute to 86% of the total downtime ownership on Cement Mill 4.

The average annual downtime per component on cement mill 4 is as shown in table 4.9 below.

Table 4-9: Average annual downtime ownership by component (in hours)

Component	Downtime ownership				
	Production	**Mechanical**	**Electrical**	**Total**	**% contribution**
Clinker Hopper	57.35	90.13	76.69	224.17	14.3743868
Clinker weigh feeder	0.81	48.88	24.27	73.96	4.74251528
Tuff hopper	106.79	247.09	189.36	543.24	34.8340184
Motor	3.29	35.27	0	38.56	2.47257151
Cement pipeline	0	72.95	0	72.95	4.67775134
Chamber	1.88	76.44	23.94	102.26	6.55718783
Pneumatic pump	63.58	250.19	33.22	346.99	22.2499375
Motor	0	7.06	0	7.06	0.4527063
Diverter	0	1.51	0	1.51	0.09682528
gypsum weigh feeder	0.3	0.06	32.36	32.72	2.09809491
tuff weigh feeder	1.98	25.54	3.81	31.33	2.00896435
Belt conveyor	4.78	11.94	0.62	17.34	1.11188771
V-belts	14.6	3.12	4.36	22.08	1.41582933
Filter	3.33	0	0	3.33	0.21352861
Silo changeover	9.64	0	0	9.64	0.61814288
Temperature sensor	10.7	0	16.44	27.14	1.74029022
Motion Detector alarm	0.21	0	0	0.21	0.01346577
Gypsum hopper	0	0	5.02	5.02	0.32189598

Using the information in Table 4.9 below, a Pareto plot was made in order to determine the most critical components on Cement Mill 4.

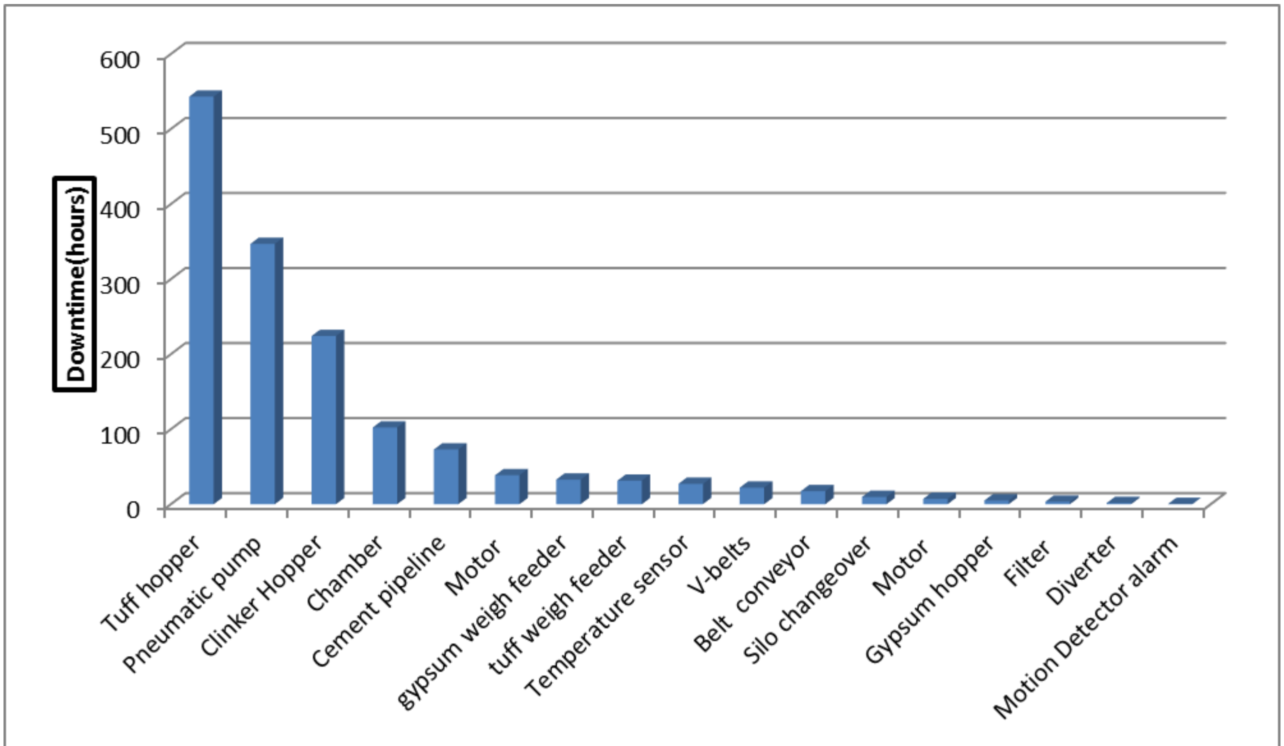


Figure 4-4: Average annual downtime ownership by component (in hours)

Basing on the total downtime ownership of mechanical, electrical and production, the most critical components on Cement Mill 4 are the tuff hopper, the pneumatic pump and the clinker hopper with the annual downtime ownership of 543, 346 and 224 hours respectively. This is as shown in figure 4.4 above. The three components contribute to downtime at EAPCC by 1114 hours every year. This means that the three components cumulatively have an annual downtime of 1.547 months. However, the tuff hopper is the most critical component because other than having the highest downtime, it also has the highest number of failures.

