RELIABILITY CENTERED MAINTENANCE IMPLEMENTATION ON THE ETHEKWINI ELECTRICITY NETWORK FOR SYSTEM MAINTENANCE PROCESS OPTIMISATION

Dissertation

by

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ABSTRACT

Much equipment in the eThekwini Electricity network has been in use for several decades. Failure of this equipment could critically impact electricity supply to customers, and result in high costs associated with loss of load and/or component replacement. The fundamental motive for any power utility is to plan, operate, and maintain power infrastructure such that customers receive reliable electric services at the minimum expense possible.

For this dissertation, the Reliability Centered Maintenance (RCM) model was implemented in the eThekwini Electricity network. This model emphasises the importance of long-term planning and allocation of resources over the life time of a transformer, or any other component. RCM is an ongoing process that entails gathering data from operating systems performance, and using this data to improve design, operation, and maintenance of the system. The eThekwini Power network failure statistics for the previous five years were collected and thoroughly analysed to identify critical components associated with higher failure rates, and associated consequences. Upon examination, it was determined that the power transformer is a critical component of the system. The transformer plays a significant role in the power system due to its remarkable effect on overall reliability, in addition to the fact that it is a major cost factor in the power grid. Transformer management comprises of identifying the appropriate type and frequency of maintenance, and the appropriate time to replace the transformer in a cost-effective manner.

The Markov model for ascertaining the transformer's remaining service life was applied on the identified critical transformer. The transformer deterioration process is modelled by representing the oil insulation by discrete stages. Using the Institute of Electrical and Electronics Engineers (IEEE) standard for interpreting the transformer insulation, the transformer under review was found to be at stage two. Further analysis was performed on system unavailability rates versus mean time to first failure (MTTFF). The analyses indicated that the higher the MTTFF, the longer the system availability whereas the lower the MTTFF, the more reduced the system availability. Improving the MTTFF rates of a system

will enhance reliability. The effective application of RCM will optimise the maintenance processes with reasonable expenditures.

DECLARATION

I, Musawenkosi Phillemon Lokothwayo, declare that the work hereby submitted for the degree of Master of Engineering at Durban University of Technology (DUT) is my own particular work and has not been beforehand submitted by me at another University for any degree. Where utilisation has been made of the work of others, it has been appropriately recognized in the text and included in the list of references.

Musa Phillemon Lokothwayo Signature __________ Date: ________

DEDICATION

To my parents, brothers, sisters, all relatives and friends, for their constant encouragement, patience, care and love.

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"O Lord my God, I will give you thanks forever." Psalm 30:12

Foremost, I give thanks to my Lord Jesus Christ for giving me the strength and wisdom to start and finish this work.

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LIST OF ABBREVIATIONS

AM	Asset Management
ASAI	Average Service Availability Index
CA	Condition Assessment
CAIDI	Customer Average Interruption Duration Index
CAIFI	Customer Average Interruption Frequency Index
CBM	Condition Based Maintenance
CM	Corrective Maintenance
DGA	Dissolved gas analysis
EE	eThekwini Electricity
EPRI	Electric Power Research Institute
FMEA	Failure Modes and Effects Analysis
FMECA	Failure Modes and Effects Criticality Analysis
FPT	First passage time
HV	High voltage
IEEE	Institute of Electrical and Electronics Engineers
IBM	Inspection based maintenance
LCC	Life Cycle Cost
LV	Low Voltage
MATLAB	Matrix Laboratory
MCP	Markov chain process
MDT	Mean down time

MM	Maintenance Management
MTBF	Mean time between failures
MTTF	Mean time to failure
MTTFF	Mean time to first failure
MTTR	Mean time to repair
MV	Medium Voltage
PD	Partial Discharge
PDF	Probability Density Function
PM	Preventive Maintenance
RCM	Reliability Centered Maintenance
RTF	Run To Failure
SA	South Africa
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index
TBM	Time Based Maintenance
TDCG	Total dissolved combustible gases

LIST OF SYMBOLS

A	Transition probability matrix
C_2H_2	Acetylene
C_2H_4	Ethylene
C_2H_6	Ethane
CH_4	Methane
CO	Carbon monoxide
CO_2	Carbon dioxide
Fr	Failure state
H_2	Hydrogen
i	Present state of the equipment
j	Future state of the equipment
k	Number of the deterioration states
kV	Kilovolts
Mij	Expected remaining life of the component
M(t)	Maintainability function
MVA	Mega Volt Amps
MW	Mega Watts
n	Total number of states
P	Probability of transiting from state i to any state k
R(t)	Reliability function
P_{ij}	Probability of moving between states
P(S)	Steady state probability of state S
P(t)	Transition probability
S	Set of states
U	Unavailability
α	Scale parameter of Weibull distribution for Failure rate

β	Shape parameter of Weibull distribution for Failure rate
γ	Inspection rate
η	Shape parameter of Weibull distribution for Failure rate
θ	Shape parameter of Weibull distribution for repair rate
λ	Transition rate between states
λ(t)	Average failure rate at year t
μ	Repair rate

PUBLICATION

Appended Paper

M.P Lokothwayo and G. Frederick d'Almaine," Reliability centered maintenance model implementation to eThekwini electricity network", Proceeding Southern African Universities Power Engineering Conference, Vereeniging, South Africa, pp.176-181, January 2016.

CHAPTER 1

INTRODUCTION

The basic function of the power system is to provide an adequate electrical supply to its customers as economically as possible with a reasonable level of reliability [1]. In the power system, distribution networks have previously received less consideration when compared to the generation and transmission parts of the overall electrical power system [2]. However, the innovation in technology from customer's load, the level of service needed by customers, and regulators from power utilities, has caused attention to move from generation and transmission networks to distribution networks [2]. Statistics reveal that distribution networks represent 40% of the expense to transport power, and 80% of customer reliability issues [3]. According to Brown and Humphrey, reliability problems in distribution networks originate from aging infrastructure, lack of skills, and lack of proper administration for asset management and maintenance planning [4]. As a result, equipment deteriorates over time, until a failure occurs, causing a termination of equipment operation [5].

The power system design, operation, and maintenance are significant factors in a power system for monetary success and customer satisfaction [2]. In South Africa, distribution utilities are compelled by certain legislations and manufacturer guidelines to conduct maintenance in a specific mode [6, 7, 8, 9, 10, and 11]. Due to unplanned and unforeseen events, maintenance activities are not always conducted as planned, and greater focus is given to corrective maintenance which results in backlogs for scheduled maintenance [12]. Billinton, Shaidehpour, and Singh state that preventive maintenance is a strategy that may be used on power system equipment to lengthen the equipment lifetime, as well as to increase the equipment availability [13]. It may also reduce the expenses associated with corrective maintenance. However, on the one hand excessively frequent maintenance may be very expensive, without offering much performance improvement, whereas on the other hand too little maintenance may lead to catastrophic equipment failure. The maintenance effect on the reliability measures of a component will reflect in the whole system because the system is integrated up to the load point [14].

Reliability centered maintenance (RCM) is condition-based, with maintenance intervals based on actual equipment criticality and historical failure rate data [15]. The RCM strategy was first developed in the late 1960s by the airline industry, which concentrates on avoiding failures whose results are almost certain to be serious. Due to the expanded size and complicated nature of these airplanes, airlines were worried that proceeding with utilisation of conventional maintenance techniques would make the new airplanes uneconomical. After the effective implementation of RCM in the aviation industry, numerous industries commenced applying the RCM concept in their sectors [16].

In 1984, RCM was introduced by the Electric Power Research Institute (EPRI) to the atomic power industry [15]. Part of the motivation for this was that the preventive maintenance approaches at numerous atomic power plants were executed based on vendors' traditionalist suggestions, without adequate thought of real obligation cycles or system functions. In different cases, too little preventive maintenance was performed on key components that had not been distinguished as critical, resulting in failures that expanded remedial maintenance expenses and decreased plant accessibility [15]. Today, RCM has been adopted by various electrical utilities. The results of a RCM investigation can bring about changes to existing preventive maintenance tasks, the utilization of condition monitoring, inspections and useful testing, or the expansion or omission of such tasks [17]. In this research work, the RCM model was applied to the eThekwini electricity power network.

1.2. Problem Statement

The power distribution sector plays a crucial role in the overall electricity transportation value chain. Without a reliable power distribution network, all the investments made in the generation sector will not give a notable financial advantage [18]. Presently in South Africa, the overall electricity business is encountering many challenges. Many components forming the distribution system have been operating for a long period of time, and their resultant failure rates are higher than accepted levels; resulting in municipalities not honouring their obligations with respect to keeping the distribution networks under their jurisdictions in operation.

The effective maintenance planning, relating to the actual condition of the equipment with regards to maintenance rates, is one of the challenges presently facing utilities. Present maintenance approaches and asset management methods within the power system sector do not promote business sustainability and economic growth. Owing to this, reliability is gradually diminishing; this is confirmed by an increase in the number of faults due to poor performing systems and failures associated with components, and related infrastructure theft (cables etc.). Failure rates in power distribution network equipment are currently showing an upward trend, indicating that the situation is becoming worse [18]. The RCM model implementation within eThekwini electricity network is presented in this work. RCM places emphasis on the significance of strategic maintenance on the reliability of power systems, and on equipment's service life management. Based on the problem described above, a research of this magnitude was justifiable.

1.3. Aim and Objectives

1.3.1 Aim

The aim of this work was to implement the RCM model to eThekwini electricity network with the ultimate purpose of identifying critical equipment, and ascertaining its remaining service life enabling key decisions to be made pertaining to the continuous operation of equipment, in other words, knowing when to classify the equipment as in failure mode (when maintenance costs are higher than repair costs).

1.3.2 Objectives

The objectives of this work were as follows:

a. To conduct a thorough analysis of eThekwini power network failure statistics in order to implement RCM;

b. To analyse the effects of maintenance rates on MTTFF;

c. To ascertain the remaining service life of the identified critical components in order to plan accordingly.

1.4 Dissertation contributions

With the countless challenges currently encountered by electricity utilities around the world to provide uninterrupted supply at all times to end users, the output of this research will assist utilities, particularly in South Africa, to improve electricity service delivery to an acceptable level, reduce interruption rates, reduce losses of unsupplied power due to failures, and reduce operating and maintenance expenditure. Furthermore, the knowledge gained by this research will assist the future scholars and industries to improve the design, operation, and maintenance techniques of power system equipment.

CHAPTER 2

LITERATURE REVIEW

2.1. Power system overview

The electrical power system is complex, hugely integrated, and very substantial. It comprises numerous overhead lines, substations, transformers, and much other equipment spread over substantial geographical territories, interconnected to transport power to customers [1]. It is challenging to simultaneously analyse the complete power system. Fortunately, the system can be divided into suitable functional areas which can be examined independently [19]. These functional areas are generation, transmission, and distribution systems. In analysing the reliability of the power system, two approaches are usually considered, these being (1) the deterministic and (2) the probabilistic approaches. The stochastic nature of the power system tends to favour the probabilistic approach for reliability analysis [20].

The attention of this work is on RCM application within the distribution network, which is the direct link between the end-users (customers) and the power utility (municipality). Figure 2.1 depicts the three main levels of electric power system, from generation to end-user.

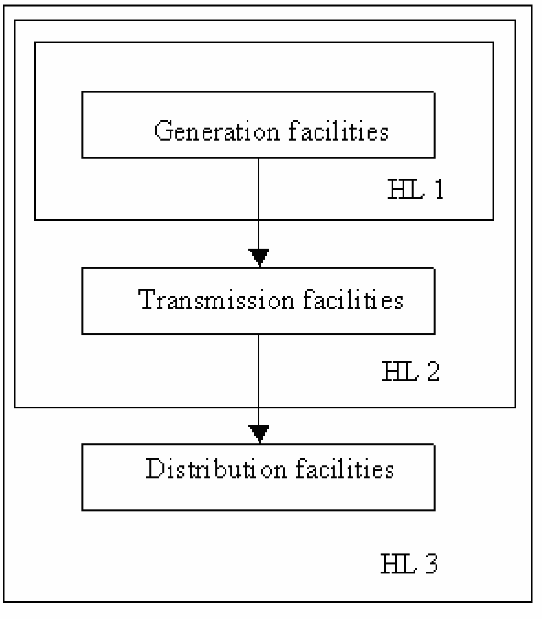

Figure 2.1: Power System – Hierarchical Levels [2]

2.1.1. Fundamentals of distribution systems

The role of the distribution system is to convey electrical power from the distribution substation to the service-entrance equipment situated at residential, commercial, and industrial customer facilities [1]. Reviewed Literature has revealed that the distribution network portion of the power system constitutes about 40% of the total power supply cost, and that about 80% all of customer reliability concerns originate from the distribution network [2]. The operational design and maintenance planning for distribution system are two of the factors which have a significant bearing on the economic gain of the power utility, as well as customer satisfaction [21]. The distribution system is segmented into three functional segments, which are the substation, primary distribution, and secondary distribution. Further, distribution systems can be classified as either radial or ring systems, depending on the network topology [22]. These configurations are briefly discussed in the following paragraphs.

2.1.2 Radial system

Many practical distribution systems consist of a single source of supply (the main feeder), and are referred to as radial systems. Radial distribution systems use primary or main feeders and lateral distributors. The main feeder originates from the substation and passes through the major load points. These have simple design and relatively low costs. However, they are susceptible to outages due to single contingencies [22]. That is, many customers can be affected by the failure of any single component. The use of a normally open tie point is often employed to improve the reliability of the radial distribution system [22]. Figure 2.2 illustrates a simple single line diagram of radial distribution system, where one feeder supplies the load points.

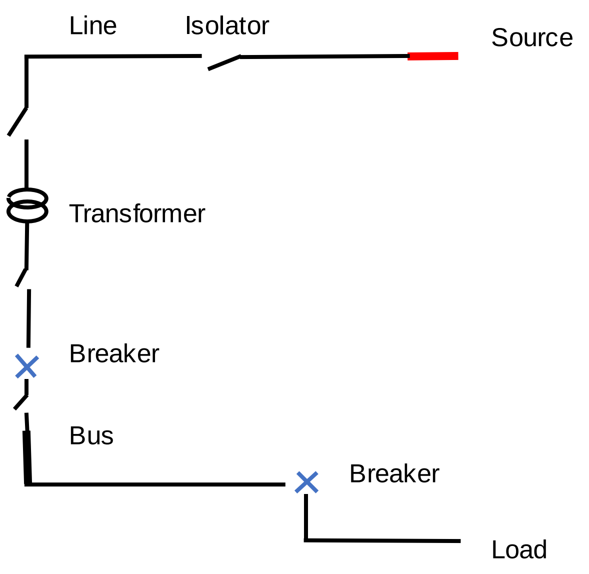

Figure 2.2: Radial feeder [1]

2.1.3 Ring system

Different from the radial system, a ring system has two sources feeding the ends forming the ring system. The ring system is understood to be more reliable than the radial system, since the load can be fed from an alternative source in the case where a fault affects one of the sources [22]. Figure 2.3 below illustrates a typical ring system.

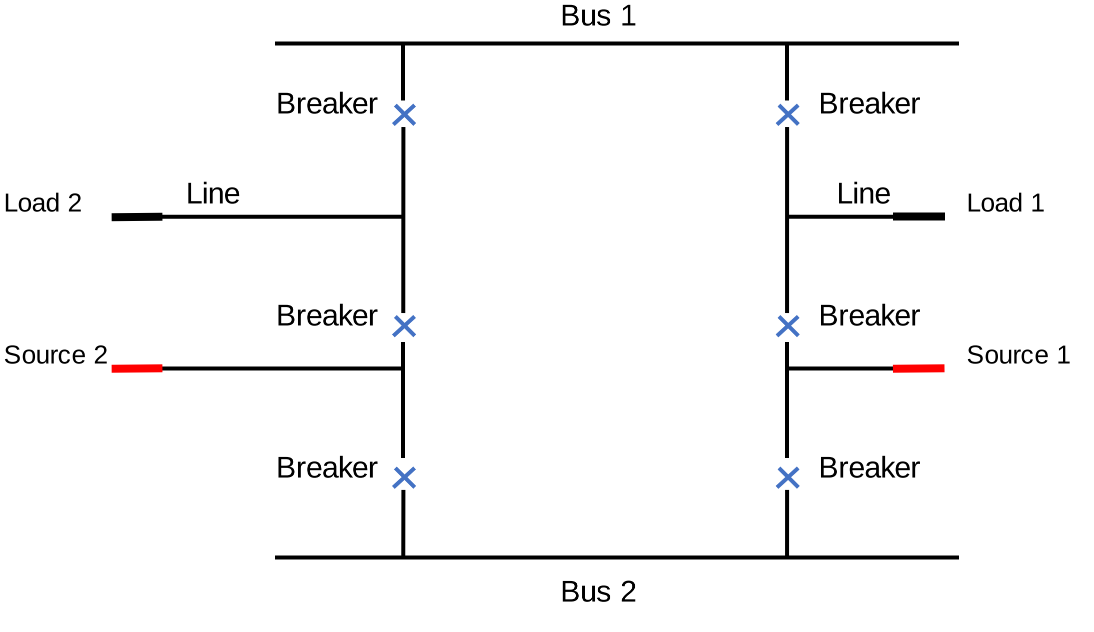

Figure 2.3: Ring System [1]

2.1.4. Distribution substations

Distribution substations form that part of the power supply system where the electric power is altered to a level convenient for eventual end use. Their main components are power transformers, switches, circuit breakers, besides other auxiliary equipment [23]. The metering system is the final component of the distribution system. Metering is useful for planning purposes and for monitoring power flow in an area [24].

2.2.1. Interruptions or outages

The distribution system comprises various components, such as lines, cables, circuit breakers, and transformers all of which are interconnected so as to convey energy to the end users. Despite the fact that the electrical power system ordinarily works for an extended period with no adjustment in system configuration, there is always the probability of a fault- or over-load condition occurring, resulting in an unplanned interruption [23]. Failure of any one of these components invariably results in the interruption of power supply to the end users.

Power supply interruption within the power distribution network can be categorised as planned and unplanned. The customers affected by planned interruption due to maintenance work are normally informed in advance; otherwise the interruption is recorded as unplanned [24]. Unplanned interruptions are viewed as random and can stem from a wide number of reasons, such as weather, equipment failure, and vandalism [24]. Unplanned interruptions in distribution systems are classified by the number of customers affected and the period of time that the power supply is interrupted. The Institute of Electrical and Electronic Engineers (IEEE) indicates three types of interruption [25]:

- *Momentary Interruptions* include the brief loss of energy to one or more customers, caused by opening and closing of switchgear;
- *Sustained Interruptions* incorporate outages not categorised as momentary events and that last for more than five minutes;
- *Major Events* are those that surpass the rational design and/or operational limits of the electrical power system and affect an extensive range of the customers served by the municipality;

2.2.2 Causes of unplanned interruptions

Power supply interruptions may occur due to various reasons, such as faults in the power system, or failures in the equipment [26]. Some of the causes of power supply interruptions are listed in Table 2.1.

Table 2.1: Causes of interruption [27]

Causes	Description
Ageing	During operation, components wear out with time and subsequently fail, resulting in interruption.
Weather	Dust, dump climates, wind, storms etc., increase the rate of component failure.
Vegetation	Trees are one of the largest factors that cause failures in distribution systems.
Animals and Pests	Some animals like birds and squirrels may get trapped and short circuit lines, for instance, which may lead to sustained interruptions.
Loading	During peak periods of power demand, the loading on the equipment is increased. This increases the operating temperatures of transformers and other equipment and may subsequently lead to their failure.
Human factors	These include scheduled maintenance, switching errors etc.

2.3 Fundamental concepts of maintenance

According to the IEEE, “Maintenance is defined as the combination of all technical and corresponding administrative actions intended to retain an asset in, or restore it to, a state in which it can perform its needed function” [28]. The role of maintenance in the electrical distribution system is to ensure equipment reliability, to extend its service life, and to maximize equipment availability so as to provide the best possible service to the customers.

Most of the equipment presently installed in power systems has been in service for quite a long time, and has thus aged. For such equipment, there is greater need for maintenance. The absence of appropriate equipment maintenance activities in the electrical distribution network will ultimately result in the failure of the equipment, as well as significant expenses to restore or repair the equipment to normal working condition.

2.3.1 Maintenance strategies classification

For maintenance of the equipment in the electrical distribution network, two fundamental approaches can be identified, namely *corrective* and *preventive* maintenance [29]. The choice of the right maintenance approach to apply is made complex by the need to maximize equipment reliability, and at the same time keep the maintenance costs as low as possible [30]. In arriving at an optimal maintenance approach, the impact of equipment inspection and maintenance rates on the equipment reliability has to be evaluated against the cost of such maintenance. Figure 2.4 below illustrates the main maintenance categories presently utilized by many municipalities.

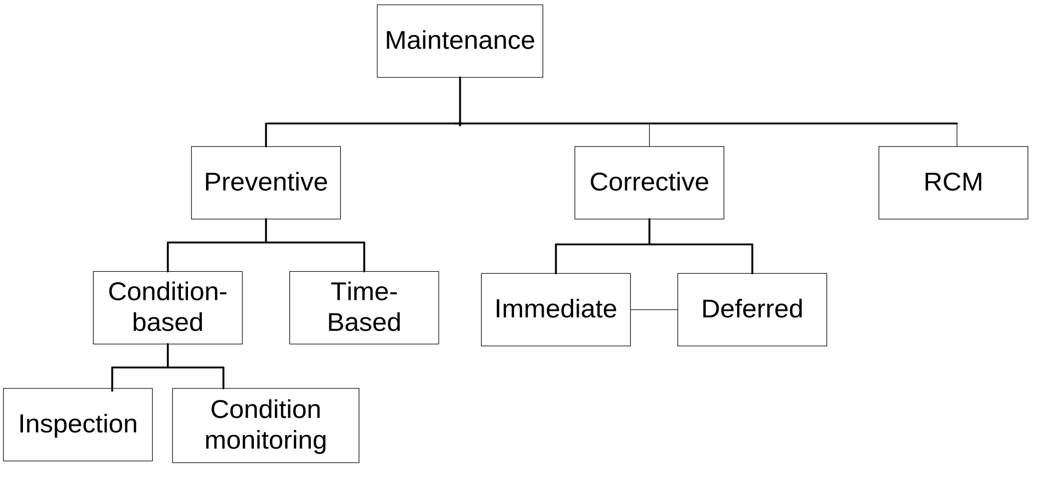

Figure 2.4: Maintenance approach overview [31]

2.3.1.1 Preventive maintenance

This is the type of maintenance that is conducted before equipment failure occurs, to keep the system in operational mode. Preventive maintenance includes the performance of routine inspections, as well as overhauling. It is normally conducted periodically, or as per the manufacturing standards guidelines [28]. The intention with this type of maintenance is to minimise the probability of failure. The benefit of preventive maintenance is that it can be planned early and the logistics of administration can be made simple [32], [33]. It can be classified into *Time-Based Maintenance (TBM)* and *Condition-Based Maintenance (CBM)* [34].

