RELIABILITY CENTERED MAINTENANCE (RCM) FOR ASSET MANAGEMENT IN ELECTRIC POWER DISTRIBUTION SYSTEM

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DECLARATION

I hereby declare that I carried out the work reported in this thesis in the Department of Electrical and Information Engineering, School of Engineering and Technology, College of Science and Technology, Covenant University, Ota, Nigeria under the supervision of Prof. C.O.A. Awosope and Prof. J.C. Ekeh.

I also solemnly declare that no part of this report has been submitted here or elsewhere in a previous application for award of a degree. All sources of knowledge used have been duly acknowledged.

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CERTIFICATION

This is to certify that this thesis is an original research work undertaken by **Anthony Uwakhonye ADOGHE** (CU05GP0125) and approved by:

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DEDICATION

This thesis is dedicated to God Almighty for his faithfulness and love towards me and to the service of Humanity.

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LISTS OF SYMBOLS AND ABBREVIATIONS

AENS Average energy not supplied per customer served

AI Artificial Intelligent

AM Asset Management

ANN Artificial Neural Network

ASAI Average Service Availability Index

CAIDI Customer Average Interruption Duration Index.

CAIFI Customer Average Interruption Frquency Index

CA Condition Assessment

CBM Condition Based Maintenance

CiGre International council on large electric systems

CM Corrective Maintenance

cm Condition Monitoring

CH_4 Methane

C_2H_2 Acetylene

C_2H_4 Ethylene

C_2H_6 Ethane

CO Carbon monoxide

CO_2 Carbon dioxide

DGA Dissolved gas analysis

DP Degree of polymerization

EPRI Electric Power Research Institute

FA Fura Analysis

FRA Frequency Response Analysis

HPP   Homogeneous Poisson Process

HST   Hot Spot temperature

HV   High voltage

H_2 Hydrogen

int.   Interruption of voltage

LOE Average loss of energy

LTA Logic decision tree analysis

LV   Low Voltage

MATLAB   Matrix Laboratory

MC   Monte Carlo

MM   Maintenance Management

MTBF   Mean Time Between Failures

MTTFF   Mean Time To First Failure

MTTR   Mean Time To Repair

MV   Medium Voltage

NHPP   Non – Homogeneous Poisson process.

PHCN   Power Holding Company of Nigeria

PD   Partial Discharge

PM   Preventive Maintenance

RCM   Reliability-Centered Maintenance

RMS   Root mean Square value

SAIDI   System Average Interruption Duration Index.

SAIFI   System Average Interruption Frequency Index

UMIST: University of Manchester Institute of Science and Technology.

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ABSTRACT

The purpose of Maintenance is to extend equipment life time or at least the mean time to the next failure.

Asset Maintenance, which is part of asset management, incurs expenditure but could result in very costly consequences if not performed or performed too little. It may not even be economical to perform it too frequently.

The decision therefore, to eliminate or minimize the risk of equipment failure must not be based on trial and error as it was done in the past.

In this thesis, an enhanced Reliability-Centered Maintenance (RCM) methodology that is based on a quantitative relationship between preventive maintenance (PM) performed at system component level and the overall system reliability was applied to identify the distribution components that are critical to system reliability.

Maintenance model relating probability of failure to maintenance activity was developed for maintainable distribution components. The Markov maintenance Model developed was then used to predict the remaining life of transformer insulation for a selected distribution system. This Model incorporates various levels of insulation deterioration and minor maintenance state. If current state of insulation ageing is assumed from diagnostic testing and inspection, the Model is capable of computing the average time before insulation failure occurs.

The results obtained from both Model simulation and the computer program of the mathematical formulation of the expected remaining life verified the mathematical analysis of the developed model in this thesis.

The conclusion from this study shows that it is beneficial to base asset management decisions on a model that is verified with processed, analysed and tested outage data such as the model developed in this thesis.

CHAPTER ONE

INTRODUCTION

1.1 Background Information

Ability to use electrical energy when required is one of the fundamental presumptions of a modern society, and the introduction of complex and sensitive machines and systems into the network had increased the need for high reliability of supply [1]. Deregulation and competition are forcing improvements in efficiency and reductions in cost while customers are becoming more sensitive to electrical disturbances and are demanding higher levels of service reliability. Since a typical distribution system accounts for 40% of the cost to deliver power and 80% of customer reliability problems, distribution system design, operations and maintenance are critical for financial success and customer satisfaction [2].

Moreover, failure statistics [3] reveal that the electrical distribution systems constitute the greatest risk to the uninterrupted supply of power. Traditionally however, distribution systems have received less attention than the generation and transmission parts of the overall electrical Power systems. This is emphasized by the clear difference in the number of publications within the various relevant fields [4].

The main reasons why distribution systems may not have been the centre of focus are that they are less capital-intensive and that their failures cause more localized effects compared to generation and transmission systems. However the focus on generation and transmission systems is moving toward distribution as the business focus changes from consumers to customers [4].

Electrical power systems have undergone major changes during the last few years due to the introduction of the deregulated or liberalized market. (Sweden, for example, was one of the first countries to deregulate its power- supply market. This happened in January 1996) [5]. This has implied that the driving factors have moved from technical to economical. New players are now making their appearance in the field. This fundamental and global-level change in the running of power utilities has brought about diversity effects, including new opportunities and new complications.

These utilities are themselves active in the deregulated market and face various market challenges. For example, customers pay for energy delivered while authorities impose sanctions/regulations, they supervise and they compensate customers depending on the degree of fulfillment of contractual and other obligations as recommended [6,7].

On the other hand, the owners expect the utilities to deliver at minimum cost. This means that electricity utilities must satisfy quantitative reliability requirements, while at the same time try to minimize their costs. One clear and predominant expenditure for a utility is the cost of maintaining system assets, for example through adopting preventive measures, collectively called preventive maintenance (PM). Preventive maintenance measures can impact on reliability by either, (a) improving the condition of an asset, or (b) prolonging the lifetime of an asset [8]. Reliability on the other hand, can be improved by either reducing the frequency or the duration of power supply interruptions.

PM activities could impact on the frequency by preventing the actual cause of the failure. Consequently, in cost- effective expenditure, PM should be applied where the reliability benefits outweigh the cost of implementing the PM measures [9].

Traditionally, preventive maintenance approaches usually consist of pre-defined activities carried out at regular intervals (scheduled maintenance). Such a maintenance policy may be quite inefficient; it may be costly (in the long run), and it may not even extend component lifetime as much as possible. In the past several years, therefore, many utilities replaced their maintenance routines based on rigid schedules by more flexible program using periodic or even continuous condition monitoring and data analysis [10]. Research findings have shown that maintenance impacts on the reliability performance of a component, that will eventually reflect on the entire system since power systems is made up of interconnected components[11]. Many programs had been used to validate this fact, such as failure effects analysis, an evaluation of needs and priorities, and flow charts for decision making [12]. Some of these approaches have been collectively termed Reliability-Centred Maintenance (RCM) [13]. In a RCM approach, various alternative maintenance polices are compared and the most cost-effective is selected.

RCM programs have been installed by many electric power utilities as a useful management tool [14]. However, the approach is still heuristic, and its application requires judgment and experience at every turn. Also, it can take a long time before enough data are collected for making such judgments. For this reason, several mathematical models have been proposed to aid maintenance scheduling [15].

Many of these models [16] deal with replacement policies only and disregard the possibility of the cheaper but less effective maintenance activity. When maintenance is modeled, most often, fixed maintenance intervals are assumed. Only recently, was a mathematical model which incorporates the concept of "maintenance when needed" was developed. Detailed literature reviews on the various maintenance approaches and models are reported in references [17] and [18].

In this research work, a probabilistic model was developed for the failure and maintenance processes, and a Markov model for estimating the remaining life of an identified critical component of distribution network was also developed.

The model is based on a quantitative connection between reliability and maintenance, a link missing in the heuristic approaches. This model is capable of improving the decision process of a maintenance manager of network assets. RCM strategies that are capable of showing the benefits of performing cost – effective PM on system networks on a selected system using reliability outage data were performed so as to identify the cirtical component for analysis. The model includes various levels of deterioration of the identified components as well as maintenance and inspection states. Assuming that the present state of component deterioration had been determined from diagnostic testing and inspection, the model allows computation of the average time remaining before failure occurs using a computer program developed in Matlab. Reliability-centered Maintenance is a process used to determine the maintenance requirements of any physical asset in its operating context. This is based on equipment condition, equipment criticality and risk.

RCM provides a tool for maintenance management (MM) by using the model to predict the remaining life of the identified component.

1.2 STATEMENT OF THE PROBLEM.

This project work addresses the importance of maintenance on the reliability of electrical distribution systems. This focuses on preserving system function, identifying critical failure modes, prioritizing important components and selecting possible and effective maintenance activities, a cost – effective preventive maintenance plan which defines reliability centred maintenance.

1.2.1 Distribution Systems Constitutes The Greatest Risk.

Electric power system is not 100% reliable. The ability to use electric energy when needed is the fundamental function of any modern utility company.

The existence of sophisticated machines and production lines had increased the need for electricity supply that is highly reliable.

Distribution aspect of electricity system had been identified as constituting the greatest risk to realizing uninterrupted power supply [19]. Studies show that a typical distribution system accounts for 40% of cost to deliver power and 80% of customer reliability problems [20]. This means that distribution systems are critical for financial success and customer satisfaction. And yet distribution systems have not received the desired attention. This was obvious from the difference in the number of publications.

The main reasons advanced for the neglect of distribution systems include the following:

- They are less capital – intensive
- Their failures cause more localized effects when compared with generation and transmission systems and

1.2.2 Introduction of Liberalised Market.

The introduction of deregulated market has introduced major changes in electrical power systems. These changes had led to the movement of the driving factors from technical to economical. As a result, new investors are coming into the power sector. This global level change in the running of power sector has brought about new opportunities and new complications. In an increasingly competitive market environment where companies emphasize cost control, operation and maintenance (O&M), budgets are under constant pressure to economize. In order to ensure that changing utility environment does not adversely affect the reliability of customer power supply, several state regulatory authorities have started to specify minimum reliability standards to be maintained by the distribution companies [21].

1.2.3 Cost-Effective Preventive Maintenance Expenditure

Electric power utilities own and operate system generation, transmission and distribution of electricity. These utilities play active role in the deregulated market. The implication of this is that they also face market requirements. This means that customers will only pay for energy delivered. The Nigerian Electricity Regulatory Commission (NERC) which is the monitoring authority in Nigeria will imposes sanctions/regulations. Investors or Owners of utilities expect the managers to deliver electricity to customers at minimum cost. This means that utilities must satisfy reliability requirements at minimum cost. To achieve this, managers of these utilities must consider maintenance cost for system assets as an important expenditure area. Preventive maintenance measure is an activity undertaken regularly at pre – selected intervals while the device is satisfactorily operating to reduce or eliminate the accumulated deterioration [22] while repair is the activity to bring the device to a non – failed state after it has experienced a failure. When the cost incurred by a device failure is larger than the cost of preventive maintenance (this cost could be cost of downtime, repair expenses, revenue lost etc.), then it is worthwhile to carry out preventive maintenance.

Preventive Maintenance measures can affect reliability in two ways:

- It helps in improving the condition of the asset and

- It aids in prolonging the life time of an asset.