Table 4.10 below shows some of the failure modes, causes and downtime contribution of components on tuff hopper.

Table 4-10: Reasons of failure of the tuff hopper

Downtime ownership	Failure	Downtime contribution (hours)
Mechanical	Faulty crane	148
	Failure of TRA 0630 pedestal	43

	bearing	
	Failure of the slewing shaft and roller	57
	Failure of the girth gear pin	20
	Breaking of the hoisting rope	7
Electrical	Faulty crane	101
	Failure of the hoisting motor	17
	Control voltage problem	5
	Failure of the thruster motor	12
	Faulty control circuit	5
	Slewing problem	22
Production	Blocking of the tuff hopper	106

From table 4.10 above, it can be noted that mechanical has the highest contribution of annual downtime on the tuff hopper (275 hours). On the other hand, electrical and production have a downtime of 162 and 106 hours respectively.

Using the information provided in table 4.10 above, a Pareto plot was made as shown in figure 4.5 below.

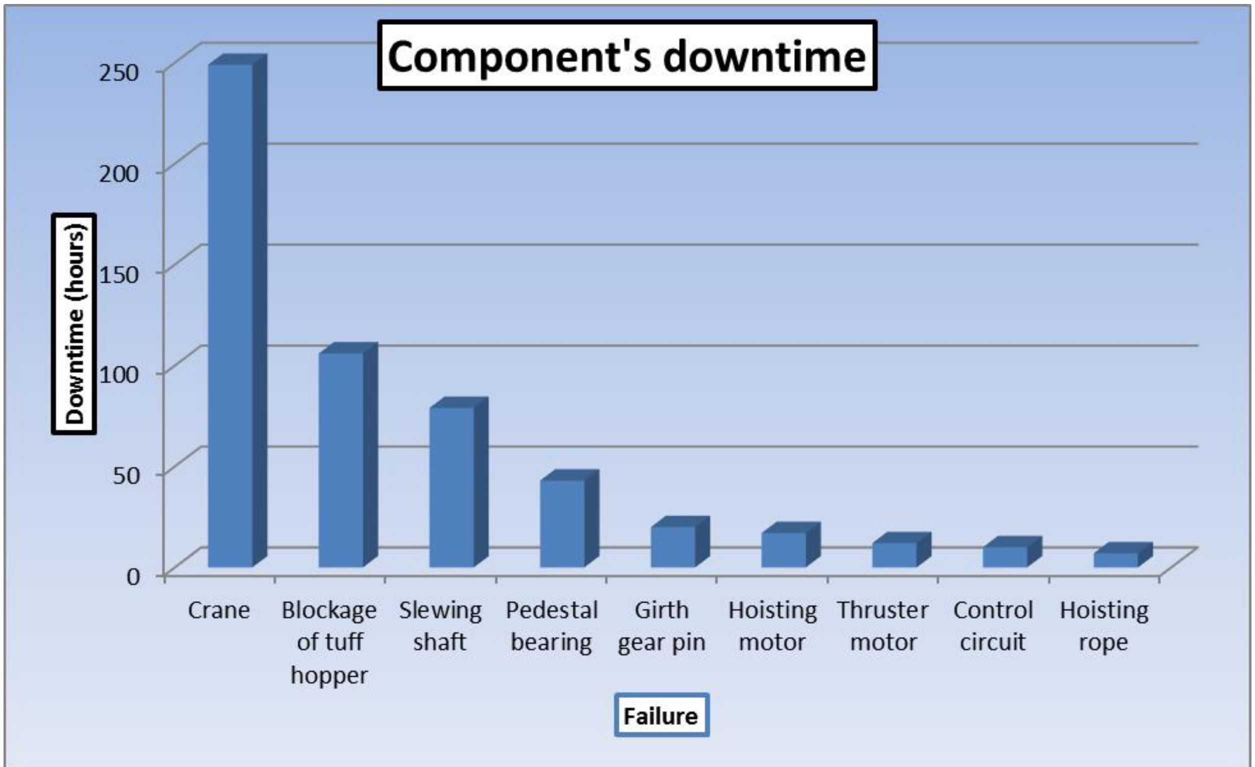


Figure 4-5: Tuff hoper's components downtime

From figure 4.5 above, it can be noted that failures as a result of the crane have the highest contribution to downtime (249 hours). It can also be noted that the blockage of the tuff hopper contributes 106 hours to downtime. Therefore, the crane failure is the chief cause of downtime on Cement Mill 4.