TBM is generally a moderate (and expensive) approach, whereby inspections and maintenance are performed at regular, fixed time intervals, mostly in line with manufacturer specifications without consideration of past condition examination [31],[32]. Based on the timetable, it can be categorized as either clock-based or age-based maintenance. Clock-based maintenance implies that the maintenance is done at determined datebook times, while age-based maintenance implies that the maintenance is conducted when equipment has reached a certain age.

CBM is based on the knowledge of the condition of the equipment, obtained from routine or continuous monitoring such as systematic inspections and measurements. Inspection can involve the use of human senses such as noise, visual inspection and monitoring techniques, or tests. CBM commonly broadens the interval between successive maintenance activities, and in this way tends to cost less than TBM, in spite of the fact that it requires a substantial amount of infrastructure investment including sensors, diagnostic technology, communication channels, data repositories, and processing software to gauge, communicate, store, and use important data describing the condition of the equipment [35], [36].

2.3.1.2 Corrective maintenance

In Corrective Maintenance (CM), also called Run-to-Failure, equipment is not maintained until it enters failure mode. The main objective of CM is to restore equipment into a working condition by repairing or replacing the faulty part of the equipment. This methodology is suitable when the cost of the failure is not extensive, and is clearly not appropriate for most equipment in power systems because of their high procurement costs [37]. The two sub-classes of this maintenance type are Immediate Maintenance and Deferred Maintenance [12] as illustrated in figure 2.4.

Immediate maintenance is performed immediately, as it is viewed as an emergency.

Deferred maintenance, on the other hand, may be planned for another period, considering criticality of equipment.

The use of CM is rarely recommended, as this implies leaving the system to operate without any maintenance until some equipment fails. Generally, CM is the least cost effective option when maintenance requirements are high [38], [34]. Additionally, when repair or replacement of any equipment is required, the downtime can be lengthy, since the logistics tend to become more problematic when things are not arranged ahead of time [32].

2.3.1.3 Reliability centered maintenance

RCM is not a new concept, but is an upgraded technique for performing maintenance activities. Maintenance plays a significant role in keeping power system assets in good state, and consequently maintaining the reliability of the entire system at a satisfactory level. RCM is the technique that has been created to determine the best approach to maintain a system or equipment, doing so at minimum expense [30]. RCM enhances the traditional types of maintenance by integrating them all and integrating the strength of each approach so as to meet the required operational level of each asset [39], [37]. RCM has effectively improved the traditional maintenance strategies by transforming the classification of equipment, which in turn provides an innovative methodology for prioritizing the maintenance activities based on equipment condition and importance [40].

The RCM characterisation of equipment comprises the following categories: *critical equipment, potentially critical equipment, commitment equipment, economic equipment, and run-to-failure equipment*.

The RCM does the characterisation by answering seven questions, namely:

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

Furthermore, RCM has been devised with the view to helping asset managers to enhance the safety and serviceability of infrastructure within the budgeted expenditure, and assisting the making of equipment replacement decisions, thus contributing to cost-effective maintenance.

RCM therefore involves setting up or enhancing a maintenance strategy in the most financially effective and technically feasible manner. This permits system and equipment usefulness to be maintained in the most prudent way [62]. In RCM, maintenance actions are organised taking into account the significance of each piece of equipment for the entire infrastructure. This significance can be indicated by Key Performance Indicator (KPI) measures set by the municipality [40], [42]. Since its main objective is maximising system reliability while reducing the related maintenance costs, RCM may rightly be considered to be the most economically viable maintenance approach. It actually represents a shift from planned or time-based maintenance, placing emphasis on the functional importance of system equipment and the associated records of failure and maintenance [43]. Two primary stages in the RCM methodology are *life time modelling* and *maintenance enhancement*. RCM is an on-going process, and permits the selection of maintenance actions that provide the necessary reliability at minimum expense. It can help reduce the expenses associated with maintenance considerably.

The fundamental rule of RCM is that maintenance should be linked to failure probability, so that maintenance of equipment is performed when its failure probability rises significantly. RCM entails separating a functioning system into its constituent parts, to such a point that the root of each possible failure mode can be pin-pointed, along with examining ways in which the identified failures may be avoided [44]. The effectiveness of using the RCM approach is strongly influenced by the accuracy of the deterioration models used to anticipate the remaining existence of the assets [45].

2.3.2 Maintenance model

Traditionally, most utilities developed maintenance procedures for equipment which included only a small, if any, quantitative approach to the system. As a result, it was often difficult to determine with a reasonable degree of confidence, the best frequency of inspection or indeed what should be inspected. Consequently, some maintenance procedures are more costly than necessary, and critical equipment is often unjustifiably taken out of service for prolonged periods of time [41]. Probabilistic maintenance models [46],[47] are ideally suited to account for these constraints in the maintenance studies, because of their simplicity and the opportunity to simultaneously take into consideration the uncertainties associated with equipment deterioration and the outcomes of inspection and maintenance. Some examples of probabilistic maintenance models are Failure Rate Estimation models, such as the Hazard Rate model and Markov model, which can evaluate the impact of maintenance on equipment deterioration and the likelihood of failure, with the objective of achieving increased equipment life time. Such analysis can further be utilized as a part of the reliability and risk investigation [48], [49].

In many probabilistic maintenance models, state diagrams are considered, mainly because of two key benefits that they provide. Firstly, state diagrams can help consolidate information about the deterioration, inspection, and maintenance of equipment, so as to form basic and clear graphical models which demonstrate associations between the discrete conditions of the equipment. Secondly, state diagrams can be straightforwardly transformed into mathematical models, referred to as Markov models, which can be easily solved by using standard strategies and analytical mathematical equations [50], [35]. Later, with the modification of the maintenance model to expand the inspection rate in light of the information on the advanced deterioration level of the equipment, non-periodic inspection rates may be introduced into the state diagrams [50], [52].

Moreover, with the utilization of probabilistic models, it is feasible to associate the equipment's aging process with its reliability, by representing it with deteriorating stages [53]. These probabilistic maintenance models have proven to be very useful in the long-term planning of equipment maintenance. They provide relevant knowledge regarding the inspection rate, maintenance intervals, and failure expenses connected with the equipment. They also help in gaining a better understanding of the Mean Time to First Failure (MTTFF) [54], [55].

2.3 3 Trend test for failure and repair processes

Faults in distribution system are usually modelled as a Homogeneous Poisson Process (HPP) [56], [57]. Some of the assumptions usually made in such a model are as follows: (1) System reliability does not vary with time; (2) Repair actions make the system as good as new; (3) The time between faults is exponentially distributed. It is difficult, if not impossible, to theoretically justify all of these assumptions. For example, ageing and wear and tear lead to the deterioration of system reliability, while regular maintenance and design enhancements tend to have the effect of improving it.

Appropriate models of the failure and repair processes can be obtained by analysing historical utility outage data. Systematic approaches for analysis of repairable systems are available [58], [59]. For a system that has a good maintenance record, this simple analysis can be performed on different components that perform the same function, and the group of feeders that are prone to failure can be very easily identified. The first step in the analysis of outage data is to determine whether the system reliability changes with time. The Laplace test is an efficient mathematical method for testing for trend. If T_1, T_2 …

… T_m, are a set of chronologically arranged outage times, the Laplace test statistic is calculated as follows;

$$U_L = \frac{\left[\frac{1}{m-1}\right] \sum_{i=1}^{m-1} Ti - \frac{1}{2}Tm}{Tm\sqrt{\frac{1}{12(m-1)}}} \tag{2.1}$$

Where

U_L = Laplace trend test statistic

T_i = Failure arrival time

T_m = Total operating time

m = Total number of failures

The conclusions drawn from the test are:

U_L = 0 indicates lack of trend. Then HPP can be assumed

U_L > 0 indicates that interval time trends are increasing, indicating system deterioration with time

U_L < 0 indicates that interval time trends are decreasing, indicating system improvement, or reliability growth with time.

For example, at the 95% confidence level, if U_L > 1.96, then the system reliability is deteriorating with time, while system reliability is improving if U_L < -1.96. The existence of a trend necessitates a time dependent model of failure and repair rate. After system failure data have been collected and trend tests conducted, maintenance policies based on the condition of the equipment can be determined.

2.3.4 Assets management

"Asset management (AM) is defined as the process of maximising the return on investment of equipment over its entire life cycle, by maximising performance and minimizing costs" [60]. AM is the well-organised use of resources, with focus on increasing the remaining useful life of the equipment. Its ultimate purpose is to effectively and efficiently use the equipment service life. It guarantees that critical assets will continue meeting the mandatory level of performance for the duration of the life of the equipment.

In the electric power business, AM has now become one of the most problematic issues. This is due to investment, operation, maintenance, replacement and eventual removal of the equipment utilised to transport electricity, incorporating the generation, transmission, and distribution parts of the power network [61]. Its recently increasing significance has mostly been due to the fact that the diminished availability of capital has suppressed investment in new equipment, and consequently utilities in many circumstances, including eThekwini Electricity have continued to operate and maintain substantially aged equipment [62]. Therefore, utilities find that the maintenance needs frequently exceed the available budgetary and human (labour) resources [62].

AM is broader than simply maintaining and repairing an asset. It denotes only one of the numerous stages in the equipment service life. Figure 2.5 shows the phases included in the AM lifecycle. Nonetheless, maintenance and repair actions may be said to represent approximately 90% of the equipment's life cycle as outlined in figure 2.6 [62]. A substantial portion of the total electrical power system running costs goes towards maintenance and capital depreciation [62]. An inclusive methodology for AM in power systems should therefore give more attention to *life-cycle costs* of specific equipment. This is where operators and managers should devote most of their time. The heart of AM lies in the undertaking of correct actions, and doing them the correct way, so as to extend the service life of an asset.

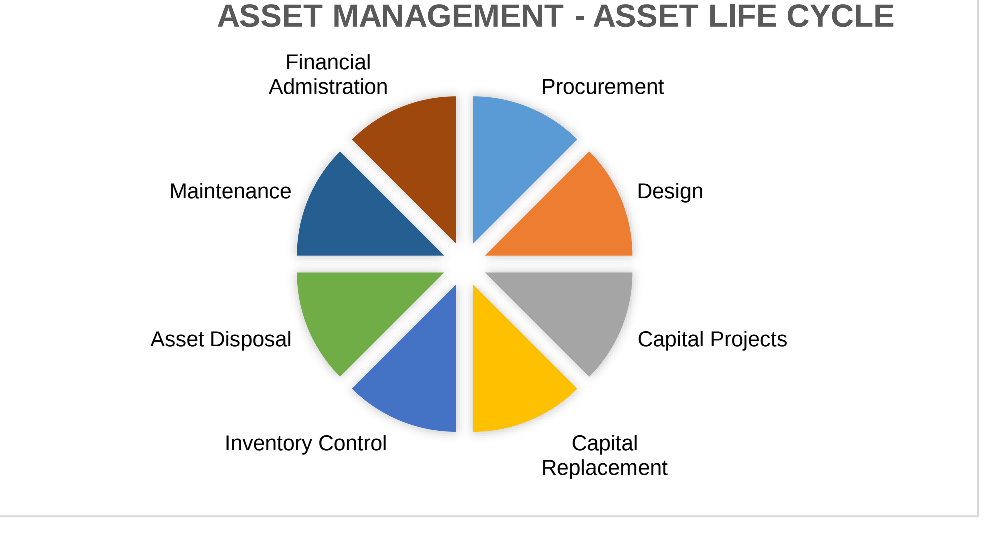

Figure 2. 5: Stages in the asset management lifecycle [62].

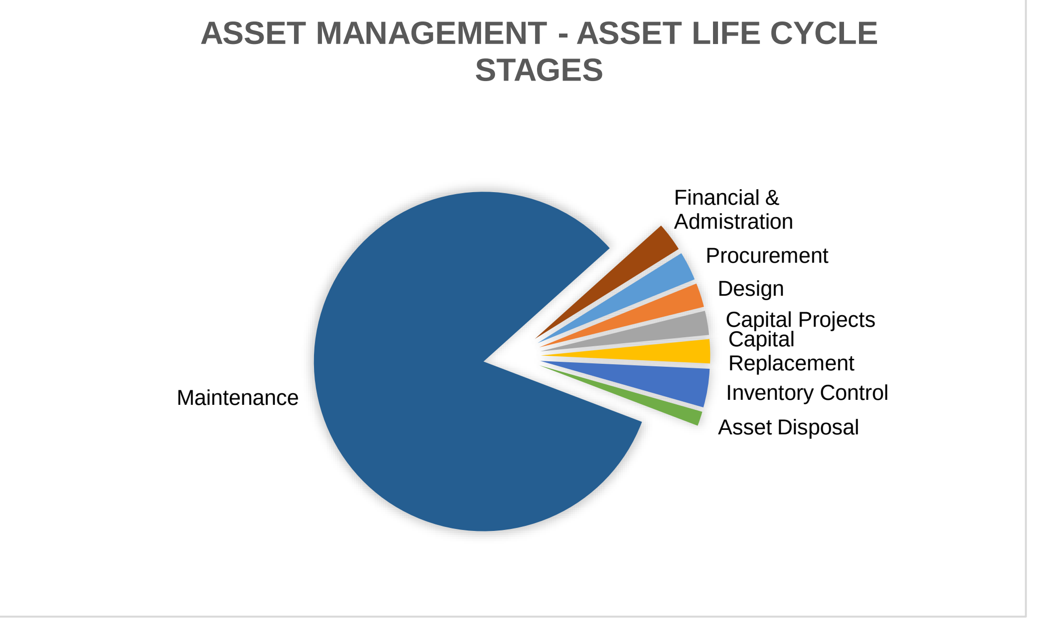

Figure 2.6: Asset life cycle with about 90% maintenance stage [62].

Maintenance is an important function of the AM structure, considerably impacting asset condition, and consequently system reliability as well. It is described in [63] as "an activity wherein an asset has, from time to time, its deterioration arrested, reduced or eliminated". Technical necessities and budget limitations are the most dominant aspects in performing maintenance activity [64]. For any utility, the objective is to increase the revenue while providing reliable service to customers. One way to achieve these objectives and to work towards an “optimal” balance is to enhance the decision-making in AM by introducing quantitative reliability strategies [65].

2.4 Reliability engineering

2.4.1. Reliability

The ultimate goal of reliability engineering is to create strategies and techniques for assessing the reliability, maintainability, availability, as well as safety systems of equipment [66]. As systems and components become more complex, the costs incurred due to the loss of operation resulting from equipment failure also grows significantly [67]. From the perspective of the distribution power network, reliability is related to the likelihood of providing customers with continuous service at all times, and with voltage and frequency which remain within the prescribed ranges around the nominal values [68]. Loss of a cable, primary supply, or a transformer will normally cut off service, as well as when any piece of service equipment must be de-energized so as to perform routine maintenance and servicing [69].

Reliability has to do with the equipment's capability to perform its intended function under certain predefined conditions during a specified period of time [70]. Reliability can be measured from multiple points of view, depending on specific circumstances. The reliability measures that manage interruptions address three factors: the frequency, duration, and extent or severity of the interruption. The extent is the number of customers or load affected [71].

2.4.2. Availability

Ordinarily, a component or system is said to perform acceptably if it does not fail during the time of service. However, components are expected to experience failures, be repaired, and then returned to working state throughout their lifespan. In this case, a more suitable measure of reliability is the availability of the component [72]. The availability measure is described as "The ability of an item to be in a state to perform a required function under given conditions at a given instant of time or during a given time interval, assuming that the required external resources are provided" [73], [74]. For instance, if a component can be utilized for 18 hours in a day, the availability of the component is said to be 18/24 [51]. A typical mathematical equation for estimation of availability is:

$$\mathrm{A} = \frac{\mathrm{Uptime}}{\mathrm{Uptime+Downtime}} \tag{2.2}$$

Where

A = Availability of component

Uptime = Time which a system is operational

Downtime = The time when the system is not working

2.4.3. Unavailability

The term unavailability is the probability that a system is not available at a state of time when it is needed [83]. Unavailability may be expressed mathematically as:

$$\text{Unavailability} = 1 - \text{Availability} \tag{2.3}$$

Or as the ratio:

$$\mathrm{U} = \frac{\lambda}{\mu + \lambda} = \frac{\mathrm{MTTR}}{\mathrm{MTTF+MTTR}} \text{ when } t \rightarrow \infty, \tag{2.4}$$

Where

μ = Repair rate (following exponential distribution)

λ = Failure rate (following exponential distribution)

MTTR = Mean time to repair

MTTF = Mean time to failure

t = Running time at the occurrence of failure number

2.4.4. Maintainability

Maintainability is characterised as the likelihood that the system can effectively be restored after some failure within a predetermined time. It is a measure of how quickly a system can be repaired and restored to a working state after a failure [66]. Maintainability addresses all scheduled and unscheduled events, which are performed to repair or replace a component that shows undesirable physical condition or performance degradation.

The Maintainability Function, M(t), for a system with the repair times distributed exponentially, is given by [66]:

$$\mathrm{M(t)} = 1 - \mathrm{e}^{\mu \, \mathrm{t}} \tag{2.5}$$

$$\mathrm{MTTR} = \frac{1}{\mu} \tag{2.6}$$

Where,

M(t) = Maintainability function

t = Running time at the occurrence of failure number

μ = Repair rate

MTTR = Mean time to repair.

2.5 Life modelling distribution function

There are some distribution functions that have been formulated by statisticians, mathematicians and engineers for the purpose of mathematically modelling or representing the lifetime behaviour of certain distribution system components in the field (for instance, the length of time the equipment's successful operation, or the length of time before failure) [75]. Presently, there are many distribution functions that are widely used for modelling, for example, normal distribution, log-normal, exponential distribution, Weibull distribution, and more. These distribution functions are applied to the modelling or component representation as an attempt to make predictions about the life of the component. This is typically done by fitting some statistical distribution function to real-life data from a representative sample of units [72]. The parameterised distribution function for the data set can then be used to estimate important life-time characteristics of the component, such as the reliability (or probability of failure at a specific time), the mean life, and the failure rate [75]. One way of modelling the lifetime of a component is consequently to assume that it can be described by the characteristics of a known distribution and then select parameter values that fit the specific purpose.

The probability density function (pdf) is a mathematical function that describes the distribution. The pdf can be represented mathematically or on a plot where the x-axis represents time. In selecting a pdf that describes the life of a component for a particular situation, it important to ensure that the properties of the distribution function do not contradict the failure behaviour of the component of the system under study. Life data analysis requires the practitioner to [75]:

- Gather life data for the asset
- Select a lifetime distribution function that will fit the data and model the life of the asset
- Estimate the parameters that will fit the distribution function to the data
- Generate plots and results that estimate the life characteristics of the asset, such as the reliability or the mean life.

It is important to consider the following criteria when choosing the most appropriate distribution function for the reliability data determination [72]:

- Use of engineering and historical knowledge of the situation (e.g. does the data follow a symmetric distribution? Is the hazard constant, increasing, or decreasing? What distribution has worked historically for similar situations?)
- Perform a distribution analysis and use probability plots to compare the candidate distributions, or to assess the appropriateness of the chosen distribution.

Part of this work considers the determination of the remaining life of an asset selected as critical, based on the Markov model, and probability theory.

2.5.1 Weibull distribution

The Weibull distribution function is a general-purpose reliability distribution function used to model material strength, and the time-to-failure of components, equipment or systems. It is a parametric probability distribution function with two parameters: the scale parameter $\alpha > 0$ and the shape parameter $\beta > 0$, are described by the following equations [76]:

$$f(\mathrm{t}) = \frac{\beta}{\alpha}\left(\frac{\mathrm{t}}{\alpha}\right)^{\beta-\alpha} \quad \mathrm{e}^{-\left(\frac{\mathrm{t}}{\alpha}\right)^{\beta}} \qquad (2.7)$$

Where

f(t) = Probability density function (PDF)
B = Shape parameter of Weibull distribution for Failure rate
α = Scale parameter of Weibull distribution for Failure rate
t = Running time at the occurrence of failure number

And the cumulative distribution function (cdf) can be represented as

$$F(t) = 1 - \mathrm{e}^{-\left(\frac{\mathrm{t}}{\alpha}\right)^{\beta}} \qquad (2.8)$$

The Weibull distribution has the probability density function (pdf) for $t \geq 0$. Where $\beta > 0$ is the shape parameter and $\alpha > 0$ is the scale parameter.

If *t* represents "time-to-failure", the Weibull distribution is characterized by the fact that the failure rate is proportional to a power of time, namely $\beta - 1$. Thus β can be interpreted as follows [77]:

- $\beta < 1$ indicates that the failure rate decreases over time.
- $\beta = 1$ indicates that the failure rate is constant over time. This might suggest random external events are causing mortality or failure.
- $\beta > 1$ indicates that the failure rate increases with time. This happens if there is an "ageing" process; e.g. if parts are more likely to wear out and/or fail as time goes on.