Effects of high reliability are:

- It reduces the frequency of power outages by preventing the actual cause of failure.
- It also reduces the duration of power supply interruptions.

In cost effective expenditure, preventive maintenance applies where reliability benefits outweigh the cost of implementing the preventive maintenance measures. Traditional preventive maintenance is made up of pre – defined activities carried out at regular intervals. This type of maintenance is costly, inefficient and may not even extend component lifetime. Many modern utilities have now replaced their routine maintenance that is based on rigid schedules with a more flexible program using periodic or even continuous condition monitoring (predictive maintenance). The predictive maintenance routines include group of programs such as Failure Modes and Effects Analysis, Evaluation of Needs and Priorities, and Flow Charts for Decision Making are some approaches that have been named reliability- centred maintenance (RCM) [23].

In RCM approach, different maintenance policies can be compared and the most cost – effective for sustaining equipment reliability selected. Reliability-Centred Maintenance program is not new. This program has been installed by some electric utilities as a useful management tool [24]. The problem with those in existence is that they cannot predict the effect of a given maintenance policy on reliability indicators (failure rate, outage time etc) and the approach adopted is still heuristic. This means that RCM in existence does not solve the fundamental problem of how the system reliability is impacted by component maintenance.The application is still based on experience and judgement at every turn. It takes a long time before enough data are collected for making such judgements. To solve one of the identified problems above, a probabilistic representation of deterioration process is modeled. A new mathematical formulation of the expected transition time from any deterioration state to the failure state (expected remaining life) has been presented. Processed outage data obtained from a selected distribution network for a component was used as input on the Markov model developed to predict the remaining life. This predicted computation is executed using computer program developed in Matlab.

Three stages will be used to describe deterioration process.

Stage 1 – represents an initial stage (D1).

Stage 2 – represents a minor deterioration stage (D2)

Stage 3 – represents a major stage of deterioration (D3).

The last stage is followed in due time by equipment failure (F) which requires an extensive repair or replacement. Maintenance is carried out on asset to slow down deterioration. Inspections are performed so that decisions on asset management can be taken. To run this model however, it was assumed that repair after failures returns the device to the initial stage (as new condition). Figure 1.1 represents the conceptual diagram of the probabilistic model.

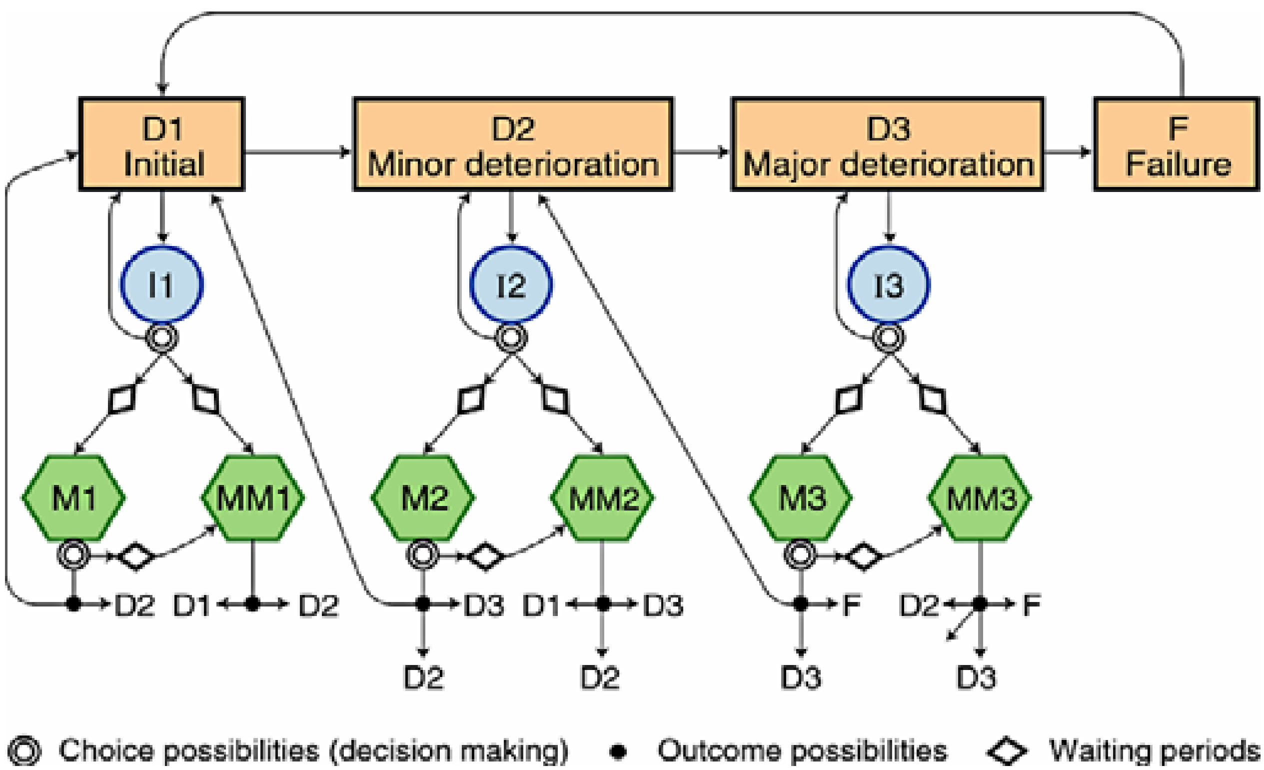


Figure 1.1 – conceptual diagram of the probabilistic model

1.3 AIM AND OBJECTIVES OF THIS STUDY

The aim of this research study is to develop an appropriate method that will aid strategies for asset management in electric power distribution systems.

These methods/strategies when developed should be cost – effective, balancing the benefits in system reliability against the cost of maintenance methods. This will lead to the utilization of the reliability-centred maintenance (RCM) method. This method will be applied to specific parts in electrical power distribution systems.

The main objectives are to

a. Determine present maintenance policies in a selected distribution network.
b. Develop a probabilistic – based model for maintenance strategies.
c. Predict the probable time of component failure, given that a certain stage in the ageing process has already been reached.
d. Develop a quantitative relationship between preventive maintenance of system components and overall system reliability.
e. Evaluate cost implications in the formulation of cost – effective PM strategies and
f. Conduct program evaluation, including general application to electrical power distribution systems.

1.4 RESEARCH METHODOLOGY

To fulfill the objectives of this work, the following methods will be adopted:

The first phase of the work is the system reliability analysis. This involves the definition of the system and the identification of the critical components affecting system reliability.

The second phase of the work is component reliability modeling. This entails detailed analyses of the components with the support of appropriate input data collected with the use of questionnaire. This will define the quantitative relationship between reliability and preventive maintenance measures.

The third and final phase are system reliability and cost/benefit analyses: This is carried out by putting the result of phase 2 into a system perspective, the effects of component maintenance on system reliability will then be evaluated and the impact on costs of different preventive maintenance strategies can now be identified.

1.5 SIGNIFICANCE OF THE STUDY

No doubt the country is in energy crisis, and the need to increase generation, manage and upgrade the existing power infrastructure becomes imperative. The costs of electric power outage to electric customers are enormous. Studies have shown [25] that the cost of electricity failures on the Nigerian manufacturing sector is quite high, as industries and firms incur huge costs on the provision of expensive back – up to minimize the expected outage cost. The average costs of this back – up are about three times the cost of publicly supplied power [25].

The main function of power utility is to supply customers with electrical energy at high level of reliability at a reasonable cost. This intended function could be affected by the problem of power outage, which is one of the measures of reliability performance.

Power outage can; in principle be reduced in two ways:

- By reducing the frequency of interruptions, that is the number of failures, or
- By reducing the outage time, that is the duration of failure.

Application of RCM technique will be used to address the first aspect above, which provides the focus for this study.

1.6 MOTIVATION FOR THE STUDY

Electricity is an aspect of the utility sector that is very essential to the smooth and meaningful development of a society. It supports the economy and promotes the well-being of individuals. Non-availability of this utility had led to a lot of challenges ranging from lack of foreign investment, high cost of living since most manufacturers depend on private generators, high rate of unemployment and security and environmental hazards resulting from individuals generating their own electricity without regulations.

A survey by Manufacturers Association of Nigeria (MAN) on power supply by the power Holding Company of Nigeria (PHCN) to industrial sectors in the first quarter of 2006 indicates that the average power outages increased from 13.3 hours daily in January to 14.5 hours in March 2006 [26].

As at July 2009, Nigeria has total installed capacity of approximately 7060MW, however, the country is only able to generate between 800MW – 4000MW from the seven major power stations and a numbers of IPP projects, because most of these facilities have been poorly maintained. Nigeria has plans to increase generation to 10,000MW by 2010. This means additional power plants, more transmission lines, as well as more distribution facilities.

In recent times, subsequent governments of Nigeria had been working very hard to see the realization of steady power supply in the country. For example, the government of Chief Olusegun Obansanjo wanted to ensure an uninterrupted power supply by the end of 2001 in Nigeria. The president then, made it clear when he gave a mandate to the then National Electric Power Authority (NEPA) to ensure uninterrupted power to the nation by 31st December 2001. It was noted that NEPA actually raised electricity output from as low as 1,600 to 4,000MW and spent over one million dollars to meet this mandate [27].

The present government also aware of this re-occurring power problem now declared during his campaign days that he will declare a state of Emergency on power sector when he assumed power. Yet as at February, 2010, Electricity reliability and availability are still a mirage.

In this context, in as much as efforts are made towards efficient power generation, the subsequent transmission and distribution of the generated power should not be overlooked. Efficient utilization of the generated power cannot be achieved without a sound maintenance plan and monitoring of the transmission and distribution network system. Any organization that expects to run an efficient day – to – day operation and to manage and develop its services effectively must know what assets it has, where they are, their condition, how they are performing, and how much it costs to provide the service [28]. Knowledge about the physical assets of the system is necessary to make strategic and maintenance/operation decisions. Thus, to make an intelligent decision vital to the smooth operations, growth and management of electricity distribution facilities, such decision must be based on a model that is verifiable and quantifiable and should not be decisions based on experience alone. This is the motivation for this project.

1.7 EXPECTED CONTRIBUTION TO KNOWLEDGE.

i. A selective maintenance method based on reliability analysis is being developed.
ii. A Markov model for estimating the remaining life of a distribution transformer is implemented using Matlab program.
iii. This will provide objectivity by converting the operator's intuition into quantifiable values that will aid in decision making process for asset management.

1.8 SCOPE AND LIMITATION.

This research work identified the following two ways in which the reliability of electric supply to customers can be improved:

i. Reducing the frequency of power outages or
ii. Reducing the duration of power supply interruption.

This research work covers the first part that uses reliability centred maintenance (RCM) to minimize the frequency of power outages by preventing the actual cause of failure. This is shown in figure 1.2. Maintenance (one of the main tools of asset management) in this context is considered as an activity of restoration where an unfailed device has its deterioration arrested, reduced or eliminated

Its goal is to increase the duration of useful component life and postpone failures that would require expensive repairs. For a successful operation of this RCM plan, the degree of risk of each fault should be identified in order to define the optimum maintenance actions. The type of maintenance action to be taken for a particular asset will depend on the risk index of that asset. Critical component will be identified from a selected network and the Markov model developed will be applied on the identified component to predict the remaining life so as to make intelligent decision on the asset.