4.4 Determination of the optimal PR interval

To gain some insights in the tuff hopper failure mode, life data analysis was carried out using *EasyFit* Computer Package (EasyFit, 2013). The point of interest was to establish whether it has increasing failure rate or random rate and its possible characteristic life. Table 4.11 below shows a summary of the maintenance KPIs on the tuff hopper during year 2012/2013.

Table 4-11: Summary of some maintenance KPIs on the tuff hopper

Month	Total Hours	Downtime	Running Hours	No. of failures	MTBF	MTTR	Failure rate
July	744	17.57	726.43	3	242.1433	5.856667	0.004032

August	744	0.4	743.6	1	743.6	0.4	0.001344
Sept	720	97.8	622.2	6	103.7	16.3	0.008333
Oct	744	70.89	673.11	11	61.19182	6.444545	0.014785
Nov	720	16.69	703.31	9	78.14556	1.854444	0.0125
Dec	744	34.75	709.25	12	59.10417	2.895833	0.016129
Jan	744	6.87	737.13	11	67.01182	0.624545	0.014785
Feb	672	36.66	635.34	14	45.38143	2.618571	0.020833
March	744	73.09	670.91	16	41.93188	4.568125	0.021505
April	720	48.56	671.44	15	44.76267	3.237333	0.020833
May	744	41.66	702.34	16	43.89625	2.60375	0.021505
June	720	98.3	621.7	20	31.085	4.915	0.027778

Failure data analysis was carried out using Weibull distribution while the repair data analysis was carried out using the lognormal distribution (Wiseman M., 2001). Wiseman asserts that about 85–95% of all failure data are adequately described with a Weibull distribution (Wiseman M., 2001). The reasons are that the Weibull distribution has the ability to provide reasonably accurate failure analysis with a small sample size, that it has no specific characteristic shape, and that, depending upon the values of the parameters; it can adapt the shape of many distributions. It is also known that the lognormal distribution is widely used to model repair times. In addition to that, the author asserts that about 85–95% of all repair times are adequately described by a lognormal distribution. This is due to the skewness of the lognormal distribution, with a long tail to the right; provide a fitting representation of the repair situation. In a typical repair situation, most repairs are completed in a small time interval, but in some cases repairs can take a much longer time (Wiseman M., 2001).

Using the Anderson – Darling statistic test, the standard deviation and the mean for the lognormal distribution for the repair data were found out to be 0.9633 and 1.076 respectively. Similarly, the beta value (shape parameter) for the Weibull distribution was found to be 1.5432 while the alpha value (scale parameter) was found out to be 292.361 days. Since the value of beta is greater than one, it gives an indication that the tuff hopper has an increasing failure rate. This means that the tuff hopper is always in a deteriorating state. On the other hand, the mean tuff hopper life of 292days may not indicate the equipment characteristic life, but just the Weibull mean for time to failure.

Another reason why optimal PM scheduling was thought to be a solution is because the cost of CM on the tuff hopper is much higher as compared to the cost of PM.

The assumptions made during this analysis include:

i. Failure data follows a Weibull distribution while repair data follows a lognormal distribution. This is according to the Wiseman (2001) analogy discussed above.
ii. The time required to perform a preventive maintenance action ***(t_m)*** is constant and equal to 56 hours.
iii. All months are assumed to be having 30 days
iv. In both cases, the value of C_p and C_c was taken to be constant and it was basically a monthly arithmetic average

In the estimation of the optimal PM interval, the adjusted ARM cost minimization model shown in the equation below is used.

$$E[cost] = \frac{C_f * F(T) + C_p * R(T)}{\int_0^T t dF(t) + t_r * F(T) + (T + t_m) * (1 - F(T))}$$

Where:

C_f is the cost of corrective maintenance

C_p is the cost of preventive maintenance

F (T) is the cumulative density function of the failure data

t_m is the time required to complete planned maintenance actions

t_r is the time required for repairs.

For a 2-parameter Weibull distribution, the probability density function (PDF) is given by the equation below.

$$f(t) = \frac{\beta}{\alpha}\left(\frac{t}{\eta}\right)^{\beta-1} \exp\left(-\left(\frac{t}{\alpha}\right)^{\beta}\right)$$

F (t) can then be calculated by determining the cumulative values of f (t). The calculated value of F (t) is related to R (t) as shown by the equation below:

$$R(t) = 1 - F(t)$$

According to Pintelon (2006), the integral part in the equation can be estimated using the Taylor's series.

By substituting the different values in the equation above, the monthly expected cost for the tuff hopper is as shown in table 4.12 below.