2.5.2 Exponential distribution

The exponential distribution is commonly used for components or systems exhibiting a constant failure rate, for $t > 0$; it can be describe by the following equations [76]:

$$f(\mathrm{t}) = \lambda \, \mathrm{e}^{-\lambda \mathrm{t}} \tag{2.9}$$

$$\mathrm{F(t)} = 1 - \mathrm{e}^{-\lambda \mathrm{t}} \tag{2.10}$$

$$\mathrm{R(t)} = \mathrm{e}^{-\lambda \mathrm{t}} \tag{2.11}$$

$$z(\mathrm{t}) = \lambda \tag{2.12}$$

$$MTTF = \frac{1}{\lambda} \tag{2.13}$$

Where

f(t) = Probability density function
F(t) = Cumulative distribution function
λ = Failure rate
t = Running time at the occurrence of failure number
R(t) = Reliability function of a component
MTTF = Mean time to failure

The properties for Exponential distribution are presented on table 2.2.

Table 2.2: Characteristics of the Exponential distribution [75]

• It has a single parameter, λ which is the mean. For reliability applications, λ is called the failure rate. • λ, the failure rate, is a constant, if an item has survived for t hours, the chance of it failing during the next hour is the same as if it had just been placed in service. • The mean-time between-failure (MTBF) = $1/\lambda$. • The mean of the distribution occurs at about the 63rd percentile. Thus, if a component with a 1 000-hour MTBF had to operate continuously for 1 000 hours, the probability of success (survival) would be only 37%

2.6 Hazard functions in reliability analysis

The hazard function is the instantaneous rate of failure at a given time. Characteristics of the hazard function are frequently associated with certain components and applications. Different hazard functions are modelled with different distribution models [75].

2.6.1 Increasing hazard function

This indicates the failure probability of equipment that is most likely to fail with time. A Weibull distribution is often used to model this type of wear-out failure [75]. The increasing hazard function is depicted in Figure 2.7.

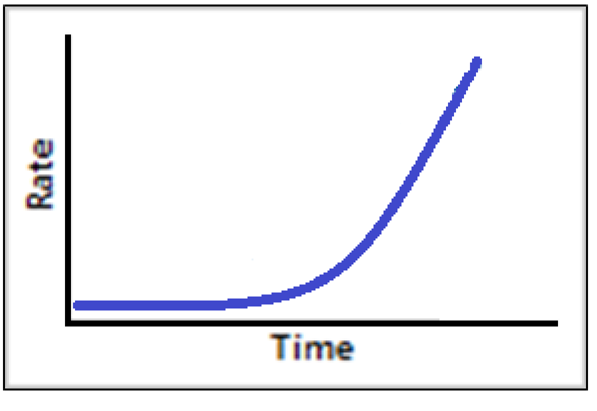

Figure 2.7: Increasing hazard function [78]

2.6.2 Decreasing hazard function

This indicates failure probability of equipment that is more likely to occur early in the life of equipment. Often, this type of data can be modelled using a Weibull distribution with a shape parameter less than 1 [75]. The decreasing hazard function is depicted in Figure 2.8.

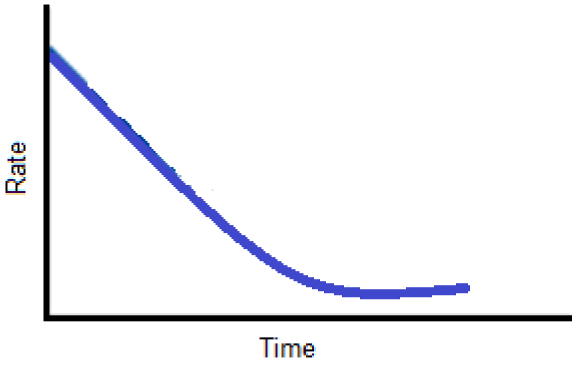

Figure 2.8: Decreasing hazard function [75]

2.6.3 Constant hazard function

A constant hazard function Indicates failures that are equally likely to occur at any time in the component's life. This relatively constant period of low failure risk characterizes the middle portion of the Bathtub Curve. This function can be modelled using the exponential distribution [75]. Figure 2.9 illustrates the constant hazard function.

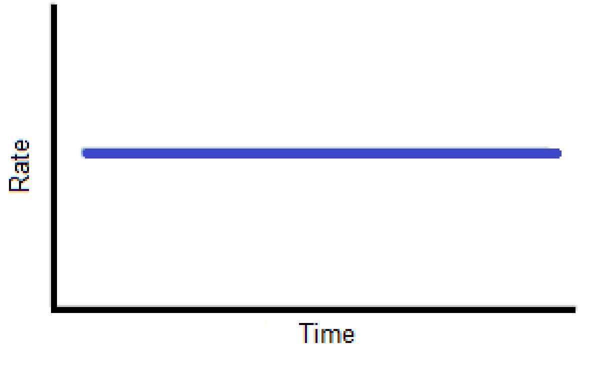

Figure 2.9: Constant hazard function [75]

2.6.4 Bathtub-shaped hazard function

Many components have failure rates that follow the "bathtub" curve. Often, the hazard rate is high initially, low in the centre, then high again at the end of the component's life. Thus, the resulting curve of the three failure periods frequently resembles the shape of a bathtub [75]. The bathtub-shaped hazard function is depicted in Figure 2.10.

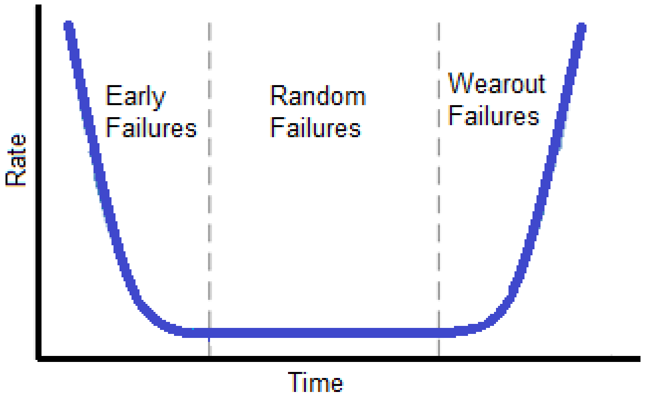

Figure 2.10: Bathtub-shaped hazard function [75].

2.7 Service life of electrical component

2.7.1 Approaches to ascertain remaining life

According to Anders [48] and Endrenyi [55], there are three ways of ascertaining the remaining life of electrical component insulation systems: (1) to ascertain the remaining life of a component (a transformer in this instance), one needs to monitor the factors which could bring about insulation failure. This methodology may not help much in measuring the remaining life; rather it serves more as a method for verifying no circumstance that is fit for reducing the life time of the system is created; (2) In this methodology, signs are looked for in the equipment that demonstrate deterioration, either with diagnostic tests during ordinary service or with inspections and tests during power failure, and therefore equipment's remaining life is assessed by matching the seriousness of the obtained indications with the corresponding previous observations (i.e. in view of experience). This methodology requires substantial knowledge, and could require substantial data failure examinations; (3) this approach to determining the remaining existence of equipment is to model *insulation deterioration stages* through a homogenous Markov model [79]. This method is adopted and used in this work.

The Markov model concept is capable of modelling the deterioration process for oil insulation using steady state analysis. The model takes into consideration the processes and mechanisms by which insulation oil deteriorates, and the different stages through which it passes, which eventually lead to failure [80]. An understanding of the fundamental deterioration process, and in addition, the stresses which have an impact on the process, is needed for the estimation of the remaining existence of any electrical equipment. Furthermore, the indicators which go along with the deterioration must be known. Some fundamental elements which can influence the occurrence and extent of deterioration include the following [81]:

- Level of temperature, voltage, and mechanical stress (winding design)
- Cycling rate of the stress (operating environment)
- Types of insulation materials and systems
- Quality of manufacture and assembly

- Maintenance (frequency and quality)
- Random events, such as mal-operation, surges, and foreign objects entering the system.

The above mentioned variables can bring about various deterioration forms, which can the lead to failure.

2.8 Stochastic processes

Many deterministic and stochastic methodologies have been created to model deterioration [82]. These models have the capability to identify the uncertainties while foreseeing the future performance of a system [83]. Stochastic models that are used to define the deterioration of electrical systems can be classified into two principal types: *time-based models* and *state-based models*. Time-based models determine the likelihood distribution of the time taken by a system to change its present condition state to the following lower condition state. State-based models determine the likelihood that a system will make transition in its condition state within a fixed time interval, and this likelihood is then collected over various time intervals [83].

2.8.1 Markov modelling

Markov modelling is a type of stochastic modelling that describes a system as a progression of likely shifts between states [84]. The Markov approach can be applied to the random behaviour of systems that vary discretely or continuously with respect to time and space. A discrete or continuous random variation is known as a stochastic process [86]. It concentrates, though, on analysing the transitions between these states; it analyses the likelihood that the system can move from the condition, *everything is operating normally*, to the condition, *component has failed*, as well as under what conditions and how long it takes to transition back. Every condition, or state, that the system could be in is identified and enumerated [85].

A Markov stochastic process is memory-less. In this way, the future condition of a system only relies upon where it is at present, not on where it has been in the past or how it reached its present position [84]. Another important distinction of Markov processes is that of *time homogeneity*. When the transition probabilities are constant regardless of the time of observation, the process is time-independent or time-homogenous, and the distribution of the number of transitions into a given state follows a homogenous or stationary Poisson process [86]. Therefore, the process must be stationary, or homogeneous, for the approach to be applicable [87]. It is clear from these two aspects, the absence of memory and the requirement of being stationary, that the Markov approach is applicable to those systems whose behaviour can be described by a probability distribution that is characterized by a *constant hazard rate*, (i.e. Poisson and exponential distributions), since only if the hazard rate is constant, does the probability of making a transition between two states remain constant at all points in all times [82]. A Poisson process follows an exponential distribution defined by the same parameter λ [86].

Markov models can be classified according to characteristics of the state space being measured and the time intervals of observation of the process [86]. Processes may be observed at restricted or discrete intervals, or can be observed continuously [85]. The term *Markov chain* is used to describe a process observed at discrete intervals, whereas a *Markov process* describes a process observed continuously [86]. The term Markov process can thus be used to collectively describe all processes and chains. For the Markov chains, the transition probabilities are arranged in a matrix form and the resulting matrix is called the transition matrix of the chain. The elements of a transition matrix hold the following conditions:

a) for any two states $\mathrm{i, j} \in \mathrm{S}, \mathrm{P_{ij}} \geq 0$; and
b) for all $\mathrm{i} \in \mathrm{S}, \sum_{\mathrm{j}} \mathrm{P_{ij}} = 1$

Where

i = Present state of the equipment

j = Future state of the equipment

$\mathrm{P_{ij}}$ = Probability of moving between states

2.8.2 Discrete time Markov chain

Consider a time-homogenous model where the transition probabilities are constant over time. The transition probability matrix P(t) contains the probabilities for the transitions. The rows represent the current state and the columns represent the future state. The probabilities are described as P_{ij} where P is the probability of moving from state *i* to state *j.* For any given cycle, which for a time homogeneous 3-state Markov model is given as follows [79]:

$$P = \begin{bmatrix} & 1 & 2 & 3 \\ 1 & P_{11} & P_{12} & P_{13} \\ 2 & P_{21} & P_{22} & P_{23} \\ 3 & P_{31} & P_{32} & P_{33} \end{bmatrix} \tag{2.14}$$

Equation 2.14: Probability transition matrix for a time homogeneous 3-state Markov model [79].

The sum of the row probabilities equals one, since each state is independent of the other, and a transition must be among the three states. The diagonals represent the probability of staying in the same state. A state is considered absorbing when the probability of leaving the state is zero.

2.8.3 Continuous time Markov process

The transition between states is viewed as a rate for a continuous-time Markov process. The transition rate does not depend on the length of the observation interval, since it is the number of transitions that occur per unit time. The transition rate matrix, Q(t), contains the components Q_{ij} which are transition rates from state *i* to state *j*. Since the rates for a time-homogenous Markov process are constant, the rate matrix could simply be written as follows [79]:

$$Q = \begin{bmatrix} & 1 & 2 & 3 \\ 1 & P_{11} & P_{12} & P_{13} \\ 2 & P_{21} & P_{22} & P_{23} \\ 3 & P_{31} & P_{32} & P_{33} \end{bmatrix} \approx \begin{bmatrix} & 1 & 2 & 3 \\ 1 & -(q_{12} + q_{13}) & q_{12} & q_{13} \\ 2 & q_{21} & -(q_{12} + q_{13}) & q_{23} \\ 3 & q_{31} & q_{32} & -(q_{12} + q_{13}) \end{bmatrix} \tag{2.15}$$

Equation 2.15: Transition intensity (rate) matrix for a time-homogenous 3-state Markov model [79].

The rate of staying in state *i* is constrained to equal the rate of leaving *j* [88]. This is imposed by the fundamental property of the Markov process that dictates that flow in and out of the state must be equal. The exception is when the state is absorbing, such that the flow out of the state is zero [88]. The probability of transition in a Markov process depends on the transition rate and the observation interval. The transition probabilities can be estimated from the transition rates. Consider the time-homogenous model where the transition rates are constant. The distribution of time between transitions follows a one-parameter exponential distribution; in fact, the exponential distribution is the only distribution that has the memory-less feature [89].

The cumulative density function of time

$$\mathrm{F_i}\,(t) = 1 - e^{-\lambda i t}, \tag{2.16}$$

Where

i = Present state of the equipment

λ_i = the rate of transition up to time *t*

F_i = Cumulative distribution function

t = the time period for which the probability is estimated [84].

The cumulative distribution function describes the probability of transition before time *t* and thus, can be used to derive the probability of transition from the rate of transition such that

$$P = 1 - e^{-\lambda i t}, \tag{2.17}$$

Where

t = the time period for which the probability is estimated

P = Probability function [78].

2.8.4 Fundamental matrix solution

The matrix solution provides an exact solution of the time spent in each state. The matrix solution is restricted to time homogeneous Markov chains. The transition probability matrix of a chain that contains absorbing states is divided into four sections: Q contains transition probabilities between transient states; R contains transition probabilities from transient to absorbing states; O is a zero matrix, and I is an identity matrix (Figure 2.11) [90].

		To:	
		Transient States	Absorbing States
From:	Transient States	Q	R
	Absorbing States	O	I

Figure 2.11: Probability transition matrix containing absorbing states into 4 components [79].

The average number of cycles during which a subject resides in transient states before absorption, given a specified starting state, is estimated from the fundamental *(N)* matrix. Calculating *N* is the matrix algebraic equivalent of taking the inverse of the transition probabilities in *Q* [90]. The *N* matrix specifies the average number of cycles that a subject resides in transient states such that

$$\mathrm{N} = \mathrm{I} - \mathrm{Q}^{-1}$$

Where

I = identity matrix and
Q = the square matrix of the transient probabilities within P [90].

Multiplication of the number of cycles by the length of the cycle gives the expected duration in each state, conditional on the starting state. The sum of these durations gives an estimate of the expected component lifetime, conditional on the starting state [90].

2.9 Conclusion

In line with the research of this work, a literature review has been conducted and presented in this chapter. Power system philosophies, maintenance approaches and methods of determining remaining life of oil insulation equipment has been reviewed. In the next chapter, the practical implementation of the RCM model and Markov process to determine the remaining life of oil insulation equipment will be presented.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 RCM model implementation to eThekwini power network

In this the chapter, the implementation of the RCM model to eThekwini electricity network is presented. A description of the eThekwini Electricity network, the data used in determining the critical component, and techniques used is presented. Five years' (from 2010 to 2014) failure records were gathered and thoroughly analysed to identify the feeder with high failure rates, with the ultimate objective of identifying the critical components in the eThekwini power network.

RCM is a systematic and structured process to develop an efficient and effective maintenance plan for assets to minimise the probability of failures while maximising return on critical assets in power distribution systems [37]. It is helpful in determining how the assets can continue performing their required functionalities at all times. It includes identifying activities that, when undertaken, will decrease the likelihood of failure, and which are also the most financially feasible.

3.1.1. EThekwini electricity network description

EThekwini Electricity (EE) is one of the largest power utilities in South Africa (SA) and serves more than 723 593 customers in a region covering about 2,000 square kilometres. It purchases power from Eskom at 275 kV and 132 kV for Kingsburgh which is then transformed to lower voltages needed by residential, business, commercial, and industrial customers at 230 V, 400 V and 11 kV respectively through power transformers. It has a maximum demand of more than 1 900 MW, a turnover of over R7 billion and an asset value of R17, 7 billion. A typical single diagram illustrating EE network is shown in figure 3.1.

EE maintains more than 10 000 transformers. Of these, approximately 250 function at voltages 275, 132 and 33 kV to provide the primary network from which the other distribution level transformers and major customers are supplied.

The ratings of these transformers, which have an average age of twenty-five years, are from 315 MVA to 15 MVA. These transformers require exceptional consideration due to their financial worth, which extends from R1 million to R14 million for each unit, and the possible consequences of failure.

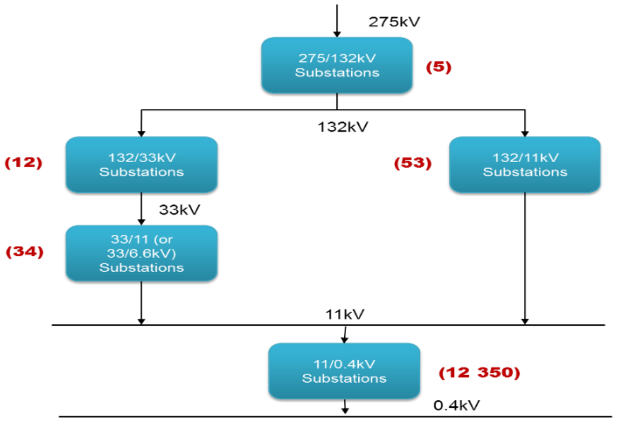

Figure 3.1: Typical line diagram for eThekwini Network [38]

EThekwini Network is highly integrated and complex, and for this reason, is segmented into three regions; these regions are named as Northern, Central and Southern. Within these regions, there are six Depots (Central, Western, Northern, North Western, Southern, South Western) responsible for the construction works and maintenance activities of the entire eThekwini network. The visual representation in figure 3.2 shows that bulk power is received from Eskom at five intake points at a voltage of 275 kV. At these stations, the voltage is transformed down to 132 kV for onward transmission via eThekwini's transmission network to over 100 major step-down substations.

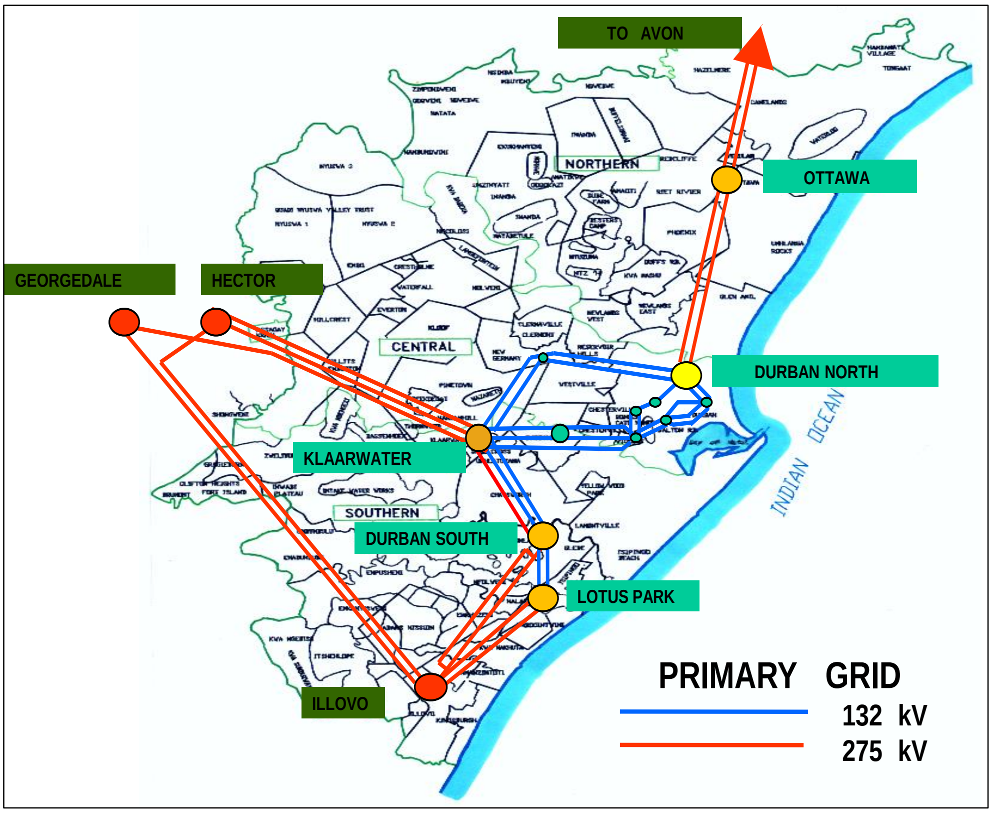

Figure 3.2: General lay-out of the Eskom/EThekwini High Voltage Network [91]

Among these Depots, the feeder with greatest failure rates was found to be in the Northern region, with particular reference to the North Western Depot during the period considered in this work. Hence, the study was centered on this region which is made up of mix of industrial, commercial, and residential customers. In figure 3.3, a single line diagram showing a portion of the northern region network, made up of seven major substations fed from Ottawa Major Substation is presented. These stations are fed by 2x315 MVA, 275/132 kV power transformers. From these seven major stations many 11 kV customer feeders are fed. The feeder that is subjected to more failures was found to be fed from Phoenix substation.