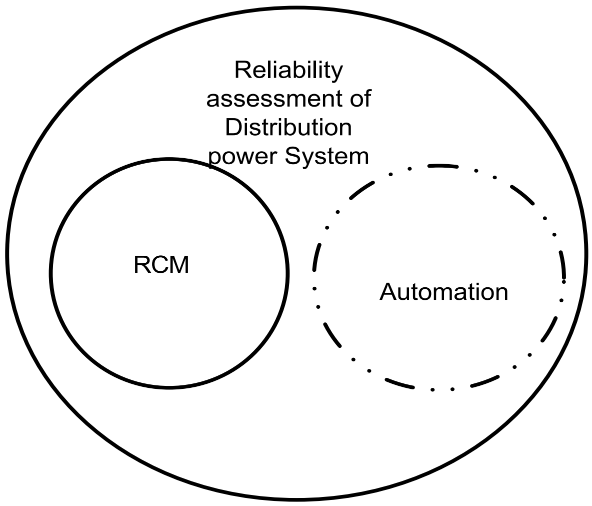


Figure 1.2 Project scope definitions

1.9 THESIS ORGANIZATION

The overall thesis structure can be broken down into individual chapters as follows:
Chapter 1 provides an introduction, background studies, research methods and the main contributions that are unique to this work.
Chapter 2 introduces and defines fundamental concepts for the analysis that follows.
Chapter 3 introduces basic evaluation methods and techniques for reliability modeling and analysis.
Chapter 4 presents the computer program developed for reliability analysis of the electric power system.
Chapter 5 introduces different maintenance procedures/strategies and provides introduction to reliability centred maintenance method (RCM) as applied to a distribution network.

Chapter 6 presents results from comprehensive study of the causes of failures in the identified critical components and then defines a model for estimating the remaining life of the identified distribution transformer.

Chapter 7 concludes the work by summarizing the results obtained. Recommendations and issues for future work are identified and discussed.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

Asset management (AM) is a concept used today for the planning and operation of the electrical power system. The aim of AM is to handle physical assets in an optimal way in order to fulfill an organization's goal while at the same time considering risk.

One of the major risks that are involved in asset management is the probability of failure occurrence and its consequence. The goal is to ensure maximum asset value, maximum benefit or minimal life cycle cost.

The only constraint to actualizing this goal is set on availability of revenues or power supply. There are different possible actions of handling these assets: They can either be acquired, maintained or replaced/redesigned.

Maintenance management (MM) is therefore defined as a strategy to handle decisions for these assets and to make right decisions on

- what assets to apply actions to.
- what actions to apply
- how to apply the actions
- when to apply the actions

The purpose of maintenance is to extend equipment life time or at least the mean time to the next failure whose repair may be costly. Further more, it is expected that effective maintenance policies can reduce the frequency of service interruptions and the many undesirable consequences of such interruptions. Maintenance clearly affects component and system reliability: if too little is done, this may result in an excessive number of costly failures and poor system performance and therefore reliability is reduced: When done too often, reliability may improve, but the cost of maintenance will sharply increase. In cost – effective scheme, the two expenditures must be balanced.

Maintenance is just one of the tools for ensuring satisfactory component and system reliability. Others include increasing system capacity, reinforcing redundancy and employing more reliable components. At a time, however, when these approaches are heavily constrained, electric utilities are forced to get the most out of the system they already own through more effective operating policies, including improved maintenance programs. In fact, maintenance is becoming an important part of what is often called asset management.

Electric utilities have always relied on maintenance programs to keep their equipment in good working conditions for as long as it is feasible. In the past, maintenance routines consisted mostly of pre-defined activities carried out at regular intervals. (Scheduled maintenance). However such a maintenance policy may be quite inefficient, it may be too costly (in the long run) and may not extend component life time as much as possible. In the last ten years, many utilities replaced their fixed interval maintenance schedules with more flexible programs based on an analysis of needs and priorities, or on a study of information obtained through periodic or continuous condition monitoring (predictive maintenance).[29]

The predictive maintenance routines include a group of programs named Reliability-Centred Maintenance, [RCM]. In an RCM approach, various alternative maintenance policies are compared and the most cost-effective for sustaining equipment reliability selected. RCM programs have been installed by several electric utilities as a useful management tool.

The implementation of RCM programs represented a significant step in the direction of “getting the most out” of the equipment installed. However, the approach and procedure is still heuristic and its application requires experience and judgment at every turn [30]. Besides, it can take a long time before enough data are collected for making such judgments. For this reason, several mathematical models have been proposed to aid maintenance scheduling [22, 23, 24 and 30].

This chapter, gives a brief review of the most important approaches and models described in the literatures. Next, present maintenance policies are then examined. Subsequently, the use of mathematical models for maintenance strategies is explored and desirable attributes of realistic probability-based models are listed. In closing, definitions of the most important concepts discussed in the work are given.

2.2 MAINTENANCE APPROACHES.

A classification of the various maintenance approaches is presented in figure 2.1. Maintenance is shown here as part of the overall asset management effort. Maintenance policy is one of the operating policies and, in a given setting; it is selected to satisfy both financial constraints.

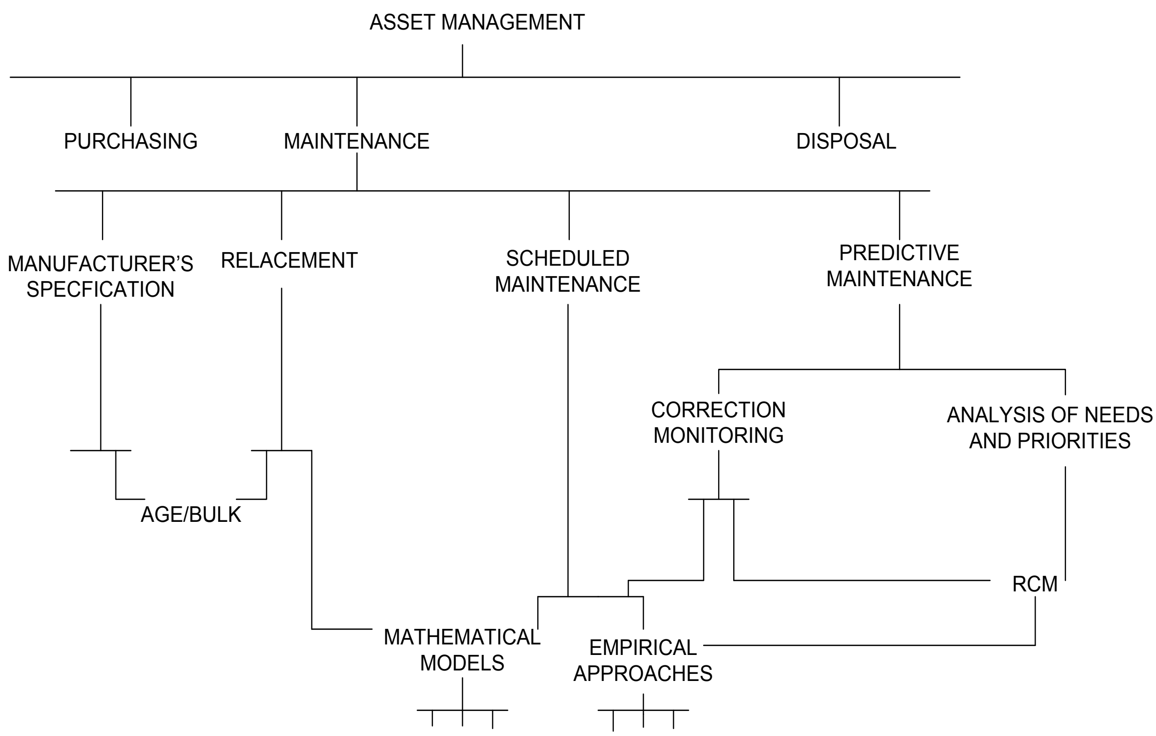


Figure 2.1 Overview of maintenance approaches

Most of the discussion in the literature concerns replacements only, both after failures and during maintenance, and they disregard the possibility of the kind of maintenance where less improvement is achieved at smaller cost. The oldest replacement schemes are the age replacement and bulk replacement policies [31]. In the first, a component is replaced at a certain age or when it fails, whichever comes first. In the second, all devices in a given class are replaced at predetermined intervals or when they fail. The last policy is easier to administer (especially if the ages of components are not known) and may be more economical than a policy based on individual replacement. Newer replacement schemes are often based on probabilistic models [31] [32] and can be quite complex. In most electrical utility applications, however, maintenance resulting in limited improvement is an established practice and replacement models have only a secondary role.

Maintenance programs range from the very simple to the quite sophisticated. The simplest plan is to adopt a rigid maintenance schedule where pre-defined activities are carried out at fixed time intervals. Whenever the component fails, it is repaired or replaced. Both repair and replacement are assumed to be much more costly than a single maintenance job. The maintenance intervals are selected on the basis of long-time experience (not necessarily an inferior alternative to mathematical models). To this day, this is the approach most frequently used.

The RCM approach referred to in the introduction is heavily based on regular assessments of equipment condition and, therefore, does not apply rigid maintenance schedules. The term RCM identifies the role of focusing maintenance activities on reliability aspects. The RCM methodology provides a framework for developing optimally scheduled maintenance programs. The aim of RCM is to optimize the maintenance achievements (efforts, performance) in a systematic way. This method requires maintenance plans and leads to a systematic maintenance effort. Central to this approach is identifying the items that are significant for system function. The aim is to achieve cost effectiveness by controlling the maintenance performance, which implies a trade-off between corrective and preventive maintenance and the use of optimal methods.

2.3 THE EMERGENCE OF RCM.

The RCM concept originated in the civil aircraft Industry in the 1960s with the creation of Boeing 747 series of aircraft (the Jumbo). One prerequisite for obtaining a license for this aircraft was having in place an approved plan for preventive maintenance (pm). However, this aircraft type was much larger and more complex than any previous aircraft type, thus PM was expected to be very expensive. Therefore it was necessary to develop a new PM strategy. United Airlines led the developments and a new strategy was created. **This was primarily concerned with identifying maintenance tasks that would eliminate the cost of unnecessary maintenance without decreasing safety or operating performance.**

The resulting method included an understanding of the time aspects in reliability (ageing) and identifying critical maintenance actions for system functions. The maintenance program was a success. The good outcome raised interest and the program spread. It was further improved, and in 1975 the US Department of commerce defined the concept as RCM and declared that all major military systems should apply RCM. The first full description was published in 1978 [33], and in the 1980s the Electric Power Research Institute (EPRI) introduced RCM to the Nuclear power industry. Today RCM is under consideration by, or has already been implemented by many electrical power utilities for managing maintenance planning.

2.4 EVOLUTION OF MAINTENANCE

RCM provides a framework which enables users to respond to maintenance challenges quickly and simply. It does so because it never loses sight of the fact that maintenance is about physical assets. If these assets did not exist, the maintenance function itself would not exist. So RCM starts with a comprehensive, zero-based review of maintenance requirements of each asset in its operating context.

All too often, these requirements are taken for granted. This results in the development of organization structures, the deployment of resources and the implementation of systems on the basis of incomplete or incorrect assumptions about the real needs of the assets. On the other hand, if these requirements are defined correctly in the light of modern thinking, it is possible to achieve quite remarkable step changes in maintenance effectiveness.

The meaning of ‘maintenance’ is explained. It goes on to define RCM and to describe the seven key steps involved in applying this process.