Table 4-12: The expected monthly cost for the tuff hopper

t	**p**	**c**	**R(t)**	**F(t)**	**Tm**	**Tr**	**E[Cost]**
0	467000	226000	1	0	30	6.4	693000
1	467000	226000	0.982934	0.017066	30	6.4	673296.2
2	467000	226000	0.95248	0.04752	30	6.4	657468.7
3	467000	226000	0.914441	0.085559	30	6.4	644543.8
4	467000	226000	0.871355	0.128645	30	6.4	634138.9
5	467000	226000	0.824935	0.175065	30	6.4	626018.3
6	467000	226000	0.776482	0.223518	30	6.4	620017
7	467000	226000	0.727025	0.272975	30	6.4	616013.4
8	467000	226000	0.677401	0.322599	30	6.4	613913.5
9	**467000**	**226000**	**0.628287**	**0.371713**	**30**	**6.4**	**613642.9**
10	467000	226000	0.58023	0.41977	30	6.4	615139.2
11	467000	226000	0.533664	0.466336	30	6.4	618347.1
12	467000	226000	0.488927	0.511073	30	6.4	623213.6
13	467000	226000	0.446274	0.553726	30	6.4	629683
14	467000	226000	0.405885	0.594115	30	6.4	637693.1
15	467000	226000	0.367879	0.632121	30	6.4	647170.9
16	467000	226000	0.332323	0.667677	30	6.4	658028.5
17	467000	226000	0.299235	0.700765	30	6.4	670159.8
18	467000	226000	0.268599	0.731401	30	6.4	683437.3

19	467000	226000	0.240367	0.759633	30	6.4	697710
20	467000	226000	0.214467	0.785533	30	6.4	712802.4
21	467000	226000	0.190805	0.809195	30	6.4	728515
22	467000	226000	0.169277	0.830723	30	6.4	744625.7
23	467000	226000	0.149764	0.850236	30	6.4	760894.4
24	467000	226000	0.132145	0.867855	30	6.4	777067.8
25	467000	226000	0.116291	0.883709	30	6.4	792886.5
26	467000	226000	0.102076	0.897924	30	6.4	808093.5
27	467000	226000	0.089372	0.910628	30	6.4	822442.7
28	467000	226000	0.078054	0.921946	30	6.4	835707.9
29	467000	226000	0.068004	0.931996	30	6.4	847690.7
30	467000	226000	0.059106	0.940894	30	6.4	858226.8
31	467000	226000	0.051251	0.948749	30	6.4	867191.4
32	467000	226000	0.044337	0.955663	30	6.4	874501
33	467000	226000	0.038269	0.961731	30	6.4	880114
34	467000	226000	0.032956	0.967044	30	6.4	797325

Basing on the assumptions made above, Figure 4.6 shown below was plotted to estimate the variation of the monthly expected maintenance cost with time. The detailed representation of the monthly expected maintenance cost is in the appendix section.

Using the information in table 4.12 above, figure 4.6 below was drawn.