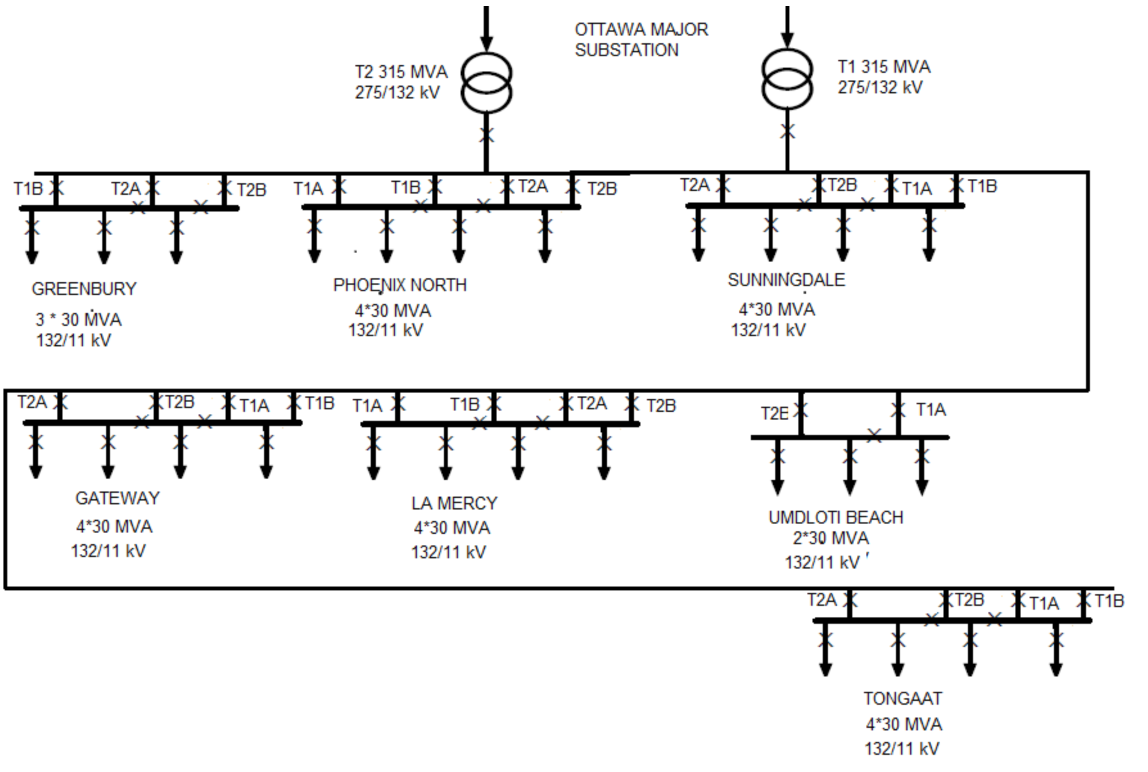

Figure 3.3: Line diagram showing major substations in the Northern region

3.1.2. Failure data gathering and analysis techniques

3.1.2.1. Failure data gathering

In present time's power systems, maintenance plays a major role in ensuring maximum returns for critical assets. The power utilities in developing countries today are faced with rapidly increasing demand, where supply is constrained by scarce resources, lack of assets management, and lack of maintenance. The maintenance planning constitutes a fundamental part of asset management. In most utilities, this important element of asset management may get no consideration at all or at best very restricted attention. The outputs of this would be frequent power interruptions associated with equipment failures/repairs. Therefore, for the present power system, an effective method for determining any signs of component failure is needed. This will also be helpful in ascertaining deterioration failure and mean time to failure (MTTF) of critical components.

The collection and building of a statistical database for failure records was seen as the foundation of this process. Having this sort of information available assists in deriving the failure sample space. It is the resulting analysis of the sample space that has given valuable knowledge into the failure rate and time to failure of each component. These are the necessary construction blocks for the RCM program. Choosing the type of data to collect and the method of collecting it, is seen as the initial step for a successful maintenance policy based on records of failure data. The competence to thoroughly examine failure sample space can result in maintenance policy alteration, e.g. from a preventive maintenance planning into a predictive maintenance one, which will attempt to arrest failure before they even happen.

EThekwini Electricity uses a system called Ellipse to facilitate business processes within the organisation. All the outages and their causes are recorded on the Ellipse System with reference to order numbers. This system enables the user to extrapolate the outage information as per user's specification. Therefore, to accomplish the objectives of this study, the outage information was exported from the Ellipse System and examined. In identifying the feeder with the higher failure rate for greater attention, five years' (2010 to 2014) outages information was collected and processed for the entire eThekwini network, which was then plotted on a histogram as presented in figures 3.4 to 3.8. The feeder with the highest failure rate was then selected for a more in-depth analysis. For the purpose of this work all the irrelevant events such as outages due load shedding and scheduled maintenance were excluded.

3.1.2.2 Data analysis techniques

The initial step for examination of the failure data was to attempt to gain a deeper understanding of the raw failure properties. To do this, the failure sample space must be thoroughly considered to be capable to extract meaningful trend from the collected data. This was achieved by building a histogram over the sample space. This basic histogram instantly provided an indication of the leading failure events and similarly the region or customer feeder that is mostly affected. Thereafter, the properties of the total component leading to failure were considered before going deeper into the statistical examination of the components. Figures 3.4 to 3.8 show a typical failure histogram built for eThekwini Network failure data integrating six Depots.

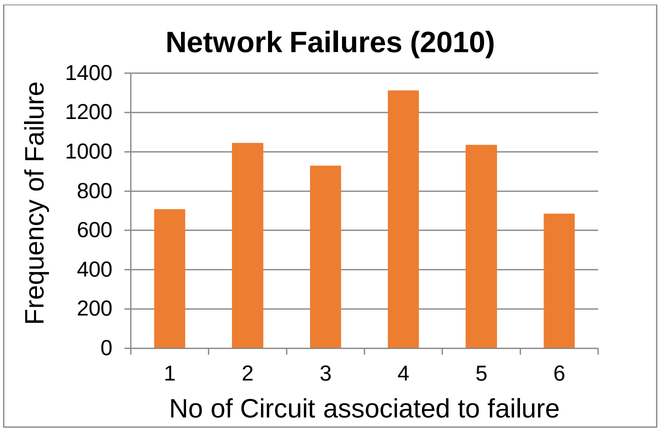

Figure 3.4: Processed 2010 failure data for EE area of supply

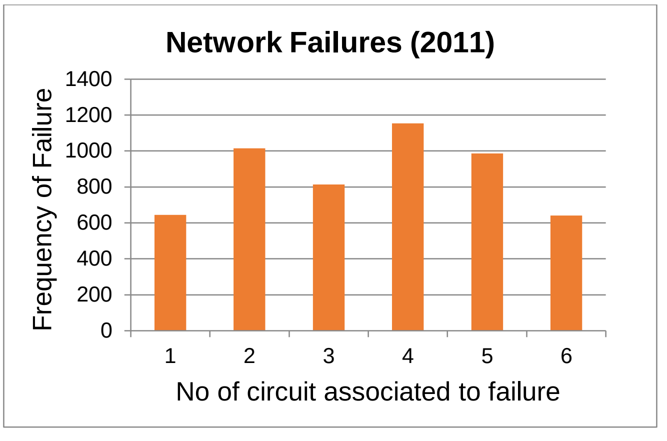

Figure 3.5: Processed 2011 failure data for EE area of supply

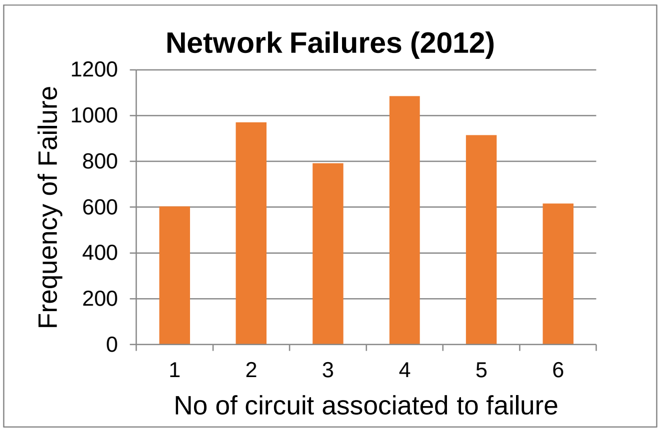

Figure 3.6: Processed 2012 failure data for EE area of supply

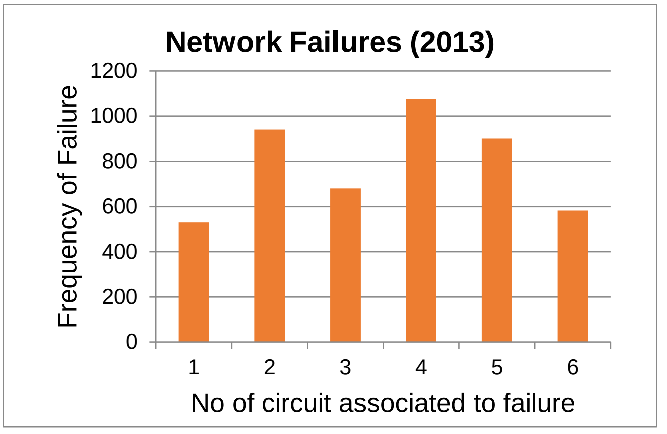

Figure 3.7: Processed 2013 failure data for EE area of supply

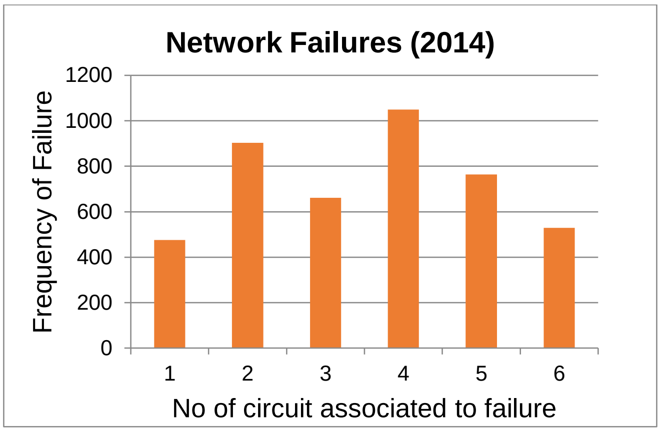

Figure 3.8: Processed 2014 failure data for EE area of supply

The North Western Depot with reference to Phoenix substation in the Northern region of EE area of supply was found to have higher failure rates, and was selected for deeper analysis. To better understand what was happening in North Western Depot, further analysis of the failure data on this particular Depot was then conducted. This was graphically illustrated in the histogram shown in (Figures 3.9 to 3.13). The information gained from this, is considered to be useful to the asset manager to help focus more attention on this feeder to ascertain the component(s) that is/ are responsible for the high rate of failure in that feeder.

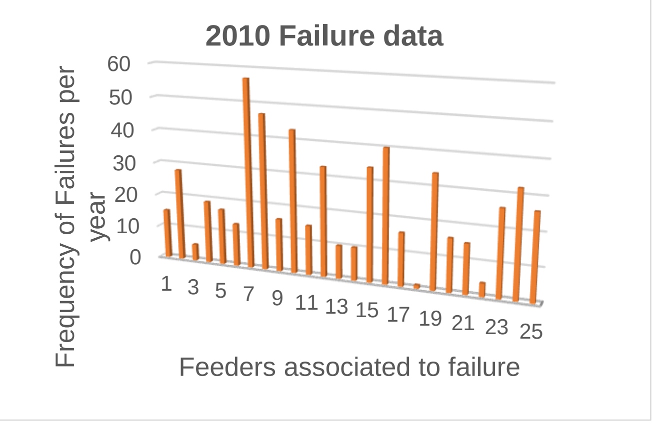

Figure 3.9: Processed outage data for Phoenix station feeders for 2010

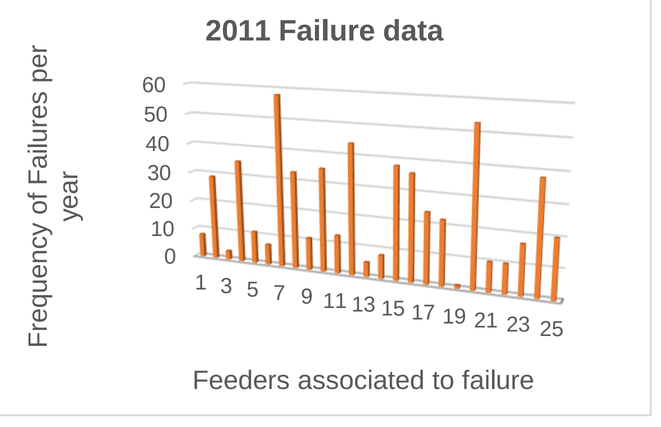

Figure 3.10: Processed outage data for Phoenix station feeders for 2011

Figure 3.11: Processed outage data for Phoenix station feeders for 2012

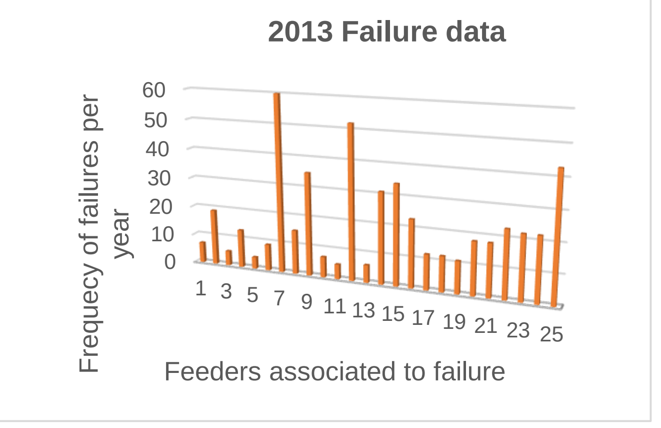

Figure 3.12: Processed outage data for Phoenix station feeders for 2013

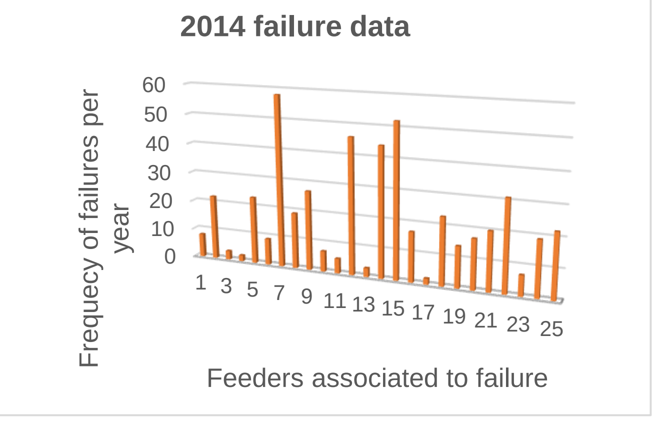

Figure 3.13: Processed outage data for Phoenix station feeders for 2014

Further analysis of the data indicated that Feeder seven (F7) with reference to Phoenix major substation in the Northern region of eThekwini area of supply has the leading failure rate. With this kind of information, one can then began to probe deeper into the working of the components that made up the network of feeder seven (F7). Six groups of electrical components are found in distribution power system, which includes (1) overhead lines, (2) underground cables, (3) protective equipment, (4) power transformers, (5) distribution transformers, and (6) capacitors. In analysing these components, only those identified as critical were considered. The analysis of the failure data collected on this critical feeder, when plotted on a histogram, showed that the components of the distribution system that presented the greatest challenge to uninterrupted operation of power included overhead line conductors, distribution transformers, and underground cables. This plot is shown in figure 3.14 to figure 3.18. From this plot, the transformer was identified as the highest contributor to customers' electric power interruption.

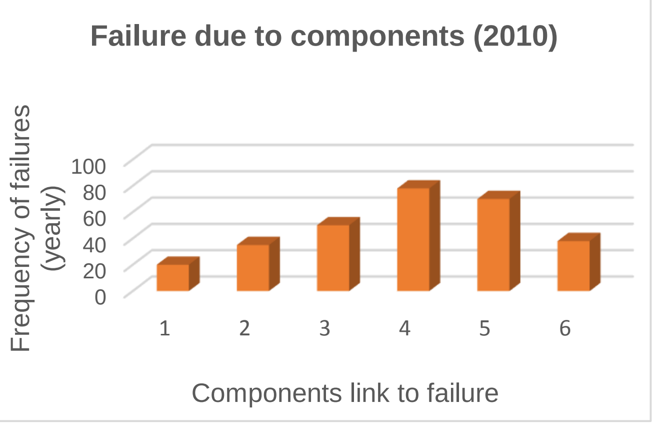

Figure 3.14: Processed components data for critical feeder (2010)

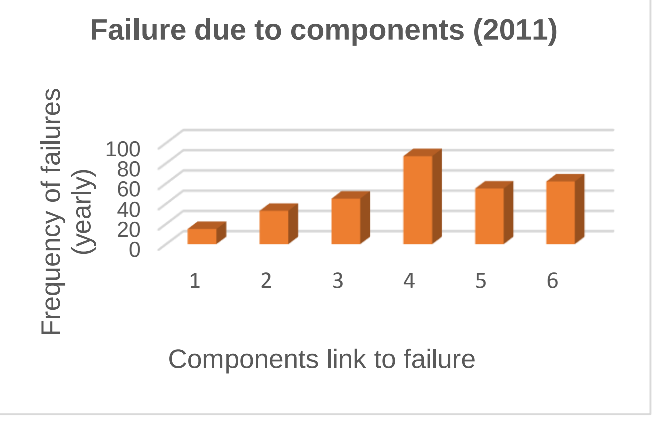

Figure 3.15: Processed components data for critical feeder (2011)

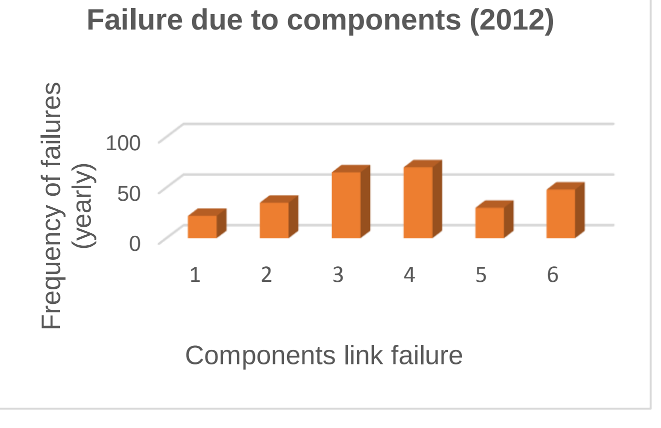

Figure 3.16: Processed components data for critical feeder (2012)

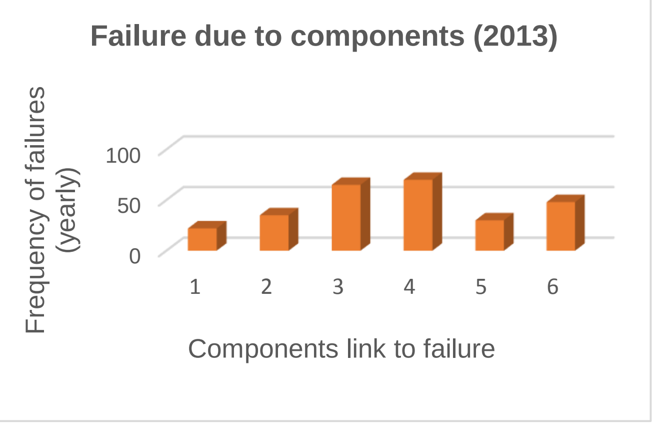

Figure 3.17: Processed components data for critical feeder (2013)

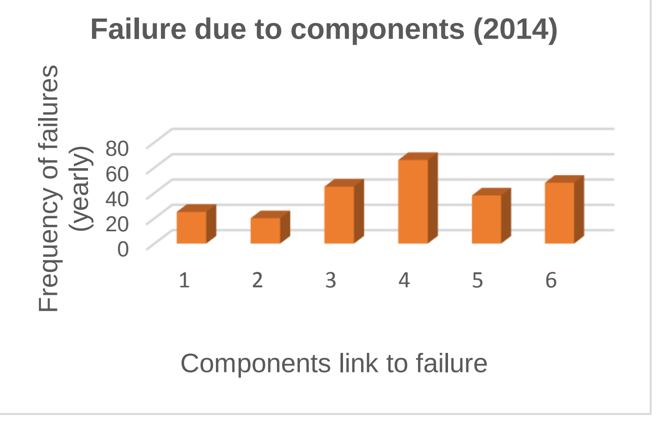

Figure: 3.18: Processed components data for critical feeder (2014)

3.3. Transformer failure modes and causes

3.3.1. Failure modes

A failure mode is a way in which a system or equipment failure can happen, in terms of how the failure is observed (in contrast to how the failure is caused) [40]. "Just as a mode of transportation is a means of getting from one place to another, a failure mode is likewise a means by which some equipment or system could fail" [92]. For instance, the dielectric breakdown of transformer oil is a failure mode, which may have numerous causes, such as oil pollution, oil oxidization, thermal decomposition, and humidity in oil from cellulose breakdown [93]. RCM focuses on the identification and examining of all the possible failure modes for a given system or equipment [94].

3.3.2. Failure causes

Transformers fail for various reasons, which can interrupt electricity supply, cause potential risk to operators, loss in industrial production, and financial losses [95]. Financial outcomes of transformer failure can be substantial, because of the expense of property harm, repair cost, and the production losses due to service interruption [96]. The most frequent causes of failures are presented in figure 3.19. The leading cause for transformer failure is insulation failure. The life of a transformer is dependent upon the life of its insulation. Transformer insulation deteriorates as a function of time and temperature [97]. The lifespan of the transformer will most likely be achieved by effective maintenance planning, site inspections, and appropriate testing during the transformer's useful life.

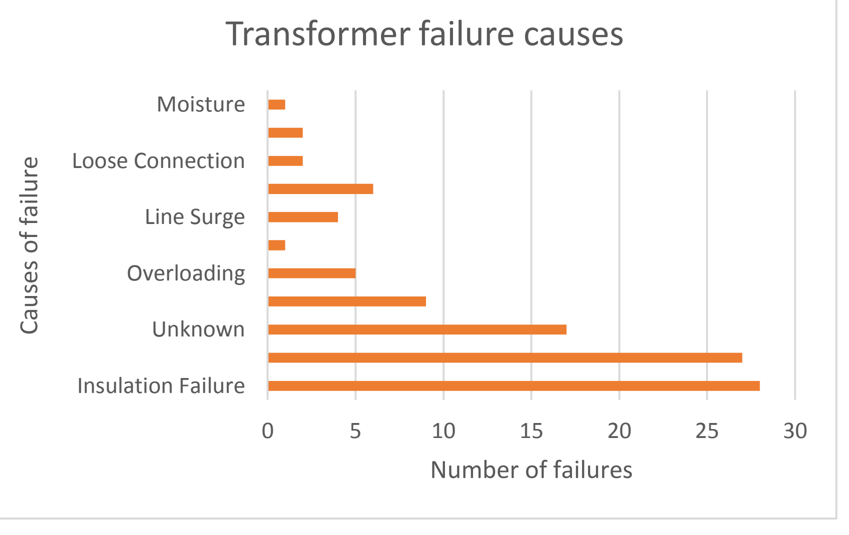

Figure 3.19: Failure mode distribution for transformers

3.4. Maintenance model description

3.4.1. Transformer maintenance model

Maintenance is conducted as a strategy to prevent failures and unreasonable deterioration. Therefore, a deterioration model and suitable failure data are needed for maintenance modelling. Many failure mechanisms can be traceable to a root cause of deterioration. Deterioration certainly prompts a deficiency that can result in failure. Henceforth, it is more precise to construct a failure model with respect to the physics of failure and the attributes of the working environment [98].