Maintenance and RCM

Considering the engineering view points, there are two elements to the management of any physical asset. It must be maintained and from time to time it may also need to be modified.

2.4.1 What Is Maintenance?

Every one knows what maintenance is, or at least has his own customized definition of maintenance. If the question is asked, words like fix, restore, replace, recondition, patch, rebuild, and rejuvenate will be repeated. And to some extent, there is a place for these words or functions in defining maintenance. However, to key the definition of maintenance to these words or functions is to miss the mark in understanding maintenance especially if you wish to explore the philosophical nature of the subject.

Maintenance is the act of maintaining. The basis for maintaining is, to keep, preserves, and protect. That is, to keep in an existing state or preserve from failure or decline. There is a lot of difference between the thoughts contained in this definition and the words and functions normally recalled by most people who are "knowledgeable" of the maintenance function, ie fix, restore, replace, recondition, etc.

Maintenance can therefore be defined, as ensuring that physical assets continue to do what their users want them to do.

What the users want will depend on exactly where and how the asset is being used (the operating context). Maintenance procedures are an integrated part of the planning, construction and operation of a system. Moreover they are central and crucial to the effective use of available equipment. The aim of maintenance activities is to continuously meet performance, reliability and economic requirements, while also adhering to the constraints set by system and customer requirements. [34].

The maintenance concept refers to all actions undertaken to keep or restore equipment to a desired state. The electrical power systems must abide by the regulations and norms for heavy current and maintenance, and in Nigeria, must follow the IEE regulations standard code. The IEE standard is the regulation governing the planning, building and maintenance of power distribution systems for 0.415 – 33kV. The first IEE standard regulation was created in the 1960s and the new handbooks have recently been developed to support more effective maintenance [35].

The cost of maintenance must be taken into consideration when handling system assets to minimize the lifetime costs of the system. However, some maintenance activities must be undertaken even if they are not profitable, such as earth – plate – metering inspections stipulated in the IEE regulations for power system. [36].

There are two types of maintenance: Preventive Maintenance and Corrective Maintenance.

Preventive Maintenance can be planned and scheduled, but corrective maintenance occurs unpredictably when failures are detected. This thesis focuses on preventive maintenance (PM).

2.4.2 Maintenance Approaches

From a basic point of view, there are two maintenance approaches. One approach is reactive and the other is proactive. In practice, there are many combinations of the basic approaches. The reactive system whose model is shown in figure 2.2 responds to the following:

- a work request order
- Production staff identified needs.
- Failed system or its component.

The effectiveness of this system will depend on response measures. The goals of this approach are to reduce response time to a minimum and to reduce equipment down time to an acceptable level.

This is the approach used by most operations today. It may well incorporate what is termed as a preventive maintenance program and may use proactive technologies.

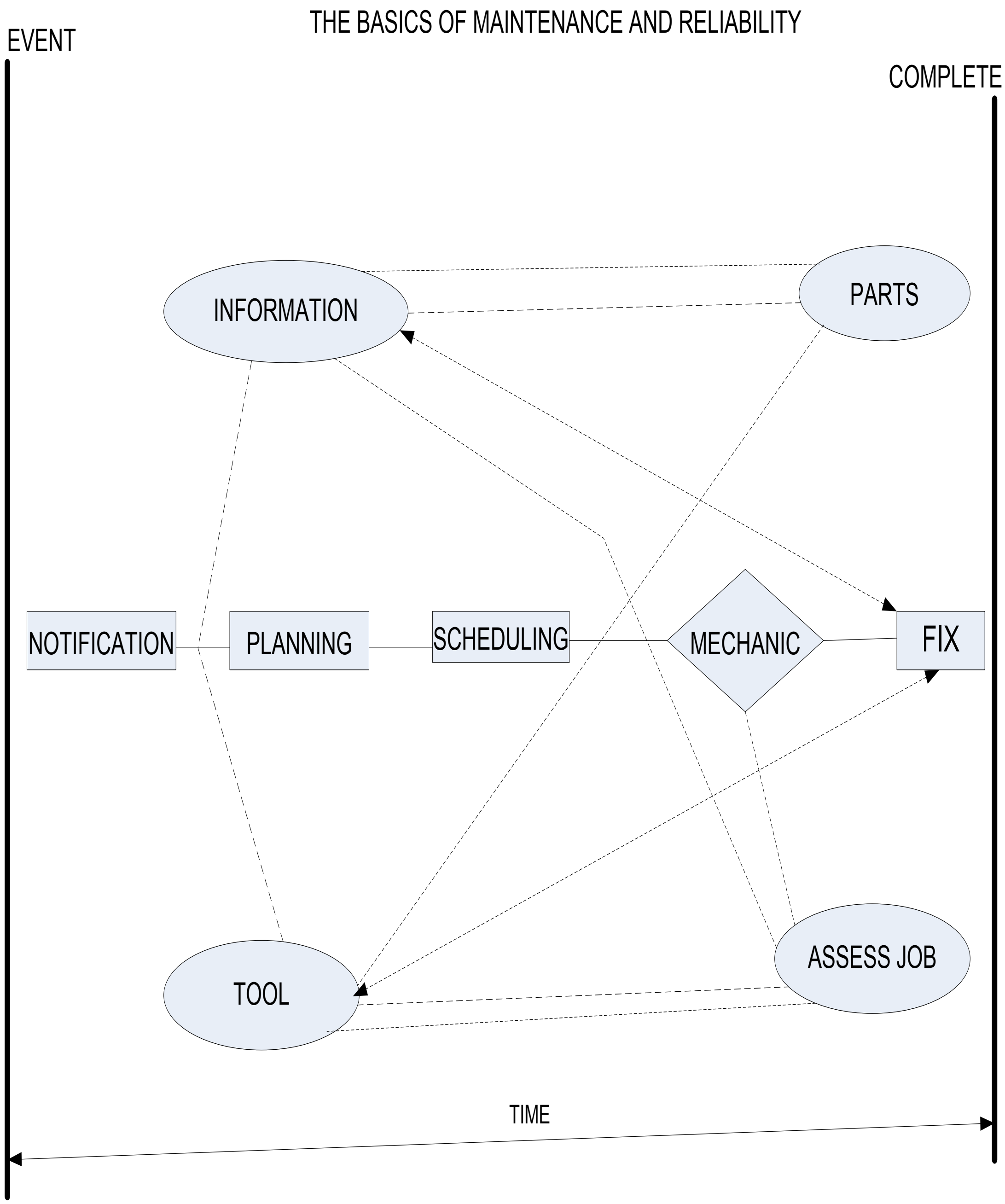


FIGURE 2.2 REACTIVE MAINTENANCE MODEL

The proactive approach (figure 2.3) responds primarily to equipment assessment and predictive procedures. **The overwhelming majority of corrective, preventative and modification work is generated internally in the maintenance function as a result of inspections and predictive procedures.**

The goals of this method are continuous equipment performance to established specifications, maintenance of productive capacity, and continuous improvement.

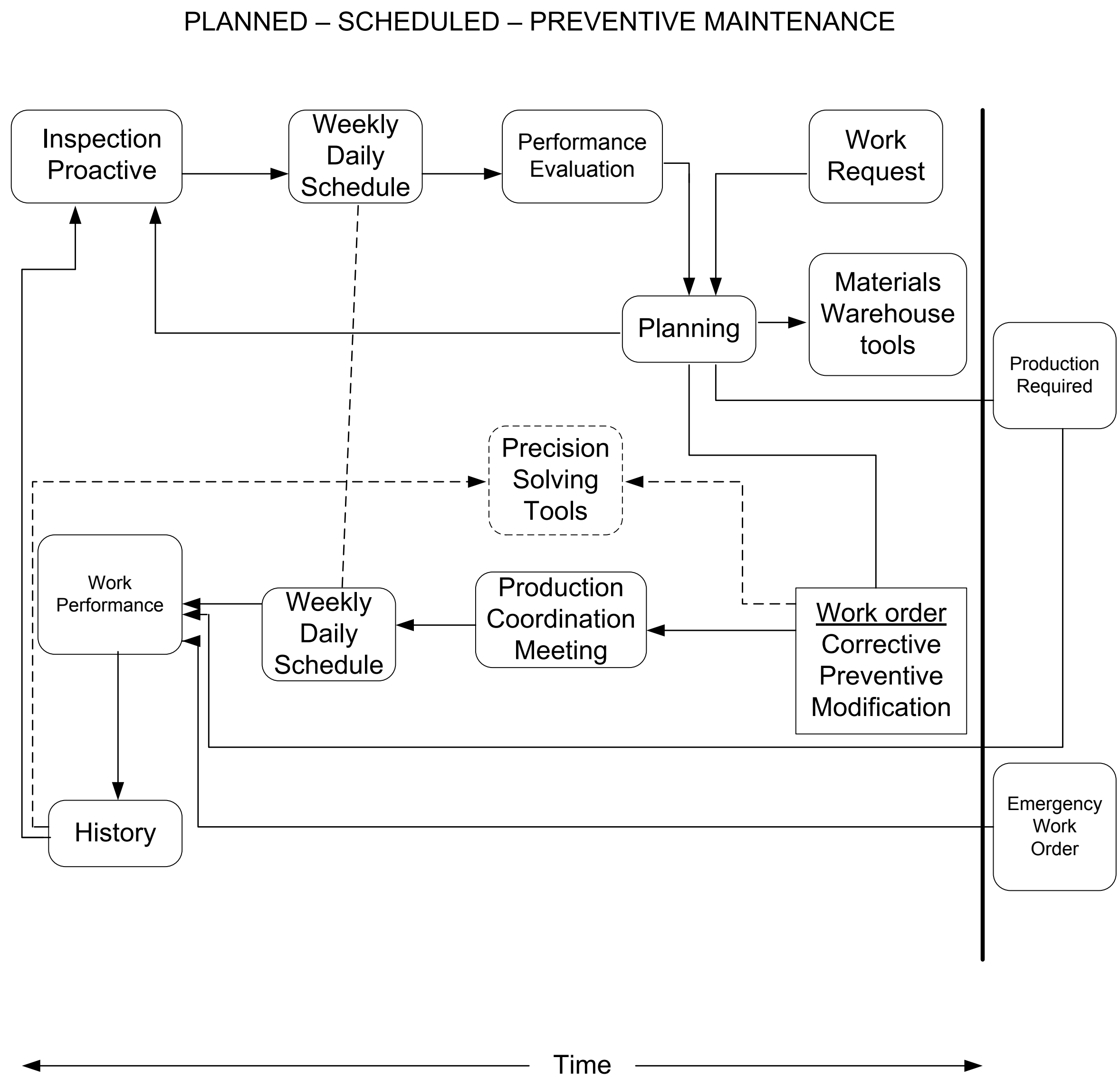


Figure 2.3 Proactive Maintenance Model

2.4.3 Changing Maintenance Trends.

The International Council on Large Electric Systems (CIGRE) is one of the leading worldwide Organizations on Electric Power Systems with headquarters in France. This is a permanent non-governmental and non-profit international association that was founded in 1921. One of CIGRE core mission issues is related to the planning and operation of power systems, as well as design, construction and maintenance of the plants. Technical work is being carried out within 15 study committees.

One of these working groups set up a questionnaire in 1997 to obtain more information about trends in future power system planning, design, operation, maintenance, extension and refurbishment.