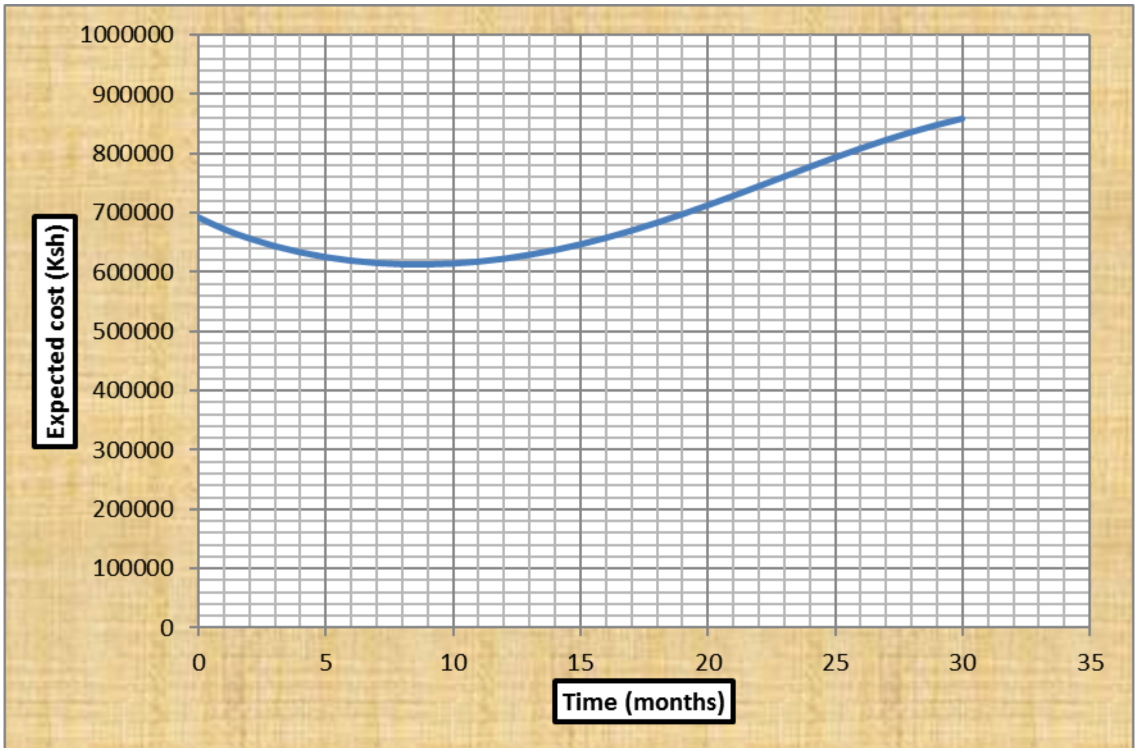


Figure 4-6: The monthly expected cost for the cement mills

From figure 4.6 above, we can note that the most optimal PM interval for the tuff hopper is at the end of the 9th month. This is because at this point, the expected maintenance cost per month is at the minimum point.

4.5 Maintenance actions on the critical component

From the failure data analysis, the tuff hopper was found to be the least reliable equipment responsible of highest failures and downtime in the system. For maintenance and asset management, the tuff hopper would be the obvious target for failure root cause analysis and reliability improvement. From the previous sections, majority of failures on the tuff hopper can be contributed to the failures to the crane and the blockage of the tuff hopper.

It is also worth noting that a good proportion of the MTTR on cement mill 4 is actually not used to perform repairs. This can be attributed to the fact that Cement Mill 4 is located far away from the maintenance department (almost 50 meters away). On average, 10 minutes are taken to go to the maintenance store and pick the necessary tools and equipment to conduct any given maintenance action.

Table 4.13 below shows the delineation of the downtime on the tuff hopper: causes and possible solution.

Downtime	Reason	Possible solution
Crane failure	Old crane	Replace the crane
Tuff hopper blockage	Wet material	Ensure material is dry
	Wrong design of the cone angle	Redesign the tuff hopper
High time to repair	Maintenance department far from cement mill 4	Tool-box option

Among the possible maintenance action alternatives for tuff hopper reliability improvement include redesign of the tuff hopper, Replacement of the crane and Tool-box option.

4.5.1 Option 1: Replacement of the crane

Since 46% (249 hours) of the total downtime on the tuff hopper can be directly linked with failures on the crane, replacement of the crane is one of suggested options. The current crane on Cement Mill 4 is more than 30 years old. The capital expenditure for replacement of the crane is approximately 140,000,000 shillings.

The assumptions made during this analysis include:

i. O & M costs will remain the same after replacing the old crane
ii. The time value of money is 9% per annum

The downtime (in hours) and the cement production (in tons) for cement mill 4 are related as shown in figure 4.7 below.

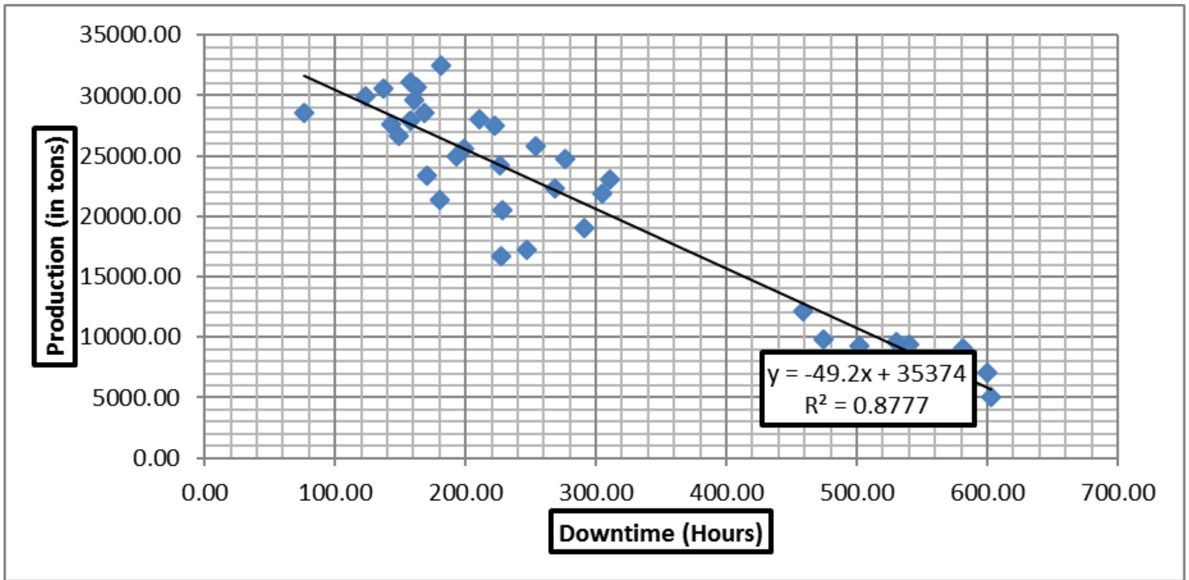


Figure 4-7: The variation of production with the downtime for the last three years.