A probabilistic model of the impact of maintenance on reliability is presented in figure 3.20. This model tracks transformer deterioration based on discrete stages. The transformer oil deterioration is approximated by three discrete stages: D_1, D_2, and D_3. At every stage, oil was reviewed to determine its condition. After the assessment, oil condition was characterised by the following criteria:

Condition one (C_1) - Satisfactory
Condition two (C_2) - Should be reconditioned for further use.
Condition three (C_3) - Poor condition, dispose and replace. [80]

The maintenance activity was then chosen based on the condition of oil. In the event that oil condition is C_1, nothing was done. If the oil condition was found to be C_2 or C_3, two alternatives are accessible and were chosen with distinctive probabilities: *oil filtering* or *oil substitution*.

In the occasion that for instance, the present stage was D_2 with oil condition C_2, the likelihood of oil filtering was higher than oil substitution. Then again, if the current state is D_2 with oil condition C_3, the likelihood of oil substitution was higher. After maintenance, the asset will have three choices, going to state D_1, D_2 or D_3. The likelihood of transferring to different states relied upon the current state and the maintenance methodology executed. Furthermore, the maintenance process is partitioned into three levels; (1) Do nothing (2) Basic Maintenance and (3) Replacement. According to the model, after the recommended maintenance action has been performed, the consequent state of the transformer can be determined.

The model uses outcomes from inspection and maintenance tasks and the repetition of performing the tasks as input parameters, and then provides the failure rates as output. The adjustments in the mean-time to failure indicator can be seen by considering diverse inspection and maintenance activities. Different inspection tests and maintenance activities performed during maintenance task of a transformer are indicated in table 3.1 and table 3.3 separately.

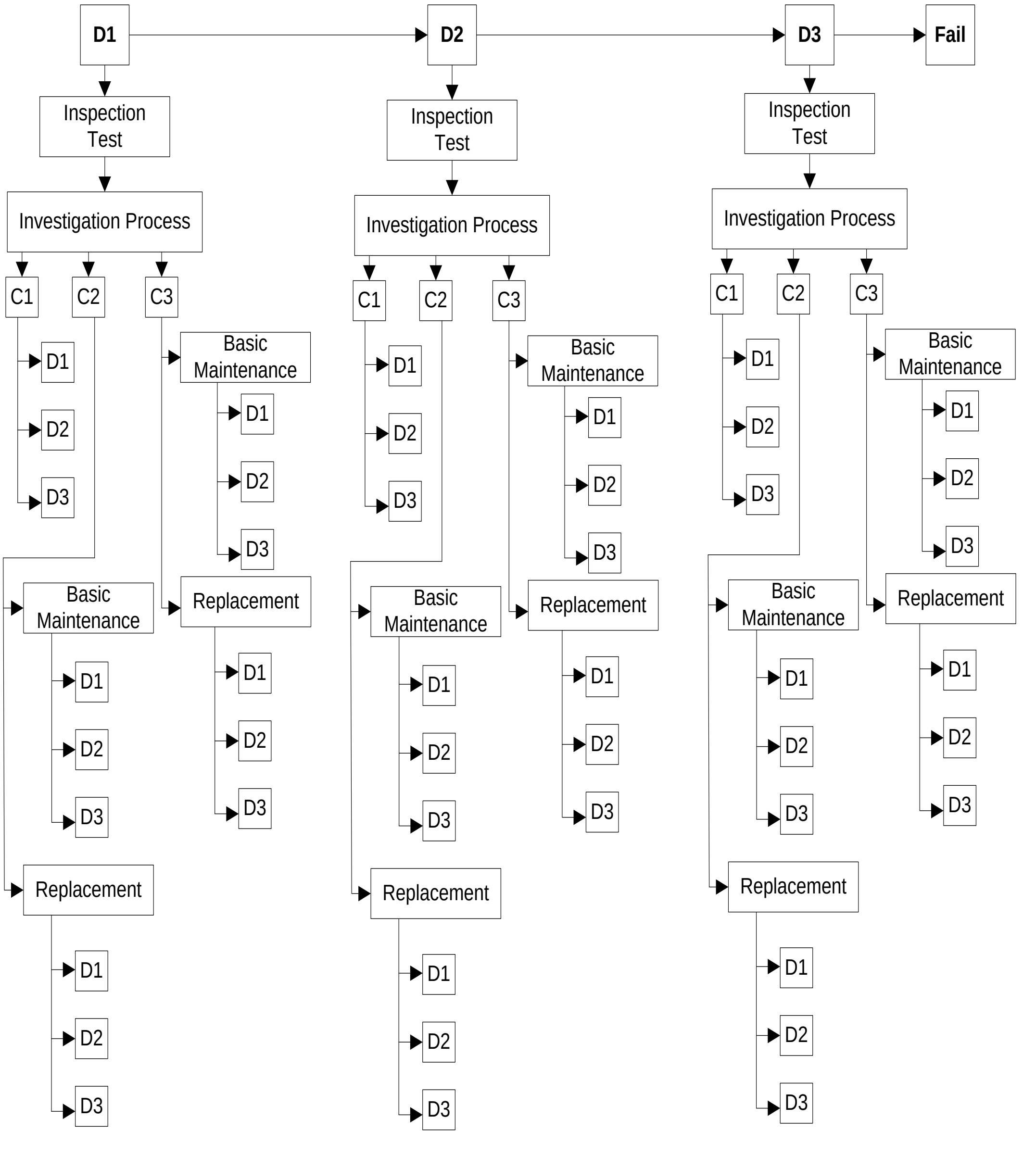

Figure: 3.20 Transformer maintenance model [47]

Table: 3.1 Transformer maintenance tasks [99]

Transformer activity task	**Standard checklist to ensure transformer availability**
Main Components	Winding, Cooling agent (for example, oil, gas or air), Bushing, Tap Changer.
Operating Mechanism	Transforms voltage from one level to another preserving the same frequency
Deterioration process	Insulation paper in the winding, oxidation of oil
Particles produced by ageing process	Sludge, water, fibre, gases (CO, CO2 etc.), Furfural, partial discharge.
Failure mode	- Thermal related faults - Dielectric related faults - General degradation related faults - Mechanical related faults
Inspection tests	- Dielectric strength, resistivity, acidity, moisture content - Routine Oil sampling test - Dissolved gas analysis - Furfural analysis - Partial discharge monitoring
Maintenance	For oil Immersed transformer - Oil filtering (online/offline) - Oil replacement

Table: 3.2: Stated limits for Service- Aged oils for Transformers [99]

Test and Method	**Transformer (Value for Voltage Class)**		
	69 kV and below	69 kV- 230 kV below	230 kV and above
Dielectric strength,^kV minimum 1 mm gap 2 mm gap	 23 40	 28 27	 30 50
Dissipation factor (power factor) 25 °C, % maximum 100 °C, % maximum	 0.5 5	 0.5 5	 0.5 5
Interfacial tension, Mn/m Minimum	25	30	32

^ Older transformers with inadequate oil preservation systems or Maintenance may have lower values

3.4.2. Model parameters

Table 3.3 presents the list and definition of the parameters that are needed for the transformer maintenance model. Parameter one (1) and two (2) can be obtained from the oil condition of a transformer, through historical recorded information. These parameters are given, although parameter 2, which is the inspection rate of every stage can be changed to accomplish high reliability with the least cost. Subsequently, this parameter is of foremost significance in deciding the effect of maintenance on transformer.

Table: 3.3: List of model parameters and definitions [47]

Model Parameters	Definitions
1. Mean time in each stage	It is defined as mean time the device spends in each stage. The inverse of the mean time is the transition rate of the corresponding stage in deterioration process.
2. Inspection rate of each stage	It is defined as the rate at which the inspection is done. The inspection may be followed by maintenance.
3. Probabilities of transition from one state to others.	These parameters are the probabilities of transition from one state to others. These probabilities include; - The oil condition after inspection - The probabilities of transferring from any oil condition to a given stage - The probabilities of filtering or replacing the oil and - Probabilities of transferring to each stage after maintenance.

3.5. Mathematical equivalent models

The transformer maintenance model presented in figure 3.20, is simplified by using two mathematical equivalent models. In these models, the transformer deterioration process is illustrated by three discrete stages. It is assumed that a decision is taken at the end of every inspection.

The following variables are used in figures 3.21 - 3.23:

γ_1 = mean time in state 1 (year)
γ_2 = mean time in state 2 (year)
γ_3 = mean time in state 3 (year)

μ_{21} = repair rate from state 2 to 1 (/year)
μ_{32} = repair rate from state 3 to 2 (/year)

μ_{31} = repair rate from state 3 to 1 (/year)

D_1 = time spent in stage one
D_2 = time spent in stage two
D_3 = time spent in stage three
F = failure stage

3.5.1 Perfect maintenance model

It is assumed that in the initial state, the transformer is in good working condition that needs no maintenance. Also, it is assumed that maintenance improves any state to the previous state; in other words, the repairs of a transformer in state 2 will improve the equipment condition to state 1, and likewise, repair of a transformer in state 3 will improve equipment condition to state 2. This model is illustrated in figure 3. 21.

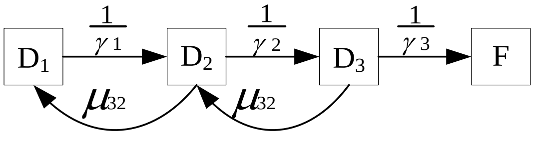

Figure: 3.21 perfect maintenance model [47]

3.5.2 Imperfect maintenance model

This model depicts the transition rate from state 1 to state 3 to describe an imperfect inspection of state 1, which makes it slightly different to the perfect maintenance model. In this model the probability of state 1 to state 3 was taken in to consideration. Therefore, this model is the equivalent model for transformer maintenance model in figure 3.20, since it included transition from state 1 to state 2. The model illustrated in figure 3.22 was used to ascertain the transformer remaining life using first passage time and steady-state probability calculation. The model for this is shown in figure 3.22 below.

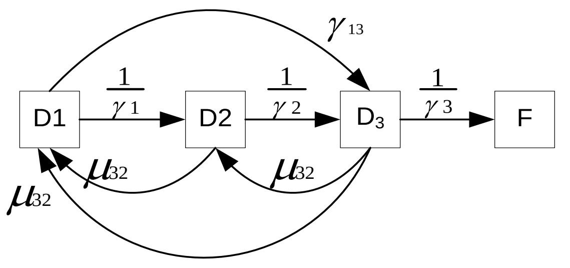

Figure: 3.22 imperfect Maintenance Model [47]

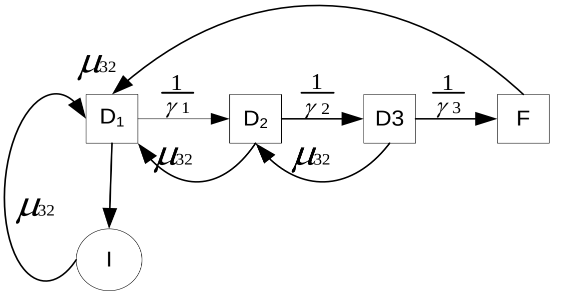

Figure: 3.23 Inspection Model [47]

3.5.3 Inspection tests

In this work, oil insulated transformers were considered. The model incorporated various inspection tests. The state of the transformer was obtained by comparing the measured parameters and the working standard. Specifically, the following tests were considered in this model:

- Dielectric strength verification,
- Resistivity, acidity and moisture content analysis
- Routine oil sampling test,
- Dissolved gas analysis and
- Furfural analysis

3.5.4 Investigation

Information gained from the inspection tests was utilised to determine the state of the transformer, with recommended maintenance activity and next inspection.

3.5.5 Maintenance action

1) Do nothing - the transformer is in an acceptable condition and no maintenance is required. The likelihood that the system is situated back to same stage is moderately high.

2) Basic Maintenance - this maintenance activity increases the likelihood of going back to the preceding stage

3) Replacement - replacement of damaged components takes the system back to its original stage i.e. its initial stage.

3.6 Transformer remaining life estimation

Markov model for determining the life of oil insulation machine found in [5] is adapted and presented in this section. Four states can be identified with reasonable precision for the transformer under review:

(a) Normal or working state

(b) Minor deteriorating state

(c) Major deteriorating state and

(d) Failure state

In this model it is expect that the system, if not maintained, will deteriorate in stages (for a general model, *k*-deterioration stages are assumed) and will eventually fail at $k + 1$. Failure can also happen as a consequence of different causes not related to ordinary aging, which will be referred to as a random or Poisson failure. If deterioration is discovered, preventive maintenance is performed which is expected to restore the system back to its original condition before deterioration (assumed). Repair maintenance, after either random or deterioration induced failure, will restore the system to a new condition. All of these presumptions are embraced in the state-space Markov model. A model in view of discrete parameter (progression of occasions) is presented. This system is described by the transition probabilities showing the likelihood of moving from state i to state j in a given time interval. Markov model indicating different phases of deterioration that will eventually culminate in failure is presented. This model is presented in figure 3.24

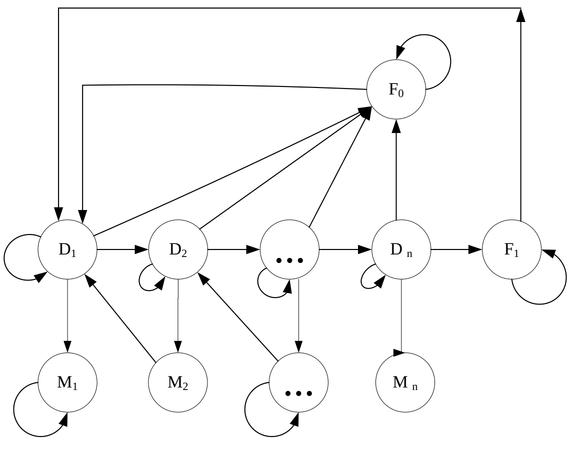

Figure: 3.24 Discrete parameter Markov model for the determination of the remaining system life [47]

In the model presented in figure 3.24, D_2… D_k are deterioration states, with D_1 being the ordinary state. M_1 … M_k indicate maintenance states respectively. The computation of the expected transition time from any of the system states to state F_1 (expected remaining life) can be performed utilizing standard Markov strategies as outlined below.

Transition probability matrix P = [P (ij)] is constructed from inspection / observation information of the identified critical component. Here i and j represent indices of all the states. The constructed matrix P can be partitioned into four sub-matrices;

$$P = \begin{bmatrix} Q & R \\ O & T \end{bmatrix} \tag{3.1}$$

Where T = P (F_1 F_1) since state F_1 is the last in the state array. From here, Matrix N, called fundamental matrix of the Markov chain, is constructed from P. i.e. N = (I – Q)-1 where i represents identity matrix and N is called the fundamental matrix of the Markov chain. N_{ij} represents the ijth element of N, T_i the sum of the entries in row i of N. B_{ij} the ijth entry of matrix B = NR.

- N_{ij} denote the average number of times the process is in the jth if it starts in the ith transient state.
- The number T_i is the average number of steps before the process enters an absorbing state if it starts in the ith transient state.
- The number B_{ij} is the probability of eventually entering the jth absorbing state if the process starts in the ith transient state.

It can be shown that the elements of N, N_{ij} give the mean number of visits starting from state i to a transient state j (deterioration or maintenance state) before entering a deterioration failure state. Therefore, if M_i is the expected remaining life of the component if the system is in state i, it can be expressed as

$$M_i = \sum N_{ij} T_j = \sum_j \left(\frac{\mathrm{N_{ij}} \,\Delta T}{\sum_{k \neq j} \mathrm{P_{(j,k)}}} \right) \qquad (3.2)$$

Where

T_j = the mean time spent in state j.

3.6 1 Methods based on continuous time

In engineering, determining transition rates are often preferable to transition probabilities. A Markov model based on continuous approach for the assessment of the remaining existence of insulation is demonstrated in figure 3.25.

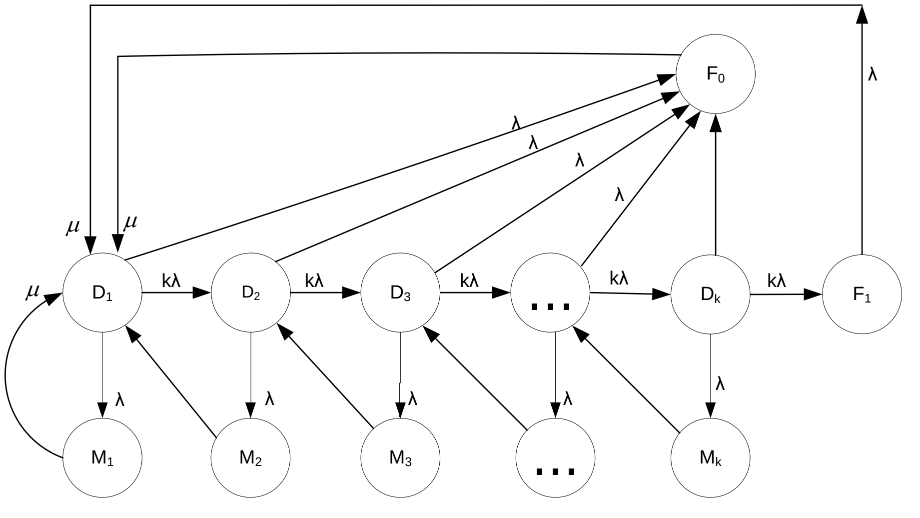

Figure: 3.25 Continues parameter Markov model [47]

3.6.2 Determination of the transition rate parameter

All parameters can be obtained from historical records, except for λ, the reciprocal of the MTTF if no maintenance is executed. The estimation of λ can be obtained as follows: μ

Observe the average time to deterioration failure T_F^*, this is the average time between faiture events and it can be easily recorded.

- Solve the Markov model for various values of λ, to obtain the function shown in figure 3.26.
- From this function, determine the values of λ corresponding to the value of T_F , recorded earlier.

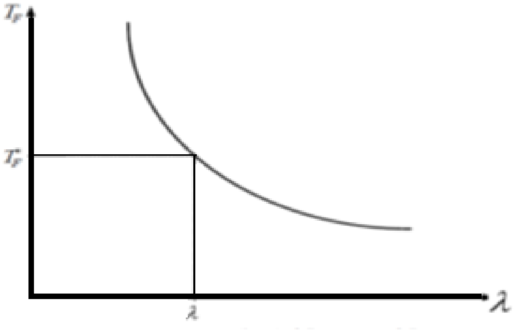

Figure: 3.26 function of the mean time to failure versus failure [79]

To determine the expected time for a component failure, figure 3.26 can now be reduced to figure 3.27 where transition rates are used instead of transition probabilities.

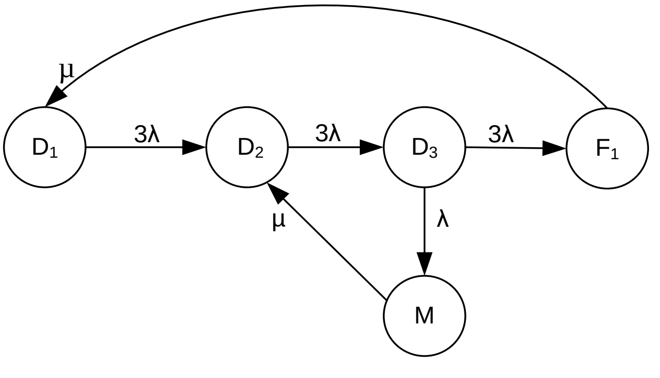

Figure 3.27 Markov model with continuous parameter [79].

For k = 3, denoted state D_2 by i and state F_1 by j. Applying the rules for state combination [62] as illustrated in figure 3.28 the following are produced

$$\lambda_{\text{is}} = 3\lambda, \lambda_{js} = \mu \tag{3.3}$$

$$\lambda_{\text{is}} = \frac{\text{PD13}\,\lambda + \text{PM3}\mu\text{M}}{\text{PD + PD3+P M3}} \tag{3.4}$$

$$\lambda_{ij} = \frac{PD13\,\lambda}{PD + PD3 + P\,M3} \tag{3.5}$$

Where

PD_1, PD_3 and PM_3 are the steady-state probabilities of the system states.