A summary of this report can be found in reference [37], based on about 50 responses obtained from utilities, manufacturers and consultants. Some of the results of particular importance to this context are pointed out in the following paragraphs:

It is evident in the results that utilities have changed their organization in response to deregulation. The primary changes of note include the privatization of companies and splitting up of generation and distribution activities. The intense pressure to reduce operational and maintenance costs has already been felt. Maintenance, design, construction and some aspect of operation are increasingly being contracted out. The driving forces behind these changes are more aligned institutional business and economic factors than technical considerations.

Another projected trend identified in the results is that manufacturers will become increasingly incorporated into the maintenance systems.

Some of the figures presented in the report are as shown below:

- Almost 40% of the utilities undertake their maintenance activities at fixed time intervals and 30% on monitoring conditions. Many utilities falling into the first category are evolving towards condition or system- reliability based maintenance, or both.
- About half the utilities and all the manufacturers that responded have performed reliability studies to optimize their maintenance. These reliability studies resulted in introducing more flexibility and diversity into the maintenance intervals.
- In the past, utilities have laboured to achieve maximum reliability. However, according to the responses, about 90% thought that aiming for optimal and thereby “more specific” reliability in different parts of the system is the trend for the future.

- Data concerning the times for repair and maintenance were stated to be available, but data on failure modes were claimed to be more difficult to find.

This study provides a similar picture of the maintenance issue to *that* identified in the introduction of this thesis. It reveals a changing situation with increasingly complicated systems that are driven by economic rather than technical factors, and with the overall objective of achieving cost effective expenditures rather than maximum reliability.

2.4.4 Changing Requirement for Maintenance Methods

The change in the way maintenance is being managed has been identified. This change implies greater requirements on maintenance procedures. For example, maintenance decisions have been traditionally based on experiences and measurements which could be supported by diagnostic method. The increase in the expectations of maintenance has kept pace with the increasing knowledge about the dynamic characteristics of the power system. These higher expectations are due to the increasingly complex systems and higher demands on cost-effective use of resources. The increasing knowledge about the system has been gained primarily by an understanding of the relationships between failure frequency, reliability and maintenance, and also by methods and continuous measurements.

2.4.5 Maintenance Specifications and Performance

To explain maintenance specifications, maintenance definition will be considered in the context of keeping, preserving and protecting machine, equipment or plant.

The challenge often faced in an attempt to perform these tasks is how to define the level to which the machine, equipment or plant is to be kept. One of the most common ways would be to say “keep it like new”. This sounds good, but it is more subjective than objective. To answer this issue of maintenance level, leads to maintenance specifications.

Specification is a detailed precise presentation of that which is required. We must have a specification for the maintenance of equipment and plant. Specifications usually exist in the mind of the maintenance Engineer, even though they may be unable to recite it. This type of specification is defined in terms of and is dependent upon time available, personnel training level, pressure to produce a current customer order now, money allocated or available, or management opinion.

Obviously, a specification like this will not qualify as a true specification, nor will it qualify as a supporting component of the act of maintaining. The true maintenance specification may be a vendor specification, a design specification or an internally developed specification. The specification must be precise and objective in its requirement.

The maintenance system and organization must be designed to support a concept based on acceptable standard. Specifications, detailed work plans and schedules may be constructed to provide the specification requirement at the maintenance level. In the maintaining context, specification is not a goal. It is a requirement that must be met. The maintenance system must be designed to meet this requirement. **The specification must be accepted as the "floor" or minimum acceptable maintenance level.** Variation that does occur should be above the specification level or floor. The specifications will probably be stated in terms of attributes and capacity.

In reference to maintenance specifications, individual equipment specifications, process specification and plant performance specifications are also included.

2.4.6 The Maintenance Function

The maintenance department is responsible and accountable for maintenance. It is responsible for the way equipment runs and looks and for the costs to achieve the required level of performance. This is not to say that the operator has no responsibility for the use of equipment under his custody. The point is that responsibility and accountability must be assigned to a single function or person whether it is a mechanic or operator. To split responsibility between maintenance or any other department where overlapping responsibility occurs is to establish an operation where no one is accountable.

The maintenance function is responsible for the frequency and level of maintenance. They are responsible for the costs to maintain, which requires development of detailed budgets and control of costs to these budgets.

Where the maintenance department or group is held responsible and accountable for maintenance, the relationship with other departments takes on new meaning. They must have credibility and trust as basis of interdepartmental relationships. This is an essential element for the successful operation of a maintenance management system.

2.5 WHAT IS RELIABILITY?

Most maintenance professionals are intimidated by the word reliability, because they associate reliability with RCM (Reliability-Centred Maintenance) and are unclear on what it actually means.

Reliability is the ability of an item to perform a required function under a stated set of conditions, for a stated period of time [39]. However, many utilities focus on fixing equipment when it has already failed rather than ensuring reliability and avoiding failure.

A common reason for this finding is the lack of time to investigate what is needed to ensure the reliability of equipment. Yet, a growing awareness among these reactive maintenance organizations is that the consequences of poor equipment performance include higher maintenance costs, increased equipment failure, asset availability problems and safety and environmental impacts. There is no simple solution to the complex problem of poor equipment performance. The traditional lean manufacturing or world class manufacturing is not the answer. These strategies do not address the true target, but if we focus on asset reliability, the result will follow.

2.5.1 Reliability-Focus Utilities

It is not possible to manage today power system operation with yesterday methods and remain in business tomorrow. Most chief executive of Companies that are doing well decide to focus on reliability because maintenance is the largest controllable cost in an organization [40] and, without sound asset reliability, losses multiply in many areas. A research carried out by over 50 key employees of the world's best maintenance organizations for a period of two years revealed the followings [41]:

When the "best practices" they found were assimilated and implemented in a disciplined and structured environment, it was found to offer the biggest return with the longest lasting results.

Corporations that truly understand reliability typically have the best performing plants. Some of the characteristics of "reliability-focused organizations" are

- Their goal is optimal asset health at an optimal cost.
- They focus on processes – what people are doing to achieve results.
- They measure the effectiveness of each step in the process, in addition to the results.
- Their preventive maintenance programs focus mainly on monitoring and managing asset health.
- Their preventive maintenance programs are technically sound with each task linked to a specific failure mode, formal practices and tools are used to identify the work required to ensure reliability.

2.5.2 System Functional Failure and Criticality Ranking.

The objective of this task is to identify system functional degradation and failures and rank them as to priority. The functional degradation or failure of a system for each function should be identified, ranked by criticality and documented.

Since each system functional failure may have a different impact on availability, safety and maintenance cost, it is necessary to rank and assign priorities to them. The ranking takes into account probability of occurrence and consequences of failure. Qualitative methods based on collective Engineering judgment and the analysis of operating experience can be used. Quantitative methods of simplified failure modes and effects analysis (SFMEA) or risk analysis also can be used.

The ranking represents one of the most important tasks in RCM analysis. Too conservative ranking may lead to an excessive preventive maintenance program, and conversely, a lower ranking may result in excessive failures and potential safety impact. In both cases, a nonoptimized maintenance program results.

2.6 RELIABILITY-CENTERED MAINTENANCE

Reliability-centered Maintenance is a process used to determine the maintenance requirements of any physical asset in its operating context.

2.6.1 RCM Method

RCM provides a formal framework for handling the complexity of the maintenance issues but does not add anything new in a strictly technical sense. RCM principles and procedures can be expressed in different ways [42]; however, the concept and fundamental principles of RCM remain the same.

The RCM method facilitates the

- preservation of system function,
- identification of failure modes,
- prioritizing of function needs, and
- selection of applicable and effective maintenance tasks.

Several different formulations of the process of creating an RCM program and achieving an optimally-scheduled maintenance program were found in the literature. Three of these formulations had been addressed. The first two were derived from the original RCM definitions, and the third is an approach based on a set of questions rather than steps.

1) Smith

Smith defined a systematic process for RCM by implementing the following features that have been defined above:

1. System selection and information collection.
2. System boundary definition.
3. System description and functional block diagrams.
4. System functions and functional failures.
5. Failure mode and effects analysis (FMEA).
6. Logic decision tree analysis (LTA).
7. Selection of maintenance tasks.

2) Nowlan

Nowlan defines the process of developing an initial RCM program when the information required is lacking, as follows [43]:

(1) Partitioning the equipment into object categories in order to identify those items that require intensive study,

(2) Identifying significant items that have essential safety or economic consequences and hidden functions that require scheduled maintenance.

(3) Evaluating the maintenance requirements for each significant item and hidden function in terms of the failure consequences and selecting only those tasks that will satisfy these requirements.

(4) Identifying items for which no applicable or effective task can be found, then either recommending design changes if safety is involved, or assigning no scheduled maintenance tasks to these items until further information becomes available,

(5) selecting conservative initial intervals for each of the included tasks grouping the tasks in maintenance packages for application,

(6) Establishing an age-exploration program to provide the factual information necessary to revise initial decisions.

The first step is primarily an activity for reducing the problem to a manageable size. The following three steps stated above are the essence of RCM analysis, constituting the decision questions as stated by Moubray in (3) below.

3) Moubray

To analyse the maintenance aspects of a system and its components, the first step is to identify the system items, and which of these ought to be analysed. Thereafter the RCM process can be formulated into seven questions for each of the selected items. [44]

The seven general questions are:

1. What are the functions and performances required?
2. In what ways can each function fail?
3. What causes each functional failure?
4. What are the effects of each failure?

5. What are the consequences of each failure?
6. How can each failure be prevented?
7. How does one proceed if no preventive activity is possible?

2.6.2 Failure Consequences

A detailed analysis of an average industrial undertaking is likely to yield between three and ten thousand possible failure modes. Each of these failures affects the organization in some way, but in each case, the effects are different. They may affect operations. They may also affect product quality, customer service, safety or the environment. They will all take time and cost money to repair.

It is these consequences which most strongly influence the extent to which we try to prevent each failure. In other words, if a failure has serious consequences, we are likely to go to great lengths to try to avoid it. On the other hand, if it has little or no effect, then we may decide to do no routine maintenance beyond basic cleaning and lubrication.

A great strength of RCM is that it recognizes that the consequences of failures are far more important than their technical characteristics. **In fact, it recognizes that the only reason for doing any kind of proactive maintenance is not to avoid failures per se,** but to avoid or at least to reduce the consequences of failure.

The RCM process classifies these consequences into four groups, as follows:

- Hidden failure consequences: This has no direct impact, but they expose the organization to multiple failures with serious, often catastrophic, consequences. (Most of these failures are associated with protective devices which are not fail-safe.)
- Safety and environmental consequences: A failure has safety consequences if it could hurt or kill someone. It has environmental consequences if it could lead to a breach of any corporate, regional, national or international environmental standard.

- Operational consequences: A failure has operational consequences if it affects production (output, product quality, customer service or operating costs in addition to the direct cost of repair).
- Non-operational consequences: Evident failures which fall into this category affect neither safety non production, so they involve only the direct cost of repair.

2.6.3 Growing Expectation of Reliability-Centered Maintenance

Since the 1930's, the expectation of maintenance can be traced through three generations. RCM is rapidly becoming a cornerstone of the third Generation, but this generation can only be viewed in perspective in the light of the first and second Generations.