As expected, an increase in downtime leads to a reduction in cement production. The regression equation and the coefficient of determination for the line of best fit are Y=-49.2X+35374 and R^2=0.8777 respectively. Where Y is the production in tons and X is the downtime in hours

Basing on the downtime of the crane on Cement Mill 3 (a newer crane), the downtime as a result of the crane failures will be reduced to 175 hours. This is because the average downtime as a result of the crane on Cement Mill 5 is 175 hours. This corresponds to the monthly downtime reduction by 6.244 hours (from 20.815 to 14.571 hours).

Therefore, the corresponding increase in production will be calculated as shown below:

$$Y = [-49.2 \times (20.815) + 35374] - [-49.2 \times (14.571) + 35374] = 307\ tons$$

With this option, 307 more tons are expected to be produced per month. This corresponds to an increase in production by 3684 tons per annum. With the current retail price of a 50-kg bag of *Blue Triangle Cement* being at 550 shillings, the company is expected to generate extra revenue of 33,770,000 shillings per annum.

4.5.2 Option 2: Redesign of the tuff hopper

Another reason that has led to the increase in the downtime on the tuff hopper is the constant blockage of the tuff hopper. During year 2012/2013, 67 failures were as a result of the blocking of the tuff hopper. This corresponds to an annual downtime of 106.55 hours. Good hopper design optimizes flow rate, allowing the most economical choice of a feeder. Improperly designed hoppers will substantially reduce feeder capacities and consequently, blocking of the hopper outlet. Another design reason that might have contributed to the blocking of the tuff hopper is the inadequate emptying, usually occurs in funnel flow silos where the cone angle is insufficient to allow self draining of the bulk solid. The last design shortage observed on the tuff hopper is mechanical arching; characterized by traffic jam as a result of too many large particle competing for the small ones at the outlet.

To solve the above problems, the cone angle of the tuff hopper should be redesigned. The discharge rate should also be checked. Silo discharging devices such as Slide valve, Slide gate, Rotary valve, Vibrating Bin Bottoms and Vibrating Grates should be included in the design.

Taking Cement Mill 5 as the benchmark, redesigning the tuff hopper will reduce the annual downtime from 106 hours to 65 hours. The corresponding increase in production will be calculated as shown below:

$$Y = [-49.2 \times (106/12) + 35374] - [-49.2 \times (50/12) + 35374] = 168\ tons$$

With this option, 168 more tons are expected to be produced per month. This corresponds to an increase in production by 2016 tons per annum. With the current retail price of a 50-kg bag of *Blue Triangle Cement* being at 550 shillings, the company is expected to generate extra revenue of 22,176,000 shillings per annum. The capital expenditure of this option is 24,000,000 shillings.

4.5.3 Option 3: Tool-box option

It is worth noting that a good proportion of the MTTR on cement mill 4 is actually not used to perform repairs. This can be attributed to the fact that Cement Mill 4 is located far away from the maintenance department (almost 50 meters away). On average, 10 minutes are taken to go to the maintenance store and pick the necessary tools and equipment to conduct any given maintenance action. For the last 36 months, the tuff hopper has been experiencing an average of 11 failures per month. This translates to 110 minutes being wasted every month as a result of picking tools and spares.

This option is aimed at reducing the time to repair (TTR) by ensuring that all the required tools and materials are in the plant to ready to use in case of a failure. Currently, some special tools are only available in workshop and time is lost travelling to the workshop during repair. The approximate cost of tool box option is 10,000,000 shillings with a potential saving of 110 minutes of repair time.

The corresponding increase in production is given by the following equation:

$$Y = [-49.2 \times (45.25) + 35374] - [-49.2 \times (43.41) + 35374] = 90\ tons$$

With the tool-box option, 90 more tons are expected to be produced per month. This corresponds to an increase in production by 1080 tons per annum. With the current retail price of a 50-kg bag of *Blue Triangle Cement* being at 550 shillings, the company is expected to generate extra revenue of 11,880,000 shillings per annum.

4.5.4 Economic evaluation of the alternatives

Net present value (NPV) analysis was used to in the economic evaluation of the options suggested in the above section. The yearly cash flow was calculated as the sum of the yearly maintenance cost savings (from avoided failures) and incremental contribution from additional production output. The incremental contribution is calculated as the product of variable margin and production output increase.