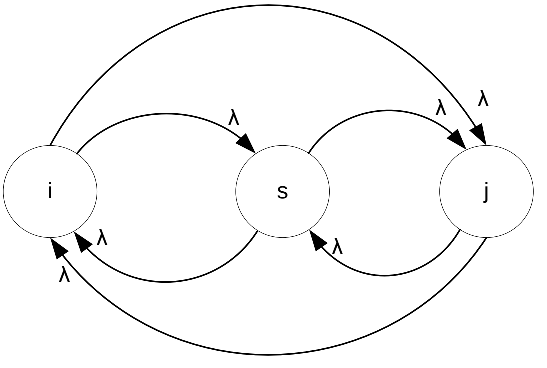

Figure 3.28: Diagram illustrating development of the mean transition time between states i and j. [79]

3.6.3 Determination of steady-state probabilities

The steady-state probabilities needed in equations 3.34 and 3.35 are determined by solving the equations P.Q =0. The pi are the unknown values which need to be determined, since they are the steady-state probabilities of the system states indicated in Figure 3.28. In the event that there are n-states in the state space, there are no such equations in n-unknowns. Unfortunately, this collection of equation is irreducible. Another equation is needed in order to solve the equations and find the unknowns. Fortunately, since {pi} is a probability distribution, it also known that the normalisation condition holds Xiϵs Pi = 1, then n + 1 equations, can be solved to find the n unknowns {Pi} where Q, the transition intensity matrix, is generated from the state transition diagram. For example, a 2-state Markov process has its state transition diagram and the generator matrix shown below.

$$Q = \begin{bmatrix} -\lambda & \cdots & \lambda \\ \vdots & \ddots & \vdots \\ \mu & \cdots & -\mu \end{bmatrix}$$

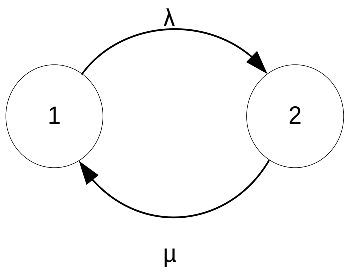

Figure 3.29: Two state Markov transition diagram [79]

If we consider the probability flux in and out of state 1, we obtain $P_1 \lambda = P_{2\mu}$ and similarly, for state 2, $P_{2\mu} = P_1 \lambda$. From the normalisation condition, we know that $P_1 + P_2 = 1$. It follows that the steady state probability distribution is $P\left(\frac{\mu}{\mu+\lambda}, \frac{\lambda}{\mu+\lambda}\right)$,these computed steady-state probabilities can now be substituted in equations 3.34 and 3.35 for evaluating λ_{is} and λ_{sj}.

3.6.4 Determination of the mean time to failure

Computing the MTTF (first passage) MD_2F_1, consider first the case where there is no direct transition between states i and j. when in state s, the system may transfer to state i or to state j. Let Psi denote the probability of moving from state s to state j i.e.

$$P_{si} = \left(\frac{\lambda_{si}}{\lambda_{si}+\lambda_{sj}}\right) \tag{3.6}$$

$$P_{sj} = 1 - P_{si} \tag{3.7}$$

From the analysis of possible transitions [61] in figure 3.28, we have

$$M_{ij} = \frac{1}{\lambda_{is}}\left(1 + P_{si} + P_{si}^2 + \cdots\right) + \frac{1}{\lambda_{sj}}\left(P_{sj} + P_{si}P_{sj} + P_{si}^2 P_{sj}^2 + \cdots\right) + \frac{1}{\lambda_{si}}\left(P_{si} + P_{si}^2 + \cdots\right)$$

$$= \frac{1}{\lambda si} \cdot \frac{1}{1-P_{si}} + \frac{1}{\lambda_{sj}} \cdot P_{sj}\left[1 + P_{si} + P_{si}^2 P_{sj} + \cdots\right] + \frac{1}{\lambda_{si}} P_{si}\left(1 + P_{si} + P_i^2 + \cdots\right)$$

$$= \frac{1}{\lambda si} \cdot \frac{1}{1-P_{si}} + \frac{P_{sj}}{\lambda_{sj}}\left[1 + P_{si}\left(1 + P_{si} P_{sj} + P_{si}^2 P_{sj}^2\right)\right] + \frac{P_{si}}{\lambda_{si}} \cdot \frac{1}{1-P_{si}}$$

$$M_{ij} = \frac{1}{\lambda si} \cdot \frac{1}{1-P_{si}} + \frac{P_{sj}}{\lambda_{sj}} + \frac{P_{si} P_{sj}}{\lambda_{sj}} \cdot \frac{1}{1-P_{si} P_{sj}} + \frac{P_{si}}{\lambda_{si}} \cdot \frac{1}{1-P_{si}} \tag{3.8}$$

Numerical example using a continuous parameter.

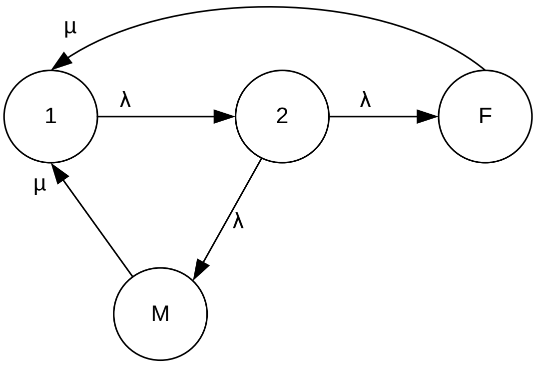

Figure 3.30: A simple maintenance model under deterioration failure [79]

To illustrate the practical application of the model, a four-state component with failure due to deterioration and a maintenance state is applied and solved analytically. From the four-state diagram shown in figure 3.30, the transition probabilities Q are constructed as shown below. Q represents the intensity matrix or transition probabilities. It is made up of a 4 by 4 matrix having the elements of D_{11}, D_{12}, D_{13} and D_{14} in the first row, D_{21}, D_{22}, M_{23} and F_{24}, in the second row, D_{31}, D_{32}, M_{33} and F_{34} in the third row and D_{41}, D_{42}, M_{43} and F_{44} in the fourth and final row. The entries in Q are obtained from the simple four-state deteriorating component model or transition state diagram shown in figure 3.9 as follows:

$\mathrm{D}_{11} = -\lambda$ (State transition from state 1 to state 2 and is negative because is transiting state 1 to state 2).

$\mathrm{D}_{12} = \lambda$ (State transition from state 1 to state 2 and is positive since the state transition is entry state 2).

$\mathrm{M}_{13} = 0, \mathrm{F}_{14} = 0$ (Since there are no transitions between state 1 and state 3 and state 4 respectively). All the entries in the other rows in Q were obtained from figure 3.9 in same way. With these transition probabilities, the steady-state probabilities were computed as illustrated in the numerical example:

$$Q = \begin{bmatrix} D11 & D12 & M13 & F14 \\ D21 & D22 & M23 & F24 \\ D31 & D32 & M33 & F34 \\ D41 & D42 & M43 & F44 \end{bmatrix}$$

$$Q = \begin{bmatrix} -\lambda & \lambda & 0 & 0 \\ 0 & -\lambda - \lambda_M & \lambda_M & \lambda \\ \mu_M & 0 & -\mu_M & 0 \\ \mu & 0 & 0 & -\mu \end{bmatrix}$$

Assuming that $\lambda = 0.65,\ \lambda_M = 0.5,\ \mu_M\ =\ 33,\ \mu = 6.1$

$$P * Q = 0,\ that\ is\ P_1\ \ P_2\ P_M\ P_F \begin{bmatrix} -0.65 & 0.65 & 0 & 0 \\ 0 & -1.2 & 0.5 & 0.65 \\ 33 & 0 & -33 & 0 \\ 6.1 & 0 & 0 & -6.1 \end{bmatrix} = 1 \tag{3.9}$$

Calculating the steady-state probabilities ($\mathrm{P_1\ \ P_2\ P_M}$ and $\mathrm{P_F}$) from the generated transition probabilities and the normalisation condition of $\sum_{xi\varepsilon S}(P_i\,) = 1,$ as follows: From equation 3.9, the following equations are formulated:

$$\begin{bmatrix} -0.65P_1 + 0 + 33P_M + 6.1P_F = 0 \\ 0.65P_1 \quad - \quad 1.2P_2 + 0 + \ 0 \ \ = 0 \\ 0 + \ 0.5P_2 - 33P_M + 0 \qquad\quad = 0 \\ 0 + \ 0.65P_2 + 0 - 6.1P_F \qquad\quad = \ 0 \end{bmatrix} \tag{3.10}$$

From equation 3.10:

$0.65P_1\ =\ 1.2P_2\ \Rightarrow\ P_1\ =\ \frac{1.2}{0.65}\ P_2$; $0.5P_2\ =\ 33P_M\ \Rightarrow\ P_M\ =\ \frac{0.5}{33}\ P_2$

$0.65P_2\ =\ 6.1P_F\ \Rightarrow\ P_F\ =\ \frac{0.65}{6.1}\ P_2$

The normalization equation gives $P_1\ +\ P_2 +\ P_M + P_F = 1$ (3.11)

Substituting for $\mathrm{P_1}$, $\mathrm{P_M}$ and $\mathrm{P_F}$ in equation 3.11,

$\frac{1.2}{0.65}\ P_2 +\ P_2 + \frac{0.5}{33}\ P_2 + \frac{0.65}{6.1}\ P_2 = 1$

$2.97P_2\ =\ 1\ \Rightarrow\ P_2\ =\ 0.3369$

$\mathrm{P_1} = 0.6220,\ \Rightarrow\ P_M\ =\ 0.0051$ and $\mathrm{P_F} =\ 0.0359$

With these values, λ_{is} and λ_{sj} can now be calculated:

$\lambda_{is} = \frac{P_{D1}3\lambda\, +\, P_{M3}\mu_M}{P_{D1}+\,P_{D3}+P_{M3}}$ and $\lambda_{\mathrm{ij}} = \frac{P_{D3}3\lambda}{P_{D1}\, +\, P_{D3}+P_{M3}}$

$\lambda_{is} = \frac{0.6220\times 0.65\ +\ 0.0051\times 33}{0.6220+\ 0.3369+0.0051} = \frac{0.5726}{0.964} = 0.593983402$

$\lambda_{sj} = \frac{0.3369\times 0.65}{0.964} = 0.227162863$

Also, from equation 3.8 we have

$P_{si} = \left(\frac{\lambda_{si}}{\lambda_{si}+\lambda_{sj}}\right)$ and P_{sj} = 1 - P_{si}

$P_{si} = \left(\frac{0.593983402}{0.593983402+0.227162863} = 0.723358836\right)$

$P_{sj} = \left(\frac{0.227162863}{0.593983402+0.227162863} = 0.276641163\right)$

Substituting these parameters into equations 3.8 reproduced below:

$$M_{ij} = \frac{1}{0.593983402} \cdot \frac{1}{1 - 0.723359} + \frac{0.276641}{0.227162863} + \frac{0.723359 \times 0.276641}{0.227162863} \cdot \frac{1}{1 - 0.276641 \times 0.723359} + \frac{0.723359}{0.5261219} \cdot \frac{1}{1 - 0.723359}$$

$M_{ij} = 12.63$ yrs.

The availability of these results allows asset managers to make informed decisions regarding which of the following actions should then be taken:

1) Replacement of the transformer before end of life
2) Refurbishment of the transformer
3) Carry out appropriate maintenance when is needed
4) Loading of the transformer

The Matlap computer algorithm for the mathematical algorithm utilised in ascertaining the remaining life of the transformer is presented in appendix A.

CHAPTER 4

RESULTS AND DISCUSSION

The analysis covers the mean time to first failure (MTTFF) with respect to transient probability and unavailability rates. MTTFF is the expected number of operating times that occurred before the failure of transformer when started from initial stage. Using the mathematical Markov processes from Anders *et al*, the remaining existence of the transformer is ascertained based on its present insulation status so that knowledgeable decisions are taken on the suitability of the consistent operation of the equipment.

4.1 Transformer analysis

For these transformers under consideration, assuming a fuse blowing philosophy and perfect up-stream reliability, the following state space diagram (Figure 4.1) and its corresponding matrix can be used to model substation transformers (normally in parallel redundancy) [99]. The analysis included the data from 2007 to 2014 as presented in table 4.1.

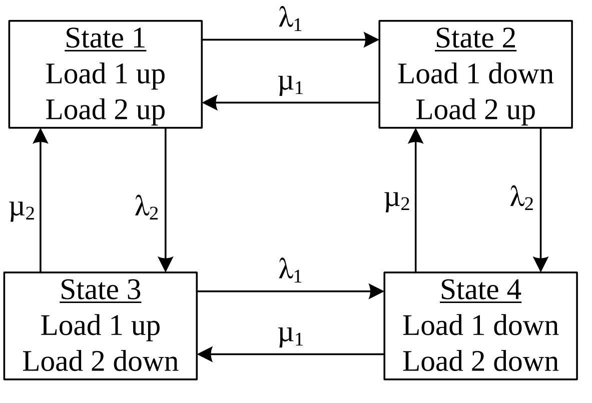

Figure 4.1: State-space diagram for two transformers in parallel

The state transitional matrix arising from Figure 4.1 is as follows:

$$P = \begin{bmatrix} 1-\lambda_1\Delta t-\lambda_2\Delta t & \lambda_1\Delta t & \lambda_2\Delta t & 0 \\ \mu_1\Delta t & 1-\lambda_2\Delta t-\mu_1\Delta t & 0 & \lambda_2\Delta t \\ \mu_2\Delta t & 0 & 1-\lambda_1\Delta t-\mu_2\Delta t & \lambda_1\Delta t \\ 0 & \mu_2\Delta t & \mu_1\Delta t & 1-\mu_1\Delta t-\mu_2\Delta t \end{bmatrix}$$

In further analysis, we assumed that Δt is implicit, hence it was ignored. In order to compute the MTTFF, the number of steps from S_i to reach an absorbing state S_j must be determined. If S_k is a transient set of states with matrix *G* obtained by truncating *P*, that is, by deleting *Mth* row and *Nth* column, the mean number of times the process is in *Sj* before absorption, if it started in Si [99], [100]

$$S\left(N_{ij}\right)=n_{ij}\leq\left|S\in S_k\right. \tag{4.1}$$

$$N=(I-G)^{-1} \tag{4.2}$$

Where

n_{ij} = the elements of *N* and *I* = identity matrix

S_j = absorbing state

S_K = transient set of states

Alternatively, the MTTFF can be obtained using a mean first passage time (MFPT) matrix. If M_Z is a fundamental matrix and $\bar{T}$ be the MFPT matrix, then from [95]:

$$M_Z=\left[I-\left(P-A\right)\right]^{-1} \tag{4.3}$$

$$MTTFF=\bar{T}=\left[I-M_Z+UM_D\right]D \tag{4.4}$$

Where

I = Identity matrix

U = Unit matrix

P = Transition matrix

A = Matrix each row of which is the limiting probability vector

α = $(\alpha_0, \alpha_1, \ldots, \alpha_n)$

M_D = A diagonal matrix of M_Z

$\bar{T}$ $=\bar{t}_{ij}$ represents the MTTFF or mean number of steps from state *i* to *j*,*D* = diagonal matrix such that $d_{ii}=1/\alpha_i$.

Table 4.1: Failure rates for eThekwini Electricity

Year	No.Trfr Installed	No. of Failures	Failure rate
2007	321	14	0.00160
2008	334	15	0.00171
2009	341	8	0.00091
2010	353	6	0.00068
2011	371	17	0.00194
2012	387	17	0.00194
2013	407	15	0.00171
2014	417	11	0.00126

Failure rate data from Table 4.1 was used to compute to obtain values of MTTFF from 2007 to 2014, assuming the transformers undergo a four state transition from uptime to downtime; and taking average repair rate of 0.077 f/yr. [99], [101].

For $\lambda_1 = \lambda_2 = 0.00160$ and $\mu_1 = \mu_2 = 0.077$, the following transitional matrix, P, arises:

$$P = \begin{bmatrix} 0.9968 & 0.0016 & 0.0016 & 0 \\ 0.0770 & 0.9214 & 0 & 0.0016 \\ 0.0770 & 0 & 0.9214 & 0.0016 \\ 0 & 0.0770 & 0.0770 & 0.8460 \end{bmatrix}$$

Mean First Passage Time (MTPT) Matrix for the above parameters (in 2007), applying equation 4.4 is given as follows:

MFPT Matrix=

$$1.0e{+}04 * \begin{bmatrix} 0.0001 & 0.0631 & 0.0631 & 1.5977 \\ 0.0013 & 0.0050 & 0.0638 & 1.5664 \\ 0.0013 & 0.0638 & 0.0050 & 1.5664 \\ 0.0020 & 0.0325 & 0.0325 & 0.2413 \end{bmatrix}$$

The corresponding MTTFF is 2413.

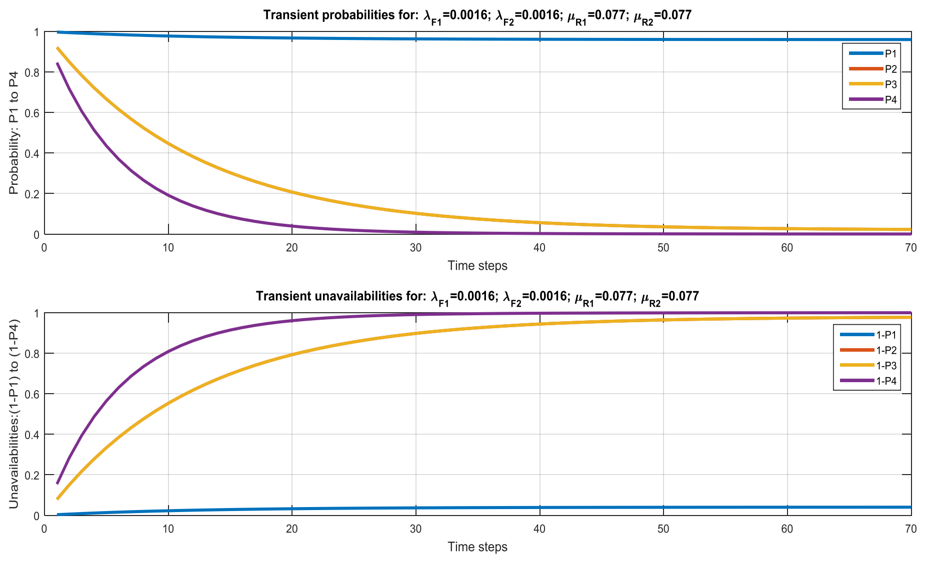

Figure 4.2: Transient probabilities and unavailabilities showing states 2 and 3 to have same probability (2007)

For $\lambda_1 = \lambda_2 = 0.00171$ and $\mu_1 = \mu_2 = 0.077$, the following transitional matrix, *P*, arises:

$$\mathrm{P} = \begin{bmatrix} 0.9966 & 0.0017 & 0.0017 & 0 \\ 0.0770 & 0.9213 & 0 & 0.0017 \\ 0.0770 & 0 & 0.9213 & 0.0017 \\ 0 & 0.0770 & 0.0770 & 0.8460 \end{bmatrix}$$

Mean First Passage Time (MFPT) Matrix for the above parameters (in 2008) is given as follows:

$$1.0e{+}04 * \begin{bmatrix} 0.0001 & 0.0591 & 0.0591 & 1.4044 \\ 0.0013 & 0.0047 & 0.0598 & 1.3751 \\ 0.0013 & 0.0598 & 0.0047 & 1.3751 \\ 0.0020 & 0.0305 & 0.0305 & 0.2119 \end{bmatrix}$$

The corresponding MTTFF is 2119

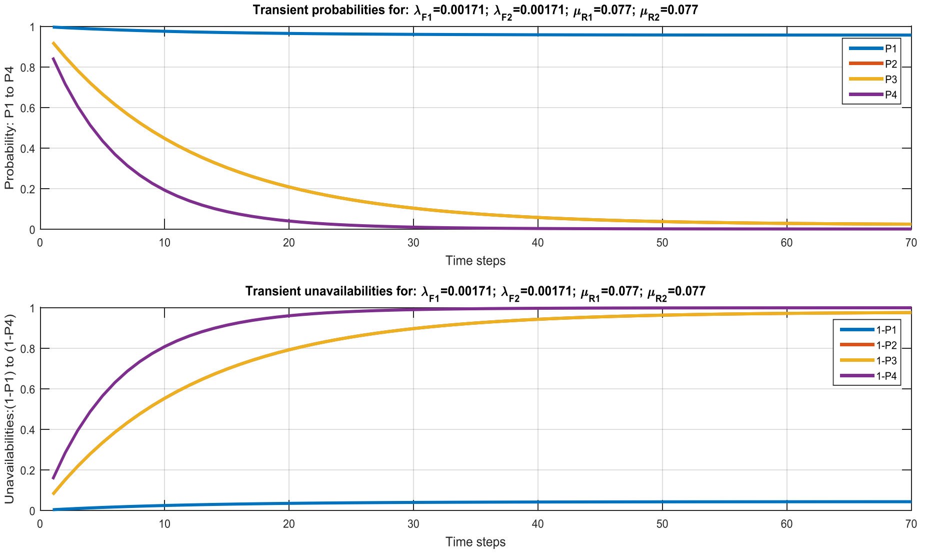

Figure 4.3: Transient probabilities and unavailabilities showing states 2 and 3 to have same probability (2008)

For $\lambda_1 = \lambda_2 = 0.00091$ and $\mu_1 = \mu_2 = 0.077$, the following transitional matrix, *P*, arises:

$$P = \begin{bmatrix} 0.9982 & 0.0009 & 0.0009 & 0 \\ 0.0770 & 0.9221 & 0 & 0.0009 \\ 0.0770 & 0 & 0.9221 & 0.0009 \\ 0 & 0.0770 & 0.0770 & 0.8460 \end{bmatrix}$$

Mean First Passage Time (MFPT) Matrix for the above parameters (in 2009), applying Equation 4.4, is given as follows:

$$1.0e{+}04 * \begin{bmatrix} 0.0001 & 0.1105 & 0.1105 & 4.8140 \\ 0.0013 & 0.0087 & 0.1112 & 4.7591 \\ 0.0013 & 0.1112 & 0.0087 & 4.7591 \\ 0.0020 & 0.0562 & 0.0562 & 0.7330 \end{bmatrix}$$

The corresponding MTTFF is 7330

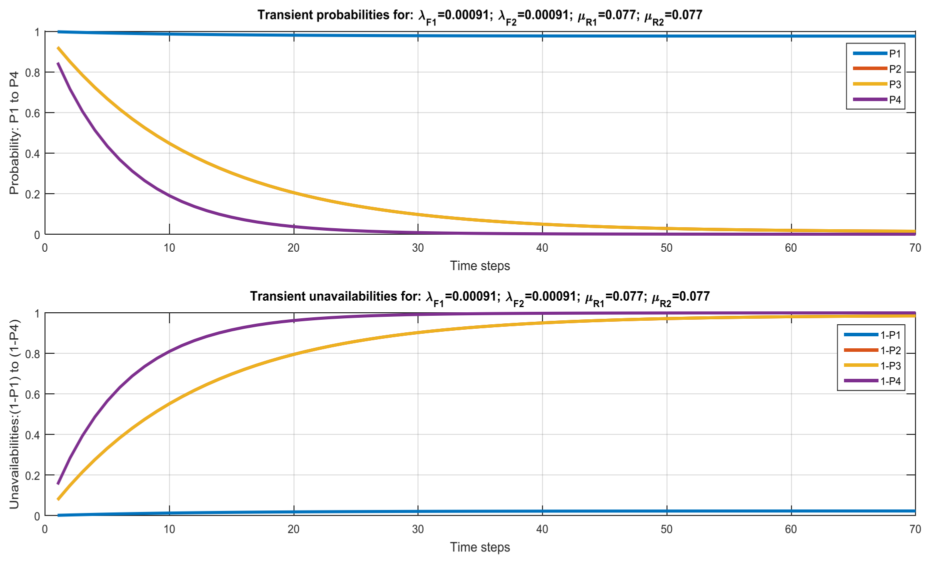

Figure 4.4: Transient probabilities and unavailabilities showing states 2 and 3 to have same probability (2010)