The first Generation

The first generation covers the period up to World War II. In those days industry was not highly mechanized, so downtime did not matter much. This meant that the prevention of equipment failure was not a very high priority in the minds of most managers. At the same time, most equipment was simple and much of it was over-designed. This made it reliable and easy to repair. As a result, there was no need for systematic maintenance of any sort beyond simple cleaning, servicing and lubrication routines. The need for skills was also lower than it is today.

The Second Generation

Things changed dramatically during World War II. Wartime pressures increased the demand for goods of all kinds while the supply of industrial manpower dropped sharply. This led to increased mechanization. By the 1950's, machines of all types were more numerous and more complex. Industry was beginning to depend on them.

As this dependence grew, downtime came into sharper focus. This led to the idea that equipment failures could and should be prevented, which led in turn to the concept of preventive maintenance. In the 1960's, this consisted mainly of equipment overhauls done at fixed intervals.

The cost of maintenance also started to rise sharply relative to other operating costs. This led to the growth of maintenance planning and control systems. These have helped greatly to bring maintenance under control, and are now an established part of the practice of maintenance.

Finally, the amount of capital tied up in fixed assets together with a sharp increase in the cost of that capital led people to start seeking ways in which they could maximize the life of the assets.

The Third Generation

Since the mid-seventies, the process of change in industry has gathered even greater momentum. The changes can be classified under the headings of new expectations, new research and new techniques.

Downtime has always affected the productive capability of physical assets by reducing output, increasing operating costs and interfering with customer service. By the 1960's and 1970's, this was already a major concern in the mining, manufacturing and transport sectors. In manufacturing, the effects of downtime are being aggravated by the worldwide move toward just-in-time systems, where reduced stocks of work-in-progress mean that quite small breakdowns are now much more likely to stop a whole plant. In recent times, the growth of mechanization and automation has meant that reliability and availability have now also become key issues in sectors as diverse as health care, data processing, telecommunications, power systems and building management.

Greater automation also means that more and more failures affect our ability to sustain satisfactory quality standards. This applies as much to standards of service as it does to product quality.

More and more failures have serious safety or environmental consequences, at a time when standards in these areas are rising rapidly. In some parts of the world, the point is approaching where organizations either conform to society's safety and environmental expectations, or they cease to operate. This adds an order of magnitude to our dependence on the integrity of our physical assets – one which goes beyond cost and which becomes a simple matter of organizational survival.

At the same time as our dependence on physical assets is growing, so too is their cost – to operate and to own. To secure the maximum return on the investment which they represent, they must be kept working efficiently for as long as we want them to.

Finally, the cost of maintenance itself is still rising, in absolute terms and as a proportion of total expenditure. In some industries, it is now the second highest or even the highest element of operating costs [45]. As a result, in only thirty years it has moved from almost nowhere to the top of the league as a cost control priority.

Table 2.1 Changing maintenance techniques

First Generation:	**Second Generation:**	**Third Generation:**
Fix it when broken	Scheduled overhauls Systems for planning and conrolling work. Big, slow computers	Condition monitoring Design for reliability and maintainability Hazard studies Small, fast computers Failure modes and effects analyses Expert systems Multiskilling and teamwork

New research

Apart from greater expectations, new research is changing many of our most basic beliefs about age and failure. In particular, it is apparent that there is less and less connection between the operating age of most assets and how likely they are to fail. However, Third Generation research has revealed that not one or two but six failure patterns actually occur in practice.

New techniques

There has been explosive growth in new maintenance concepts and techniques. Hundreds have been developed over the past fifteen years, and more are emerging weekly. [46].

2.7 RELIABILITY ENGINEERING

The general power evaluation term “reliability”, such as availability, can be seen as a combination of three factors: Reliability of a piece of equipment or a part of the system, maintainability, which is the possibility to detect failures and to read and restore the components and the maintenance support or supportability i.e. spare parts, maintenance equipment and the ability of the maintenance staff. The availability concept and parameters of importance are illustrated in figure 2.4. All three areas are affected when underground cables replace overhead lines.

80 % of the failures in distribution network are related to the electrical components, such as overhead lines, cable systems, secondary substations or medium voltage switchgear stations, [47] these components are made up of different parts of which all have a probability to fail. Cable system faults are not only faults on the cables but also on joints and terminations. In addition to the condition of individual components, network topology and environmental factors influence the ability of the system to perform a required function.

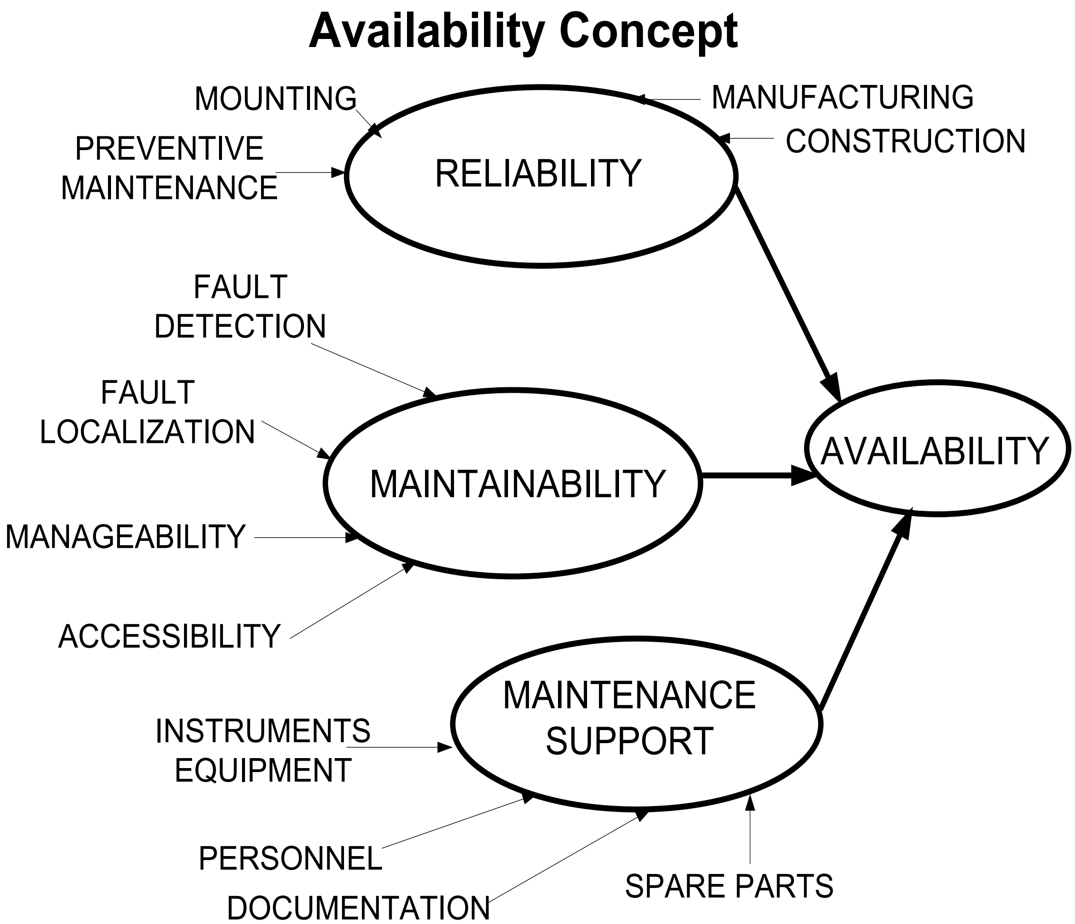


FIGURE 2.4 Composition of availability and its controlling parameters.

2.8 THE RELIABILITY ENGINEERING PROCESS.

One approach to reliability engineering is to divide the process into four basic steps;

- Past system behaviour
- Reliability calculation methods.
- Calculation of reliability indices and
- Prognosis of future system. [48]

It is mainly the activities in step one, the collecting of data in order to create models of outages and failures, that differ between networks with an extensive amount of cable and traditional overhead line networks. The failure rates of different components, calculated in step one, are of the engineering process.

2.9 RELIABILITY EVALUATION

In most of the literature, the fundamental problem area considered is that of failure events in electric power systems. To make the analysis of this fundamental issue possible, abstract models were created using mathematical language instead of presenting the problem analogously. An abstract model can either be deterministic or probabilistic. In a deterministic model, reality can be approximated with a mathematical function. In a stochastic or random model, the unknown behaviour is included in the model. Probability theory is used to analysize this random behaviour.

Reliability theory is well documented and this section presents some fundamental aspects directly related to the analysis performed in this work.

2.9.1 Evaluation Techniques Compared.

Like all mathematical analysis, reliability analysis concentrates firstly on modeling the mathematical problem, and secondly on finding the solutions to the problem using the model. Furthermore, the model can be used to solve the problem directly and mathematically (analytical method), or indirectly by numerical experiments (simulation method). A comparative study of these two fundamental techniques for assessing reliability is explained briefly below:

2.9.2 Analytical Method

In this method, reliability evaluation techniques are used directly on the model by solving the mathematical equations. To provide solution to this mathematical equation, two fundamental techniques are used for reliability evaluation. They are, network modeling and Markovian modeling. From the literature, network modeling technique is the most commonly used. Other reliability evaluation methods whose technique is based on network modeling are RelNet program from UMIST in the UK, [49] and RelRad from EFI in Norway [50].

The program by the name R-RADS developed at the University of Washington had its technique based on the Markovian modeling [50].

One of the reasons for the popularity of network modeling techniques arises from its simplicity and the natural similarities between network model and the distribution system topology.

2.9.3 Network Modeling

A technical system can always be thought of as being composed of components. In the network modeling techniques, the structural relationships between a system and its components are considered. The physical system is converted into a reliability network using the system operational logic and knowledge about the physical behaviour and requirements of the system. Details of these techniques have been presented in the literature [51].

One of the central problems in reliability analysis is modeling the failure behaviour of the system. This can be done by deducing possible failure modes as the minimal cut set does.

A cut – set is a set of components which upon failure causes a failure of the system. A cut-set is minimal when it cannot be reduced any further and still remains a cut-set.

There are a number of different approaches to obtaining minimal cut-set. A distribution system can be treated as a system composed of load points and subsystems. One approach referred to as the load-point driven technique, deduces minimal cut sets for each load point by identifying each event that leads to a failure of that load point. Further more, reliability indices are deduced for each load point and these indices are then combined to provide the system indices.

A path is a set of components that when operating, guarantees the operation of the system. A path is minimal when it cannot be reduced any further and still remains a path.

Another approach for obtaining cut sets not based on reliability networks is the MOCUS algorithm [52]. This algorithm uses fault trees for evaluating the failure probability of a subsystem. A fault tree is a logical diagram that displays the relationship between an undesired event in the system and the cause of that event. The aim is to identify events via logical conditions that lead to the event that is under investigations (the top event).

In a comparative study, a load-point driven approach has been compared with an event-driven approach. The principle of the event-driven approach is to treat each failure event separately, and see the effect of the failure on the whole system by identifying the affected load points. Consequently, the major difference between the two approaches is that in the load-point driven approach all failure events for each load point are considered in turn, but in the event-driven approach, all load points affected by one failure event are considered in turn [52].

2.9.4 Markovian Modeling

In the Markovian modeling, it is assumed that in an interval of given length, the probabilities of a working component failing (or a failing component being repaired) are only dependent on the state of the system at the beginning of this small interval, [53]. This property of lack of memory means that information on how the system entered the current state or when it entered the state is not needed.