The NPV was calculated as shown by the equation below:

$$NPV = -I + \sum_{t=1}^{t} \{(S + A)\frac{1}{(1+i)^t}\}$$

Where I is the investment, A is the additional production revenue, S is the maintenance saving, (i) is the interest rate, approximated as 9% (based on the banks rates of 5% and risk factor of 4 %) and t is the time of the analysis. Table 4.13 below shows a summary of the details of the different improvement options.

Table 4-13: The economic details of the improvement options

Option	**Investment cost (Ksh)**	**Maintenance cost saving (Ksh)**	**Output increase (tons)**	**Additional production revenue (Ksh)**
1	140,000,000	16,000,000	307	33,770,000
2	24,000,000	9,600,000	168	22,176,000
3	10,000,000	0	90	11,880,000

For easy comparison, the information in table 4.13 above was used to plot figure 4.8 below.

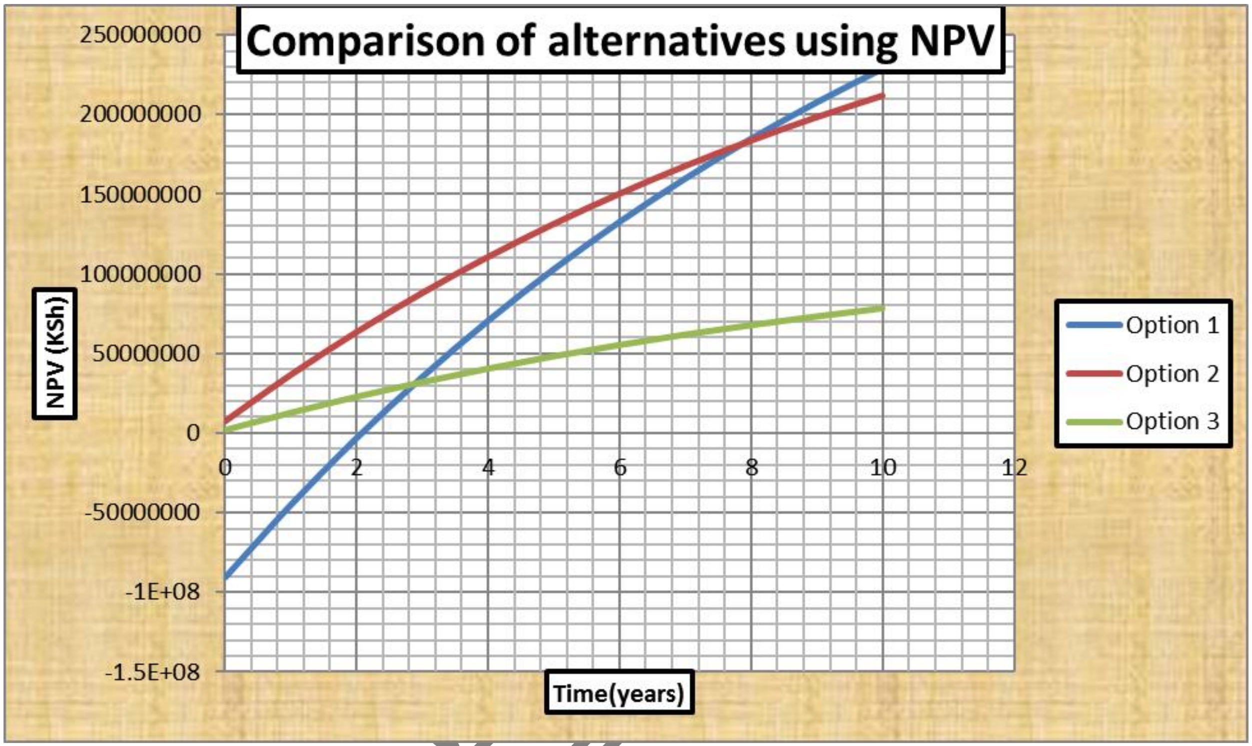


Figure 4-8: Investment analysis of the different options

From investment analysis in figure 4.8 above, we find out that option 1 (replacement of the crane) has the least attractive NPV for a shorter time interval. This can be attributed to the high investment cost involved in the purchasing and installation of a new crane. However, for a longer time interval (t), option 1 (replacement of the crane) has the most attractive NPV. On the other hand, for a shorter time interval, option 4 has the most attractive NPV. This can be attributed to the fact that the capital investment for this option is zero. However, for a longer time interval, this option has the least attractive NPV. However, it is cheaper and easier to implement this option, unlike the other alternatives where shutdown is required. Option 3 (The tool box option) demonstrates the potential of the 'small' improvement initiatives and efforts, which eventually drives overall system continuous improvement.