For $\lambda_1 = \lambda_2 = 0.00068$ and $\mu 1 = \mu 2 = 0.077$, the following transitional matrix, P, arises:

$$P = \begin{bmatrix} 0.9986 & 0.0007 & 0.0007 & 0 \\ 0.0770 & 0.9223 & 0 & 0.0007 \\ 0.0770 & 0 & 0.9223 & 0.0007 \\ 0 & 0.0770 & 0.0770 & 0.8460 \end{bmatrix}$$

Mean First Passage Time Matrix for the above parameters (in 2010), applying Equation 4.4 is given as follows:

$$1.0e{+}04 * \begin{bmatrix} 0.0001 & 0.1477 & 0.1477 & 8.5467 \\ 0.0013 & 0.0115 & 0.1484 & 8.4732 \\ 0.0013 & 0.1484 & 0.0115 & 8.4732 \\ 0.0020 & 0.0748 & 0.0748 & 1.3050 \end{bmatrix}$$

The corresponding MTTFF is 13050

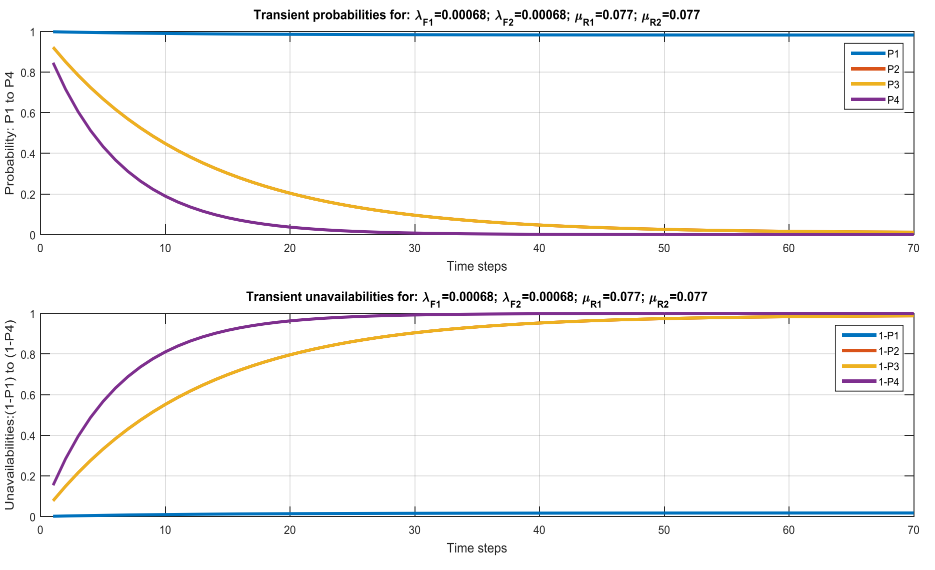

Figure 4.5: Transient probabilities and unavailabilities showing states 2 and 3 to have same probability (2011)

For $\lambda_1 = \lambda_2 = 0.00194$ and $\mu 1 = \mu 2 = 0.077$, the following transitional matrix, P, arises:

Mean First Passage Time (MFPT) Matrix for the above parameters (in 2011), applying Equation 4.4 is given as follows:

$$1.0e{+}04 * \begin{bmatrix} 0.0001 & 0.0522 & 0.0522 & 1.1003 \\ 0.0013 & 0.0042 & 0.0528 & 1.0745 \\ 0.0013 & 0.0528 & 0.0042 & 1.0745 \\ 0.0020 & 0.0271 & 0.0271 & 0.1656 \end{bmatrix}$$

The corresponding MTTFF is 1656

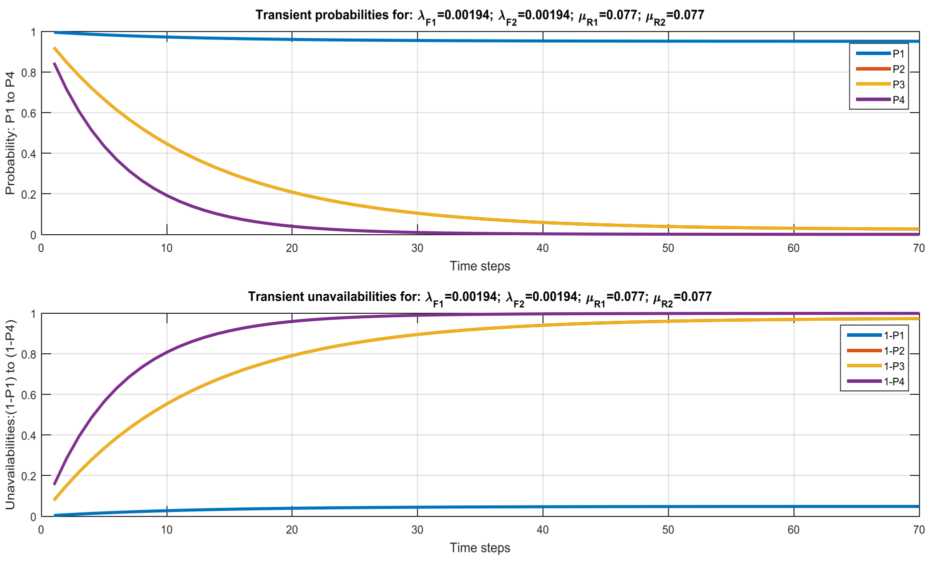

Figure 4.6: Transient probabilities and unavailabilities showing states 2 and 3 to have same probability (2013)

For $\lambda_1 = \lambda_2 = 0.00126$ and $\mu_1 = \mu_2 = 0.077$, the following transitional matrix, P, arises:

$$P = \begin{bmatrix} 0.9975 & 0.0013 & 0.0013 & 0 \\ 0.0770 & 0.9217 & 0 & 0.0013 \\ 0.0770 & 0 & 0.9217 & 0.0013 \\ 0 & 0.0770 & 0.0770 & 0.8460 \end{bmatrix}$$

Mean First Passage Time Matrix for the above parameters (in 2014), applying Equation 4.4 is given as follows:

$$1.0e{+}04 * \begin{bmatrix} 0.0001 & 0.0800 & 0.0800 & 2.5441 \\ 0.0013 & 0.0063 & 0.0807 & 2.5044 \\ 0.0013 & 0.0807 & 0.0063 & 2.5044 \\ 0.0020 & 0.0410 & 0.0410 & 0.3858 \end{bmatrix}$$

The corresponding MTTFF is 3858.

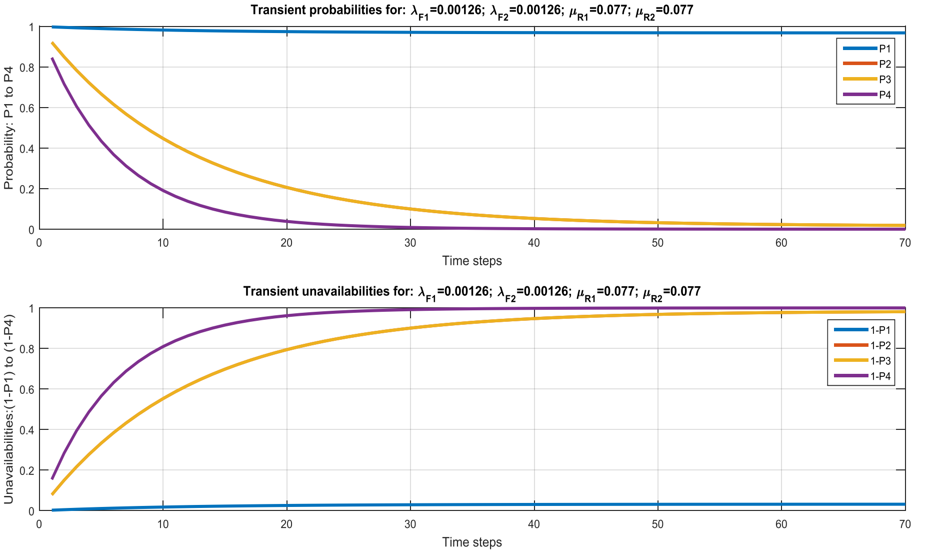

Figure 4.7: Transient probabilities and unavailabilities showing states 2 and 3 to have same probability (2014)

Table 4.2: Computed MTTFF values with respect to failure rates

Year	**No.Trfr Installed**	**Failure rate**	**MTTFF**
2007	321	0.00160	2413
2008	334	0.00171	2119
2009	341	0.00091	7330
2010	353	0.00068	13050
2011	371	0.00194	1656
2012	387	0.00194	1656
2013	407	0.00171	2119
2014	417	0.00126	3858

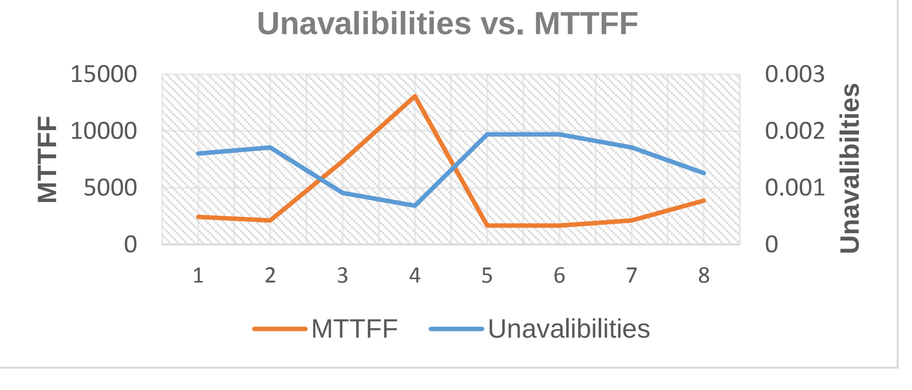

Figure 4.8: Unavailabilities vs. MTTFF

The observations that could be made from these simulation results are: Unavalibilities rate is seen to decrease with an increase in MTTFF, and likewise, an increase for unavailability is seen with a decrease in MTTFF. Therefore, a decrease in unavailabilities rates indicates a decline in availability and reliability of the system whereas an increase indicates system improvement. According to Mkandawire, Ijumba and Saha, the higher the value of the MTTFF, the lower the maintenance costs on those transformers [99]. Therefore, Table 4.1 is reproduced as Table 4.2, with MTTFF values inserted for further analysis. It is observed in Table 4.2 that, failure rates are higher when the MTTFF measure is lower, implying that maintenance expenditure are also higher. Improving the MTTFF reliability measure using the RCM model will result in system reliability enhancement at reasonable maintenance cost.

4.2 Ascertaining the remaining life of the transformer

A Markov model for ascertaining the remaining life discussed in the previous chapter was used for ascertaining the remaining life of eThekwini power transformer. Based on the oil deterioration of a transformer the remaining expected life of the transformer was computed. The discrete stages (D_1, D_2, and D_3) were used as approximations for transformer oil deterioration process. At each stage, oil was inspected to determine its condition. After the inspection, oil condition was determined according to the IEEE standard [102]. This standard categorises oil condition into three groups as shown in Table 4.3.

Table 4.3: Transformer oil condition categorization [102]

State	**Condition**
D_1	Oil in good working condition
D_2	Oil required reconditioning before use
D_3 *or F*	Oil in poor condition and will require replacement or it will fail

The goal of the algorithm was to compute the transformers' mean life using the failure records, and maintenance and repair rates generated from the outage data of the groups of transformers under investigation. These parameters were used as input for this program. We then considered three states of deterioration as shown in the Markov model below.

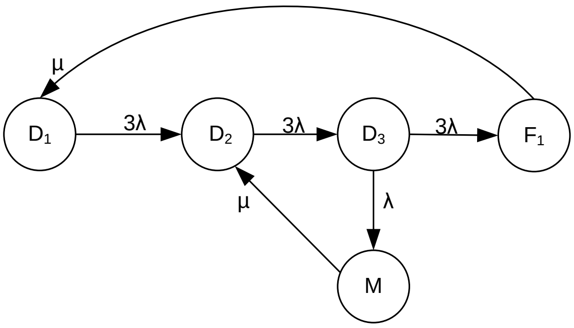

Figure 4.9: Markov model with continuous parameter.

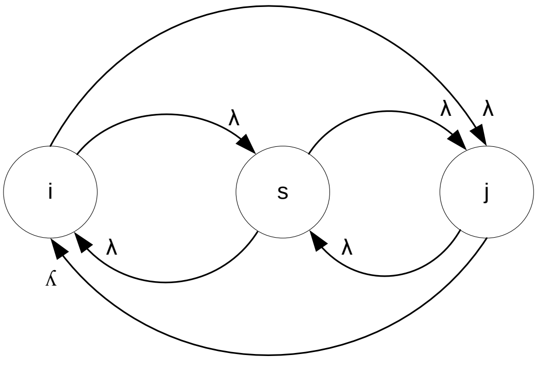

Figure 4.10: Diagram illustrating development of the mean transition time between states i and j.

Note therefore that k = 3, referring to Figure 4.10, state D_2 is denoted by *i* and state *F* by *j*. When the rule of states combination is applied, the following equations are obtained:

$$\lambda_{\text{is}} = 3\lambda, \lambda_{js} = \mu \tag{4.5}$$

$$\lambda_{is} = \frac{PD13\lambda + PM3\mu M}{PD + PD3 + P\ M3} \tag{4.6}$$

$$\lambda_{ij} = \frac{PD13\lambda}{PD + PD3 + P\ M3} \tag{4.7}$$

$$\lambda_{is} = \frac{P_{D1}3\lambda + P_{M3}\mu_M}{P_{D1} + P_{D3} + P_{M3}} \text{ and } \lambda_{ij} = \frac{P_{D3}3\lambda}{P_{D1} + P_{D3} + P_{M3}} \tag{4.8}$$

P_{D1}, P_{D3}, and P_{M3} are the steady-state probabilities of the system states. Using these system states, the transition matrix was constructed with the parameters obtained from the outage of the system selected. Following the steps listed, the mean time to first failure of each transformer was then determined using the MATLAB program.

4.2.1 Steady states probabilities determination

The intensity matrix (Q) was generated from the state transition diagram using the 5-state Markov process (Figure 4.11), as illustrated below:

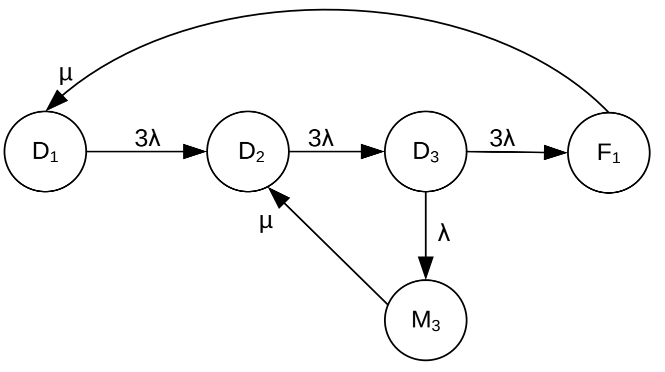

Figure 4.11: Markov model for generating intensity matrix

Using the outage data of the selected system, the following failure and maintenance data were obtained.

$\lambda = 0.35;\ \lambda_{\mathrm{M}} = 0.5;\ \mu_{\mathrm{M}}\ 27;\ \mu = 3.1$

$$Q = \begin{bmatrix} \mathrm{D11} & \mathrm{D12} & \mathrm{M13} & \mathrm{F14} \\ \mathrm{D21} & \mathrm{D22} & \mathrm{M23} & \mathrm{F24} \\ \mathrm{D31} & \mathrm{D32} & \mathrm{M33} & \mathrm{F34} \\ \mathrm{D41} & \mathrm{D42} & \mathrm{M43} & \mathrm{F44} \end{bmatrix}$$

$$Q = \begin{bmatrix} -\lambda & \lambda & 0 & 0 \\ 0 & -\lambda - \lambda_M & \lambda_M & \lambda \\ \mu_M & 0 & -\mu_M & 0 \\ \mu & 0 & 0 & -\mu \end{bmatrix}$$

$$\mathrm{P} * \mathrm{Q} = 0, \qquad \text{that is,} P_1\ P_2\ P_M\ P_F \begin{bmatrix} -0.35 & 0.35 & 0 & 0 \\ 0 & -0.9 & 0.5 & 0.35 \\ 27 & 0 & -27 & 0 \\ 3.1 & 0 & 0 & -3.1 \end{bmatrix} = 1$$

The steady state probabilities were obtained by solving the equations *P.Q = 0*. P_{D1}, P_{D2}, P_M and P_F were unknown, they are the values we wanted to find since they are the steady- state probabilities of the system states indicated in Figure 4.11. If there are n-states in the state space, there are n such equations in n-unknowns. Unfortunately, this collection of equations is irreducible. We needed another equation in order to solve it and find the unknowns. Fortunately, since {*pi*} is a probability distribution, we also know that the normalisation condition holds.

$$P_1 + P_2 + P_M + P_F = 1 \qquad (4.8)$$

Calculating the steady-state probabilities (P_1 P_2 P_M and P_F) from the generated transition probabilities and the normalization condition of $\sum_{xi\varepsilon S}(P_i) = 1$, from equation 4.8, the following equation was formulated.

$$\begin{Bmatrix} -0.35P_1 + 0 + 27P_M + 3.1P_F = 0 \\ 0.35P_1 \; - \; 0.9P_2 + 0 + 0 \; = 0 \\ 0 + 0.5P_2 - 27P_M + 0 \qquad = 0 \\ 0 + 0.35P_2 + 0 - 3.1P_F \qquad = 0 \end{Bmatrix}$$

Using the MATLAB program, the steady-states probabilities were computed as shown below:

```
% linear algebra is used to solve for steady state probabilities

% the transition matrix for the system

q1=[-0.35,0,27,3.1;0.35,-0.9,0,0;0,0.5,-27,0;0,0.35,0,-3.1;1,1,1,1];

q2=[0;0;0;0;1];

x1=linsolve(q1,q2)

P_D1=x1(1,1),P_D2=x1(2,1),P_M=x1(3,1),P_F=x1(4,1)

P_D1 = 0.6907; P_D2 = 0.2723; P_M = 0.0052; P_F = 0.0319;
```

Determination of mean time to first failure

The model below is used to ascertain the mean first passage time from state D_2 to failure state (F_1).

$$\mathrm{M_{ij}} = \frac{1}{\lambda\,\mathrm{si}} \cdot \frac{1}{1-\mathrm{P_{si}}} + \frac{\mathrm{P_{sj}}}{\lambda\,\mathrm{sj}} + \frac{\mathrm{P_{si}\,P_{sj}}}{\lambda\,\mathrm{sj}} \cdot \frac{1}{1-\mathrm{P_{si}\,P_{sj}}} + \frac{\mathrm{P_{si}}}{\lambda\,\mathrm{si}} \cdot \frac{1}{1-\mathrm{P_{si}}}$$

% computer program for computing the mean time failure

```
% calculating the values for first passage time

lamda=0.35;

mew=3.1;

mewm=27;

lamdam=0.5;

P_D1=0.6120;

P_D3=0.3459;

P_M3=0.0052;

lamdais=(P_D1*lamda)+(P_M3*mewm)/(P_D1+P_D3+P_M3);

disp('lamdais is')

lamdais

lamdasj=(P_D3*lamda)/(P_D1+P_D3+P_M3);

disp('lamdasj is:')

lamdasj

P_si=lamdais/(lamdais+lamdasj);

disp('P_si is:')

P_si

P_sj=lamdasj/(lamdais+lamdasj);

disp('P_sj is:')

P_sj

vera_1=(1/(1-P_si)*(1/lamdais));

disp('vera_1 is')

vera_1

vera_2=P_sj/lamdasj;

disp('vera_2 is')
```

```
vera_2

vera_3a=(P_sj*P_si)/lamdasj;

vera_3b=1/(1-(P_si*P_sj));

vera_3=vera_3a*vera_3b;

disp('vera_3 is:')

vera_3

vera_4=(P_si/lamdais)*(1/(1-P_si));

disp('vera_4 is:')

vera_4

m_ij= vera_1+vera_2+vera_3+vera_4;

disp('m_ij is:')

m_ij
```

P_D1 = 0.6907; P_D2 = 0.2723; P_M = 0.0052; P_F = 0.0319

lamdais = 0.3600; lamdasj = 0.1257; P_si = 0.7412; P_sj = 0.2588

vera_1 = 10.7332; vera_2 = 2.0590; vera_3 = 1.8883; vera_4 = 7.9552

m_ij = 22.63

The mean remaining life of the component is = 22.63 yrs.

The transformer remaining life was obtained from ascertaining deterioration state as above. This kind of knowledge was useful in addressing the following questions:

a. How many years on average will a transformer take to move from a certain state of oil deterioration to a failure state?
b. How many years will the insulation reside in a certain deterioration state?
c. On average, what is the possible duration of each deterioration state to last?
d. What is the appropriate time to replace the transformer?

In brief, in this project the failure data has been examined. Among other critical components such as cables, lines, etc., we found a transformer to be the most critical component in the network studied, based on the implications when it fails. Transformers are one of the assets that have a critical function in the power system. It is in this way significant to know the condition and performance of power transformer in the system, and as such, Markov modelling for determining the MTTFF to evaluate the transformer remaining life has been presented.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

In this work, the RCM model has been implemented using eThekwini network statistical failure data. RCM model implementation has been achieved by examining eThekwini network failure data, identifying a critical component, and ascertaining its remaining service life using the Markov Model. This knowledge is useful in decision making regarding the continuing operation of the transformer or any other critical asset on the network.