The major drawback with this technique is the large number of states needed to model a system. This is due to the fact that the number of states increases exponentially with the number of factors studied. As a result, many simplifying assumptions have to be made to limit the Markov model to a manageable size.

2.9.5 Simulation Method

In the simulation method, an actualization of the process is simulated and after having observed the simulation process, for a given period, estimates are made of the unknown parameters; the simulation is consequently treated as a series of real experiments. There are several types of simulation processes. In reliability analysis, simulation often concerns stochastic processes that are of random events. These simulation methods are commonly referred to as Monte Carlo simulations.

Stochastic simulation can be used in a random or a sequential way. In the random approach, the simulation creates randomly chosen intervals and in the sequential approach the intervals are chosen in chronological order. This implies that if a system model is simulated, where events for the system model in one interval depend on the previous interval, then the sequential approach is appropriate, which is often the case in reliability studies.

The simulation process is intended for examining and predicting the stochastic behaviour of a system in simulated time. Therefore, during the simulation period, events are made to occur at randomly determined times obeying predetermined probability distributions. By using random numbers and converting them into distribution functions that represent the behaviour of the system, the actual behaviour of the system can be realized.

2.10 LIMITATIONS OF RCM.

This fundamental fact of managing physical assets highlights two flaws with the case of capturing data for designing maintenance programs. First, collecting failure information for future decisions means managing the asset base in a way that runs counter to basic aims of modern maintenance management. Second, even if a company was to progress down this path, the nature of critical failures is such that they would not lend themselves to extensive statistical review.

By establishing an effective or reliability-centered maintenance regime, the policy designer is in effect creating a management environment that attempts to reduce failure information and not to increase it. The more effective a maintenance program is, the fewer critical failures will occur, and correspondingly less information will be available to the maintenance policy designer regarding operational failures. The more optimal a maintenance program is, the lower the volume of data there will be.

Designing Maintenance Policy

When maintenance policy designers begin to develop a management program, they are almost always confronted with a lack of reliable data to base their judgments on. It has been the experience of the author that most companies start reliability initiatives using an information base that is made up of approximately 30 percent hard data and 70 percent knowledge and experience.

One of the leading reasons for this is the nature of critical failures and the response they provoke. However, there are often other factors such as data capturing

processes, consistency of the data, and the tendency to focus efforts in areas that are of little value to the design of maintenance policy. With Enterprise Asset Management (EAM) technologies changing continually, there are often upgrade projects, changeover projects, and other ways that data can become diluted. There are still other key reasons why data from many EAM implementations are of limited value only. Principal among these is the fact that even with well-controlled and precise business processes for capturing data, some of the critical failures that will need to be managed may not yet have occurred. An EAM system managing maintenance program that is either reactive or unstructured will only have a small impact on a policy development initiative.
At best they may have collected information to tell us that faults have occurred, at a heavy cost to the organization, but with small volumes of critical failures and limited information regarding the causes of failure. RCM facilitates the creation of maintenance programs by analyzing the some fundamental causes of critical failures of assets;
These includes
(a) Poor asset selection (never fit for this purpose)
(b) Asset degradation over time (becomes unfit for this purpose)
(c) Poor asset operation (operated outside of the original purpose)
(d) Exceptional human errors (generally following the generic error modeling [GEM] principles)
The RCM analyst needs to analyze all of the reasonably likely failure modes in these four areas, to an adequate level of detail (reasonably likely is a term used within the RCM standard SAE JA1011, to determine whether failure modes should, or should not, be included within an analysis; reasonableness is defined by the asset owners). Determining the potential causes for failures in these areas, for a given operating environment, is in part informed by data, but the vast majority of the information will come from other sources.
Sources such as operators' logs are strong sources for potential signs of failure, as well as for failures often not found in the corporate EAM. Equipment manufacturers' guides are also powerful sources for obtaining information

regarding failure causes and failure rates. However, all pieces of information from a manufacturer need to be understood in the context of how you are using the asset, and the estimates of the manufacturer. For example, if there are operational reasons why your pumping system is subject to random foreign objects, for whatever reason, then failure rates for impeller wears can become skewed. Other sources of empirical data can be found in operational systems such as Supervisory Control and Data Acquisition (SCADA) or commercial databanks, user groups, and at times consultant organizations. Similarly for information from manufacturers, there is a need to understand how this applies to the operating environment of your assets. Asset owners require more and more technologically advanced products. Most items that come into the market are with limited test data in operational installations, which further complicates the issues of maintenance design data.

The factors that decide the lengths that an RCM analyst should go to collect empirical data is driven by a combination of the perceived risk (probability X consequence), and of course the limitations set on maintenance policy design by commercial pressures. Even when all barriers are removed from the path of RCM analysts, they are often faced with an absence of real operational data on critical failures.

The vast majority of the information regarding how assets are managed, how they can fail, and how they should be managed, will come from the people who manage the assets on a day-to-day basis. Potential and historic failure modes, rates of failure, actual maintenance performed (not what the system says, but what is really done), why a certain task was put into place in the first place, and the operational practices and the reasons for them, are all elements of information that are not easily found in data, but in knowledge.

This is one of the overlooked side-benefits of applying the RCM process—that of capturing knowledge, not merely data. As the workforce continues to age, entry rates continue to fall in favor of other managerial areas; and as the workforce becomes more mobile, the RCM process and the skills of trained RCM analysts provide a structured method to reduce the impact of diminishing experience.

2.11 OBSERVATIONS AND FINDINGS FROM LITERATURE SURVEY.

From the foregoing issues, a number of gaps exist in the literature which defines the context of this research.

First, most of the approaches used in all the literatures consulted are still heuristic, and their applications require judgment and experience for any maintenance decision. Data on most of the components failure rate that may be required for such decisions on asset management are not readily available.

Secondly, most of the literature addresses replacement only, neglecting the possibility that maintenance may result in smaller improvements at smaller costs.

And finally, when maintenance is modeled, most often, scheduled maintenance intervals are assumed, a mathematical model which incorporates the concept of ‘maintenance when needed’ that is capable of predicting how far a components will last before failure when in its operating state had not been explored.

2.12 The proposal of Reliability-Centred Maintenance (RCM) for Asset Management in Electric Power Distribution System.

2.12.1 Justification of the proposed work.

The fundamental objective of any electric utility is to plan, operate, maintain and implement expansion of facilities so that customers receive reliable electric services at the lowest possible cost.

Deregulation and competition are forcing improvements in efficiency and reductions in cost while customers are becoming more sensitive to electrical disturbances and are therefore demanding higher levels of service reliability. Since a typical distribution system accounts for 40% of the cost to deliver power and 80% of customer reliability problems, distribution system design and operation is therefore critical to financial success and customer satisfaction.

This distribution system is made up of inter-connected components that make-up the system. The majority of the reliability problems are associated with the failure of any of these components. Achieving the objective of these electric Utilities is therefore further complicated by the ageing nature of these components.

Most of these assets (components) are capital intensive, and therefore need to be preserved so that it can continue to perform its required function without failure.

From our definition of reliability, power outages are one of the measures of reliability performance. Unavailability of power can be reduced in two ways:

1) By reducing the frequency of power outages or
2) By reducing the outage time

To address the first part of the identified problem, RCM that applies a probabilistic model for predicting the remaining life of a critical distribution component will be the main focus for this project. This will enhance an intelligent maintenance decisions for asset managers.

2.12.2 Description of the project

For a power system, components do not exist as separate entities, but are parts of the entire system.

Therefore, all component maintenance policies must be put into system context.

The goals of component maintenance are to maximize system reliability or minimize system operating costs, and ultimately these fit into system maintenance too.

The overall logic of evaluating the effects of component maintenance on system reliability is shown in figure 2.5

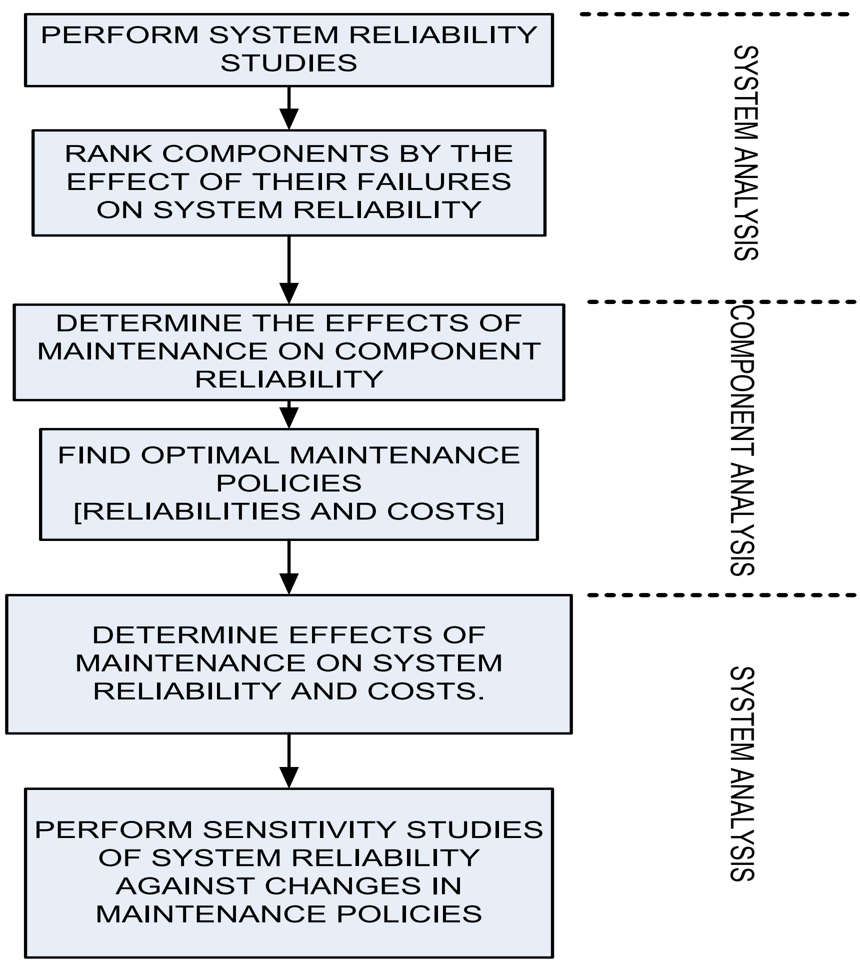


Figure 2.5 Logic of relating component maintenance system reliability with operating costs.

This project is carried out in three phases as described below:

Phase one

The system is defined and critical components are identified (ie those components whose failures have the largest effects on the selected system reliability indices) This can be carried out by performing system reliability analysis and evaluating the effects of component failures on system reliability.

Phase two

The causes and types of failures of the identified critical components are further investigated so that the effects of various maintenance policies on the reliability of the critical components are determined using established mathematical model. From this, optimal maintenance policies are identified.

Phase three

The critical components with their optimal failure rates obtained from above are fed into the Markov model as input, so that the remaining life of the component can be predicted. This will be implemented in Matlab program and the result compared with that obtained from the Transformer Maintenance Model Simulation. This will assist in making an intelligent decision on asset managegement.

2.13 SUMMARY AND COMMENTS

The chapter presents the views of different authors on the subjects of the most frequently used maintenance strategies. Distinction was made between strategies where maintenance consists of replacement by a new component and where it is represented by a less costly activity resulting in a limited improvement of the component's condition. Most of the literatures consulted had shown that methods were also divided into categories where maintenance was performed at fixed intervals and where it is carried out as needed. It was also revealed in most of the literatures that most of the maintenance was based on heuristic methods. A distinction was then made between heuristic methods and those based on mathematical models; the models themselves can be deterministic or probabilistic.