4.6 Deductions from chapter four

From the analysis in chapter 4, the following deductions can be made:

- Cement Mill 4 is the most critical plant
- The tuff hopper is the most critical equipment
- The tuff hopper's crane is the most critical component
- The optimal PM interval for the most critical component is 9 months
- For long term organizational goals and objectives, the crane should be replaced while the tuff hopper should be redesigned

5 CHAPTER FIVE: CONCLUSION

5.1 Review of research objectives

The objective of this research was to come up with an optimal PR timing whose objective is to minimize machine breakdown, maximize equipment availability and minimize the cost associated with maintenance. To achieve this objective, the critical plant, equipment and components were identified. The PR timing for the critical component was then determined using the classical ARM model

5.2 Key findings

Using MCDM, Cement Mill 4 was identified as the most critical plant. Narrowing down to the equipment level, the most critical equipment was identified as the tuff hopper. Furthermore, narrowing down to the component level, the most critical component was found out to be the crane. Therefore, to minimize downtime, maximize the availability, maximize productivity and consequently the profitability at EAPCC; special attention should be placed on the tuff hopper's crane. It was found out that the most optimal time to carry out PM on the critical component is after the end of the 9th month.

Three alternatives concerning the maintenance actions on the critical component were suggested as means of minimizing the downtime: replace the crane, redesign the tuff hopper and the use a tool box. For a longer time interval, the replacement and redesign options have the most attractive NPV. The replacement and design options have a potential of increasing the annual cement output by 307 and 168 tons respectively. This translates to an annual increase in revenue by 33,770,000 and 22,176,000 shillings respectively. Furthermore, it was noted that the tool-box option and the can be implemented in combination with the other two options because they require a small capital investment.

5.3 Recommendations

For long-term organizational goals and objectives the tuff hopper should be redesigned. Even though this venture has a capital investment of 24,000,000 shillings it has the capability minimizing the annual maintenance cost by 9,600,000 shillings and increasing the monthly output by 168 tons. Another option that the management should consider adopting is replacing the tuff hopper's crane. This is the most expensive option (140,000,000 Shillings) but the most attractive; considering the NPV.

In order to meet the organizational goal of 1.5 million metric tons of cement per annum, the PM interval should be reconsidered from the current 12 months to 9 months. PM, if well scheduled can help the company in minimizing the number of breakdowns, maximizing the availability, reducing the risks and accidents, minimizing the maintenance costs, maximizing the productivity and consequently maximizing the profitability. This can in turn help in minimizing the customers waiting time and chances of negative feedback reviews on the global and competitive market.

5.4 Future works

This research was only limited to developing a PM model while taking into account the aging of the machines. External factors were not considered. For better results in future, a PM model should be developed that considers both the external and internal factors influencing PM decision making. External factors (covariates) are factors such as environmental effect, technology improvement, human skills and product types which contribute to the component failure, while the internal factor refers to the aging of the component, where it is usually measured in the unit of time. In addition to that, the age-based PM model used in this research is limited to cost and reliability attributes. To provide a more comprehensive view for decision makers, other attributes such operability should be incorporated into the model.

Furthermore, this research does not analyze maintenance supportability and it is assumed to be satisfactory. However, as maintenance supportability significantly affects systems downtime and availability, an extension of the study to incorporate maintenance supportability is essential.

5.5 Research contributions

5.5.1 Contribution to theory

Most researchers tend to use one maintenance KPI in the selection of critical components and equipments. However, this research has demonstrated how MCDM can be used for cases of conflicting criteria in the selection of a critical component.

5.5.2 Contribution to practice

The study presented in this thesis can assist maintenance engineers and managers at EAPCC in determining the most critical component that accounts for the highest downtime. Furthermore, it can help the management in predicting an accurate PM interval. This can help a lot in minimizing the maintenance cost and hence maximizing the profitability. Consequently, the competitiveness of EAPCC on the local and global market will be enhanced.

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Appendices

Appendix 1: Determination of the parameters

% Determination of the values of alpha and beta in a Weibull distribution

% The monthly MTBF

MTBF=[242.14 743.6 103.7 61.2 78.1 59.1 67.01 45.3 41.9 44.8 43.89 31.08];

% The frequency of the MTBF

f=[1 1 1 1 1 1 1 1 1 1 1 1];

% Remove censoring from the data

c=[0 0 0 0 0 0 0 0 0 0 0 0];

% Estimation of the confidence interval

alpha=0.05;

[parmhat,parmci]=wblfit(MTBF,alpha,c,f)

Determination of the parameters associated with the time to repair

MTTR=[5.85 0.4 16.3 6.44 1.85 2.89 0.62 2.62 4.57 3.24 2.61 4.92];

% Estimation of the mean and the standard deviation

parmhat=lognfit(MTTR)