A Markov Model based on mathematical formulation for estimating the remaining life of the electrical insulation of the transformer was implemented. The model was applied to a transformer identified as a critical component in the eThekwini network. The main strength of this model is that it allows one to assess the state of insulation of several different groups of transformers relative to each other. In conclusion, the findings of this study show that, the approach of reliability centered asset management has the ability to optimise system operation and maintenance planning, hence helping the economic sectors in industries.

5.2 Recommendations

During the study period, it was realised that sufficient availability of information about historical equipment records was a main challenge. Therefore, it is recommended that a standardised database system that includes all the equipment operational records to be developed in order for utilities to begin implementing the RCM model in a cost effective manner, thus increasing system availability and reliability.

5.3 Future research work

In conclusion, it is proposed that this study should be extended to other assets forming the power system which were not considered in this work, for example the underground cables and the overhead lines. Additionally, the production of a maintenance policy that considers the probability of failure for these assets is recommended for future work.

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APPENDICES

Appendix-A: Computer program for ascertaining the remaining life of an oil transformer

The MATLAB program for computing the remaining mean life for the identified distribution component is as illustrated below for the example in figure 3.27.

```
% computer program for computing the mean time failure
% calculating the values for first passage time
% the transition matrix for the system
q1=[-0.65,0,33,6.1;0.65,-1.2,0,0;0,0.5,-33,0;0,0.7,0,-6.1;1,1,1,1];
q2= [0;0;0;0;1];
% Linear algebra used to solve for steady state probabilities
x1=linsolve(q1,q2)
P_D1=x1(1,1),P_D2=x1(2,1),P_M=x1(3,1),P_F=x1(4,1)
% Assuming that
lamda=0.65;
mew=6.1;
mewm=33;
lamdam=0.5;
P_D1=0.6120;
P_D3=0.3459;
P_M3=0.0052;
lamdais=(P_D1*lamda)+(P_M3*mewm)/(P_D1+P_D3+P_M3);
disp('lamdais is')
lamdais
lamdasj=(P_D3*lamda)/(P_D1+P_D3+P_M3);
disp('lamdasj is:')
lamdasj
P_si=lamdais/(lamdais+lamdasj);
disp('P_si is:')
P_si
P_sj=lamdasj/(lamdais+lamdasj);
disp('P_sj is:')
```

```
P_sj
vera_1=(1/(1-P_si)*(1/lamdais));
disp('vera_1 is')
vera_1
vera_2=P_sj/lamdasj;
disp('vera_2 is')
vera_2
vera_3a=(P_sj*P_si)/lamdasj;
vera_3b=1/(1-(P_si*P_sj));
vera_3=vera_3a*vera_3b;
disp('vera_3 is:')
vera_3
vera_4=(P_si/lamdais)*(1/(1-P_si));
disp('vera_4 is:')
vera_4
m_ij= vera_1+vera_2+vera_3+vera_4;
```

lamdais is: 0.5760, lamdasj is: 0.2334,P_si is: 0.7116,P_sj is: 0.2884

vera_1 is: = 6.0198, vera_2 is:= 1.2354, vera_3 is:= 1.1061,vera_4 is:= 4.2836

The mean remaining life of the component is: m_{ij} = 12.64 yrs.

Appendix-B: Publication Paper at SAUPEC

RELIABILITY CENTERED MAINTENANCE (RCM) MODEL IMPLEMENTATION TO ETHEKWINI ELECTRICITY NETWORK

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Abstract: Traditionally power utilities have developed and conducted maintenance activities on their equipment without using a quantitative approach to the system. When maintenance measures are utilised effectively they can impact on reliability by either enhancing the state of equipment or extending the lifetime of equipment at a minimum budget. Presently, maintenance activities are heuristic. This paper presents a model for the implementation of reliability centered maintenance to the eThekwini power network. In selecting a critical component, historical data of failure is thoroughly analysed. Transformer was found to be a critical component for the system under study.

Keywords: Maintenance; Reliability; asset management; transformer; Heuristic; IEEE Std C57.104-1991

1. INTRODUCTION

Power system planning, design, operations and maintenance are significant factors for the financial success and customer satisfaction of a power system [1]. Traditionally, municipalities have conducted equipment maintenance according to predetermined schedules based on manufacturer guidelines [2]. Consequently, it often difficult to determine with a reasonable degree of confidence, what the best frequency of inspection is or even what should be inspected. As a result, some maintenance techniques are far more costly than they should be, and critical equipment is often unnecessarily taken out of service for prolonged periods of time [3].

The implementation of reliability centered maintenance (RCM) in the power system sector can optimise maintenance processes with minimum cost [21]. RCM is condition-based, with maintenance intervals based on actual equipment criticality and historical failure data [4]. The RCM model was first developed in the late 1960s, by the airline industry which concentrates on avoiding failures whose results are almost certain to be serious [5]. On account of the increased size and complicated nature of commercial aeroplanes, airlines were worried that utilising conventional maintenance techniques would make the new aeroplanes uneconomical [5]. After the effective implementation of RCM in the aviation industry, numerous industries commenced applying the RCM concept in their sectors [6]. In this paper, the RCM model is applied to the eThekwini electricity (EE) network.

2. NETWORK DESCRIPTION

EThekwini Electricity is one of the largest power utilities in South Africa (SA) and serves more than 723 593 customers in a region covering about 2,000 kilometers with approximately 1 900 MW system maximum demand [23]. It has a turnover of over R7 billion and an asset value of R17, 7 billion [23]. EE receives bulk power from Eskom at five intake points at 275 kV which is then transformed to the lower voltages required by residential, business, commercial and industrial customers at 230 V, 400 V and 11 kV via power transformers. The visual representation in figure 1 indicates the EE geographical map and bulk power received from Eskom at the five intake points. At these stations, the voltage is transformed down to 132 kV for onward transmission via eThekwini's transmission network to over 100 major step-down substations.

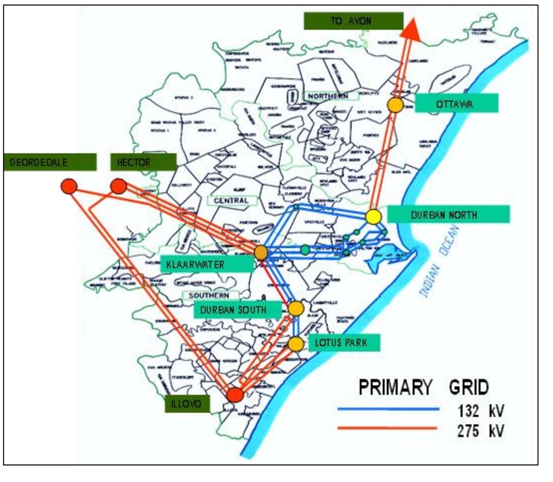

Fig. 1: Shows general lay-out of the Eskom/EThekwini High Voltage Network

The EE Network is complex and highly integrated and, for this reason, is segmented into three regions; (1) Northern, (2) Central and (3) Southern. Within these regions, there are six construction works Depots namely; Central, Western, Northern, North Western, Southern, South Western which are responsible for the construction works and maintenance activities of the entire EE network. North Western construction works Depot with

Depot with reference to Phoenix substation, had the feeder with the greatest failure rates for the period considered. Therefore, the study was centered on this region which is made up of a mix of residential, commercial and industrial customers.

Fig. 2 shows a single line diagram indicating a portion of the Northern region network, made up of seven major substations fed from Ottawa Major Substation These stations are fed by 2x315 MVA, 275/132 kV power transformers. From these seven major stations many 11 kV customer feeds are tapped off. The feeder subjected to most failures was found to be fed from Phoenix substation.

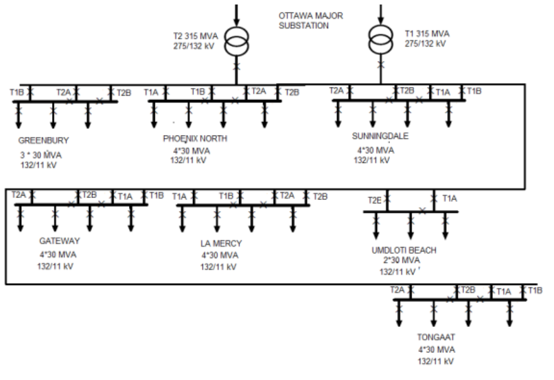

Fig. 2: Line diagram showing major substations in the Northern region

1. RCM MODEL IMPLEMENTATION

1.1. Failure Data Gathering

RCM starts with collecting and examining failure data for the system considered. Maintenance planning constitutes a fundamental part of asset management [2]. In most utilities, this important element of asset management may get no consideration at all or at best very restricted attention. The outputs of this would be frequent power interruptions associated with equipment failures/repairs.

The present power system requires an effective method for determining maintenance activities of critical components. The collection and development of a components database is the foundation of this process. This will assist in deriving the failure sample space. It is the resulting analysis of the sample space that will give valuable knowledge into the failure rate and time to failure of each component. These are the necessary construction blocks for the RCM program [5]. Choosing the type of data to collect and the method of collection is the initial step for a successful maintenance policy based on records of failure data [14]. EThekwini Electricity uses a system called Ellipse to facilitate business processes within the organisation. All the outages and their causes are captured and recorded on the Ellipse System referred by their order numbers. This system enables the user to extrapolate the outage information as needed at that certain time. To accomplish the objectives of this study, the outage information was exported from the Ellipse System and examined. In identifying the feeder with the higher failure rate for greater attention, five years (2010 to 2014) of outages information was collected and processed from the Ellipse system for the entire EE network. This was then plotted on the histogram presented in figures 3. The feeder with the highest failure rate was then selected for deeper analysis. For the purpose of this work all the irrelevant events such as outages due load shedding and scheduled maintenance were excluded.

1.2. Data Analysis Techniques

The failure sample space must be thoroughly considered in order to produce meaningful results from the collected data. This was achieved by building a histogram over the sample space. This basic histogram instantly gives indication of the leading failure events and similarly the region or customer feeder that is mostly affected. Thereafter, the properties of the total component leading to failure can be considered before going deeper into the statistical analysis of the components. Figures 3 shows the failure histogram built for EE Network failure data consisting of six Depots.

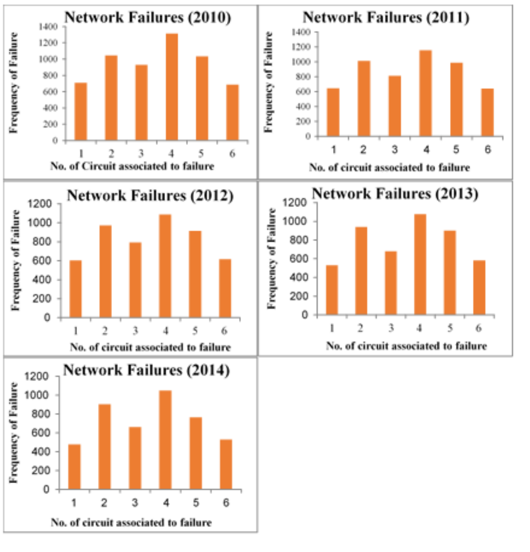

Fig.3: Processed failure data for EE area of supply

The Phoenix substation in the North Western Depot in the Northern region of the EE area of supply was found to have higher than normal failure rates and was selected for deeper analysis. In order to better understand exactly what is going on in North Western Depot, further analysis of the failure data of this particular Depot was conducted. This was graphically illustrated in the histogram shown in figures 4. This information is useful to the asset manager to help focus more attention on this feeder to determine the component/components responsible for the high rate of failure in that feeder.

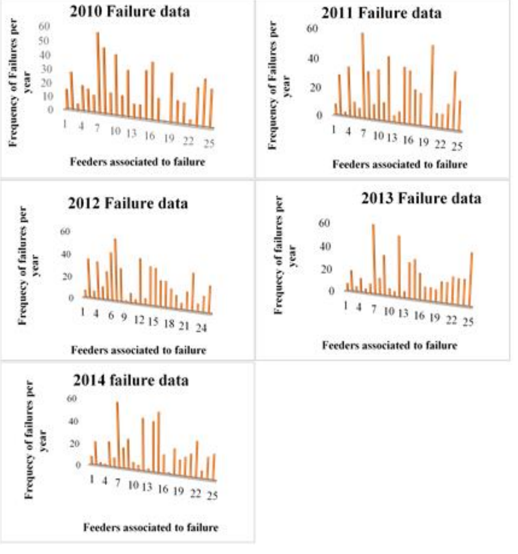

Fig. 4: Processed Outage data for Phoenix station feeders

Further analysis of the data indicates that, Feeder seven (F7) of the Phoenix major substation has the leading failure rate. Using this information the components making up feeder 7 (F7) were probed in greater depth. Six groups of electrical components are found in distribution power system, which includes; (1) overhead lines, (2) underground cables, (3) protective equipment's, (4) power transformers, (5) distribution transformers, and (6) capacitors. In analyzing these components, only those maintenance impact was identified as critical were considered. The analysis of the failure data collected on this critical feeder when plotted on the histogram showed that the components of the distribution system presenting the greatest challenge to uninterrupted operation of power included; overhead line conductors, power transformers and underground cables. This plot is shown in figure 5. From this plot the transformer was identified as the critical item of equipment to customer‘s electric power interruption.

Fig. 5: Processed components data for critical feeder

Transformers are one of the assets that have a critical function in power systems. The failure of a transformer can results in massive financial losses because of unsupplied power to customers, repair expense including labor, and negatively affects supply reliability to customers [7]. It is therefore important to know the condition and performance of power transformer in the system. EE is responsible for the maintenance of more than 10 000 transformers. Of these, roughly 250 function at voltages between 275, 132 and 33 kV to provide the primary network from which the other distribution level transformers and major customers are supplied. The ratings of these transformers, which have an average age of twenty-five years, are from 315 to 15 MVA. The economy is highly dependent on electricity and the maintenance of transformers and discovery of faults in them is an essential factor of infrastructure support for the economy [7]. A typical single line diagram for eThekwini network is presented in figure 6 below.

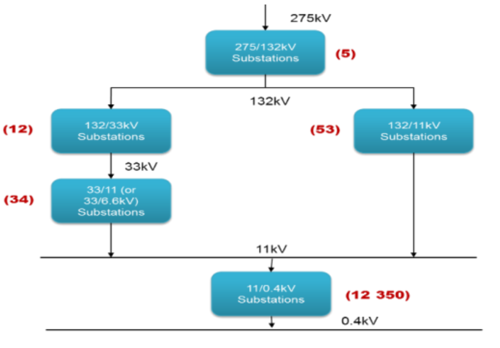

Fig 6: Typical line diagram for eThekwini Network [22]

1. MAINTENANCE TASK SELECTION

Maintenance task selection involves the identification of appropriate tasks to address the cause of critical failure modes identified as a result of the RCM systems evaluation i.e. selecting tasks involves the identification of applicable and cost effective approaches to maintenance that are best suited to maintain system equipment [8]. According to figure7, the maintenance is classified into corrective maintenance, preventive maintenance and reliability centered maintenance.

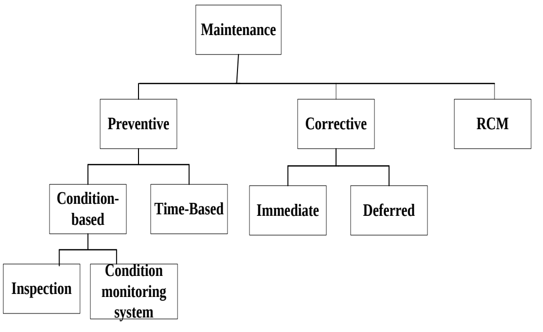

Fig. 7: Classification of maintenance activities [8]

To appropriately select the maintenance tasks necessary to address the causes of critical equipment failure modes, a standardized approach was used.

1.1. Transformer Failure Modes

A failure mode is a way in which a component or machine failure can happen, usually in terms of how the failure is observed (in contrast to how the failure is caused) [3]. For instance, the dielectric breakdown of transformer oil is a failure mode, which may have several reasons, for example, oil pollution, oil oxidization, thermal decomposition, and humidity in oil from cellulose breakdown [9].

1.2. Transformer Failure Causes

Transformers fail for various reasons, which can interrupt electricity supply, cause potential risk to operators, loss in industrial production and to economic losses [13]. Financial outcomes of transformer failure can be substantial, because of the expense of property damage, repair cost, and the production losses due to service interruption [10]. The most frequent causes of failures are presented in figure 8. The leading cause of transformer failure is an insulation failure. The life of a transformer is dependent upon the life of its insulation [11]. Transformer insulation deteriorates as a function of time and temperature [11]. The lifespan of the transformer is generally achieved by effective maintenance planning, site inspections and appropriate testing during the transformers useful life.

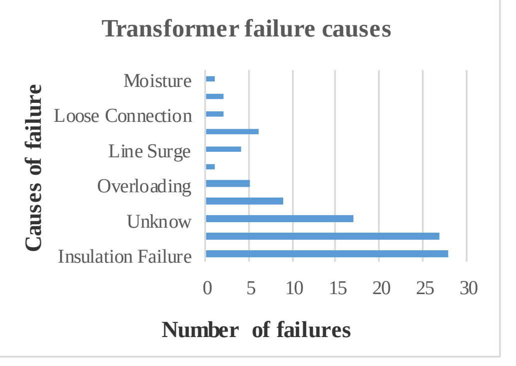

Fig. 8: Failure mode distribution for transformers [12]

2. TRANSFORMER CONDITION EXAMINATION

The transformer oil insulation condition examination is conducted with reference to eThekwini transformer identified as critical. Power transformer's serve as the one of the most critical assets in eThekwini's power network. Transformer procurement comprise about 60 percent of the total substation costs [16]. These transformers need significant attention due to their cost, which extends from R1-million to R14-million for each unit, and the possible consequence of failure [15]. Examining the oil state of the transformer can assist in detecting any premature deterioration [17]. A typical picture of 132/11 kV, 30 MVA is illustrated in figure 8 below.

Fig. 9: Picture of 132/11 kV Transformer, 30 MVA

1.1. Dissolved Gas-In-Oil Analysis

According to [20], Dissolved gas analysis (DGA) can be interpreted by various international guidelines. Nevertheless, interpretation of DGA is more of an art than an exact science [20]. DGA test measures various gas ppm levels that are present [17]. Inside the transformer the gasses will dissolve in the oil which indicate different types of thermal and electrical stress developing [16]. "The health of the oil reflects the health of the transformer itself" [19]. The DGA results is very useful to help in diagnosing a fault [17]. DGA is conducted by taking oil samples test from the transformer least once a year depending on the age and state of the transformer [12]. In this work, oil tests are interpreted using the criteria found in [18] for the transformer under consideration.

1.2. Dissolved gas analysis Interpretation

Table 1 provide the oil sample test taken from the eThekwini transformer under consideration. These results are interpreted base on the IEEE standard criteria in [18]. This criteria classify oil condition under four groups as follows:

(1) ***Condition one (C_1) means*** - Satisfactory;
(2) ***Condition two (C_2) means*** - Should be reconditioned for further use;
(3) Condition three (C3) indicates - level of decomposition (additional investigation required);
(4) ***Condition three (C_4) means*** - Poor condition, dispose and replace (Continued operation could result in failure of the transformer).

Using this criteria, for the transformer under consideration we found the oil condition to be condition two (C_2). So, this mean that the oil can reconditioned for further use. Please refer to appendix A1 for more detail.

Table 1: DGA from 132/11kV eThekwini transformer

Sample Date	CO	H2	CH4	C2H4	C2H6	C2H2	TDCG
2001/07/25	604	81	16	22	24	26	**773**
2002/10/23	700	61	14	0	30	29	**834**
2004/12/20	650	54	11	26	30	20	**791**
2005/06/15	708	47	0	0	0	0	**755**
2007/06/22	755	46	11	0	0	0	**812**
2009/01/07	750	0	27	34	0	16	**827**
2010/09/15	780	0	1	3	0	2	**787**
2011/11/23	680	43	27	35	21	16	**822**
2012/06/19	850	42	8	1	13	6	**920**
2013/10/23	860	43	28	5	10	4	**950**

The maintenance activity is chosen based on the condition of oil. In the event that oil condition is C_1, nothing is done. On the possibility that oil condition is C_2, C_3 or C_4, three alternatives are accessible and are chosen with distinctive probabilities: ***oil filtering*** or ***oil substitution or oil replacement***.

2. APPENDIX A

Status	H_2	CH_2	C_2H_2	C_2H_4	C_2H_6	CO	CO_2	TDCG
Condition 1	100	120	35	50	65	350	2500	720
Condition 2	101-700	121-400	36-50	51-100	66-100	351-570	2501-4000	721-1920
Condition 3	701-1800	401-1000	51-80	101-200	101-150	571-1400	4001-10000	1921-4630
Condition 4	>1800	>1000	>80	>200	>150	>1400	>10000	>4630

Appendixes A1: Dissolved gas concentrations limits (ppm)

3. CONCLUSION

In conclusion, this paper has presented the implementation of the RCM model to eThekwini electricity network. The RCM model has been discussed in details. The transformer was selected as a critical component for the network under consideration and examined in detail. Transformer outage has risky effects on the system and can be assumed as one of the most catastrophic outages. Accordingly, maintenance of the transformers should be planned carefully to avoid harmful outages. The RCM approach in power system is promising to provide an opportunity to justify one of the most vulnerable economic sectors in developing countries by improving design, operations and maintenance of equipment or system. The adaption of the RCM model to power system equipment's will aids to optimization of resources there by decreasing maintenance expenditures while improving the overall system reliability and improve service delivery to the end users. The RCM model is not only limited to power transformers, it can be applied to any asset in the power system.

4. RECOMMENDATION

It is recommended that EThekwini Electricity give more attention on acquiring and understanding the state of all transformers in the system. Moreover, development of computer models to determine the equipment's average remaining life are needed in today power system.

5. ACKNOWLEDGMENT

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APPENDIX

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Appendixes A1: Dissolved gas concentrations limits (ppm)