From the analysis of the consulted literatures on the present maintenance policies in electric utilities it was concluded that maintenance at fixed intervals is the most frequently used approach. The growing expectations of RCM were also traced through literature. It can be seen that RCM are now increasingly being considered for application in some part of North America, but methods based on mathematical models are hardly ever used or even considered. Yet only mathematical approaches where component deterioration and condition improvement by maintenance are quantitatively linked can determine the effect of maintenance on reliability.

Therefore in this study, we propose a model that will provide a quantitative connection between reliability and maintenance, a link missing in the heuristic approaches. The component failure process will be modeled, and the mean remaining life of the identified component will be computed using a computer program implemented in Matlab.

CHAPTER THREE

THEORY OF RELIABILITY EVALUATION

3.1 Introduction

This thesis analyzes the fundamental problem of failure events in electric distribution systems. To make this possible, abstract models have been created using mathematical language. An abstract model can either be deterministic or probabilistic. In a deterministic model, reality can be approximated with mathematical functions. In a stochastic random model, the unknown behavior is included in the model. Probability theory is used to analyze this random behavior. The techniques used in this work are based on stochastic models.

Reliability theory is fully covered in most textbooks and some aspects directly related to the analyses performed in this work are hereby summarized in this thesis. Sources of the materials contained in this section include [54], [55], [56], and [57].

3.2 DEFINITIONS AND TERMINOLOGY

3.2.1 Electrical Power Distribution Systems.

Electricity becomes a matter of interest to Engineers and Researchers from about 1870s. Experiments were conducted to learn more about electrical phenomena, and batteries were the main source of power. Generators which could only provide greater electrical currents than battery was invented by Zenobe Gramme, a Belgian researcher. This brought about the beginning of breakthrough in electrical machines for industrial and residential users, electrical feeders were built from small and large power plants. The very first Incandescent lamp was invented simultaneously by the American Thomas Alva Edison and Englishmen Joseph Swan in around 1880. It was after this discovery that the benefits of Electricity for daily use became clearer. The demand for Electricity for day to day activities had finally provided the rationale for electrical power delivery systems.

3.2.2 Power Distribution Systems

Electrical power distribution systems consist of transmission and distribution systems for the movement of electrical power from producers to customers.

These consist of several overhead lines, substations, transformers and other equipment spread over large geographical areas, and interconnected to deliver power on demand to customers. The major design of a Transmission and Distribution (T&D) system is based on two physical and economical constraints:

The first constraint being that it is more economical to transport power at high voltages because of reduction in losses, but higher voltage transmission requires equipment with greater capacity which in turn is more expensive. However, in Nigeria, the voltage level that customer utilizes is 240/415V (three phase). This is not an economical level for transmission; therefore costly voltage transformers are required.

The second constraint is that power is more economical to produce in large amounts, but it must be delivered in small quantities at low voltage levels (120 – 250V). However, with the introduction of deregulation, it is now more cost – effective to construct distributed generation with this, it becomes quicker and cheaper to produce smaller or larger quantities of power based on economical rather than technical factors. For this, the second constraint is now only partially true.

Basically, the T&D system is designed to transport power from a few large generating plants to many sites (the customers). This has to be done using voltage levels, from high to low. For example, in Nigeria, generation is at 11kV, 15.8kV and 16.1kV. Transmission of electricity is done at 132kV and 330kV, and distribution is done at 33kV, 11kV and 0.415kV.

The fundamental question that had always been asked before now is, which part of the whole system is the distribution systems. In [58], three types of distributions between distribution and transmission system have been identified.

(1) Voltage levels: transmission >= 132kV and distribution <=33kV.

(2) Functions: distribution includes all overhead lines that feed service transformers.

(3) Configurations: transmission includes a network, and distribution includes only radial equipment in the system.

In UK, distribution system is defined for the voltage levels and so it follows the first distribution listed above.

However, this has been redefined recently to include 132kV. Further more, a distinction by function is made in some places where three different hierarchical levels have been used in the analysis of the power system, namely [59] generation, transmission and distribution. Item 3 is not applicable to all these references because the distribution systems described are not only radial.

The electrical power distribution system considered in this thesis is that of voltage levels or network configurations. The characteristics of the system are instead based on the two roles played by customers and utility that receives or provides electrical power respectively. The technical system has been greatly simplified in regard to the voltage and current phenomena, and all the dynamic characteristics have been disregarded. This simplification is more suitable to lower voltage levels, which therefore justifies its use in evaluating distribution system.

Terms

The following definitions are based on the Institution of Electrical and Electronics Engineers regulating standard.

- Customer: The customer is the purchaser of electricity from a supplier.
- Supplier: The supplier is the party who provides electricity via a public distribution system (referred to here as an electricity utility).
- The supply-terminals: The supply –terminals are the points of connection to the public system used by the customer, for example the electricity metering point or the point of common coupling (referred to here as load points).
- The supply voltage (V_s) is the root mean square value of the voltage at a given time at the supply-terminals, measured over a given time interval.
- The supply interruption is a condition where the voltage at the supply-terminals is lower than 1% at the declared voltage. A supply interruption can be classified as:

- ✓ Prearranged (or planned) when consumers are informed in advance, or
- ✓ Accidental, when caused by failures. Failure can for example be related to external events or to equipment. Accidental interruptions are classified as :
  - Long interruptions (interruptions ≥ 3min) or
  - Short interruptions (interruptions ≤ 3min)

However, different definitions are used for interruptions; for example in the UK, the limit is 1min

In Sweden, information is recorded for each accidental and planned supply interruptions. This information consists of the number of interruptions, duration of interruption and the number of customers affected.

- A disturbance in a power system (or component) implies an event which results in an involuntary decrease of the system's ability to deliver electrical power.
- If a system that is normally under-voltage becomes dead or disconnected, it suffers an interruption of voltage.
- Interruption of voltage can be involuntary (for example a disturbance), or voluntary (for example, planned or scheduled). If an interruption of voltage causes customers to lose supply, they are exposed to an interruption of supply.

The supply interruptions in this thesis are referred to as outages or failures. These denote the state of a component when it is not available to perform its intended function due to some event directly associated with the component.

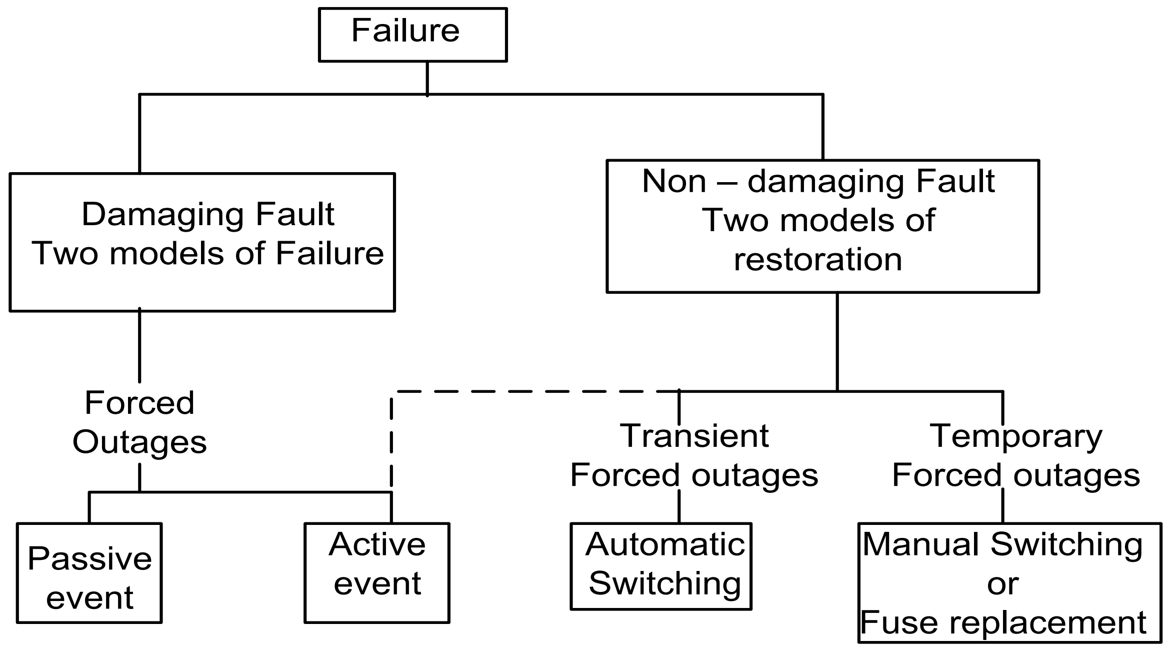


Fig 3.1 Definitions of Failure

The general definition of failure that is used in this thesis can be structured according to figure 3.1. Failure can be divided primarily into damaging faults and non-damaging faults. Outages caused by damaging faults are usually called permanent forced outages, while outages caused by non-damaging faults are categorized again after the action of restoration into:

(i) Transient forced outages when the system is restored by automatic switching and the outage time is negligible, and

(ii) Temporary forced outages when the system is restored by a manual switching or fuse replacement.

Long interruptions are often caused by damaging faults (permanent faults) and short interruptions are often caused by transient faults.

Furthermore, damaging faults can be separated into two models of failure; Passive failure and active failure defined as follows:

- An active failure of an item is the one which causes the operation of the protection devices around it and results in the opening of one or more fuses.
- A passive failure is a failure that is not an active failure

The failed item (component) by an active failure is consequently isolated and protection breakers are re-closed. This leads to service restoration to some or all of the load points. However, for the passive failure, service is restored by repairing or replacing the failed component (or by re-closing a disconnector and using another feeder for supply).

The outage time of a failure is made up of various items depending on the cause.

Figure 3.2 shows two different time sequences following active and passive failures. As can be seen in the figure, the active failures can be restored by either repair or replacement, or by switching. The dotted line in figures 3.1 indicates active failures that are restored by switching and not caused by a damaging fault. These are referred to as additional active failures.

- Definition: An additional active failure is a failure mode that occurs when a component fails actively and causes interruption through its impact on other components

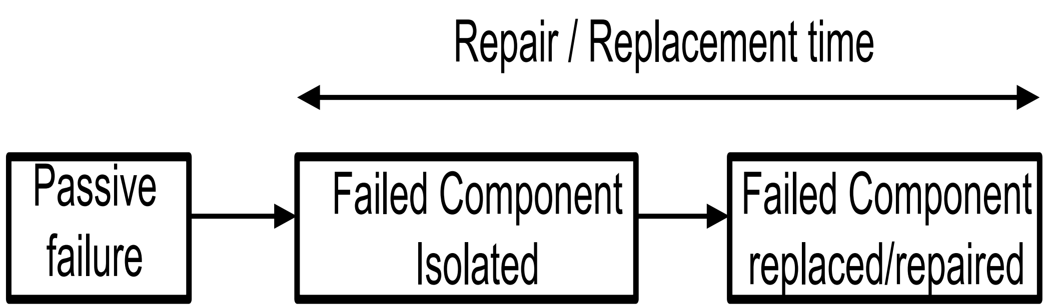


Figure 3.2 Total time for repair/replacement of a passive failure

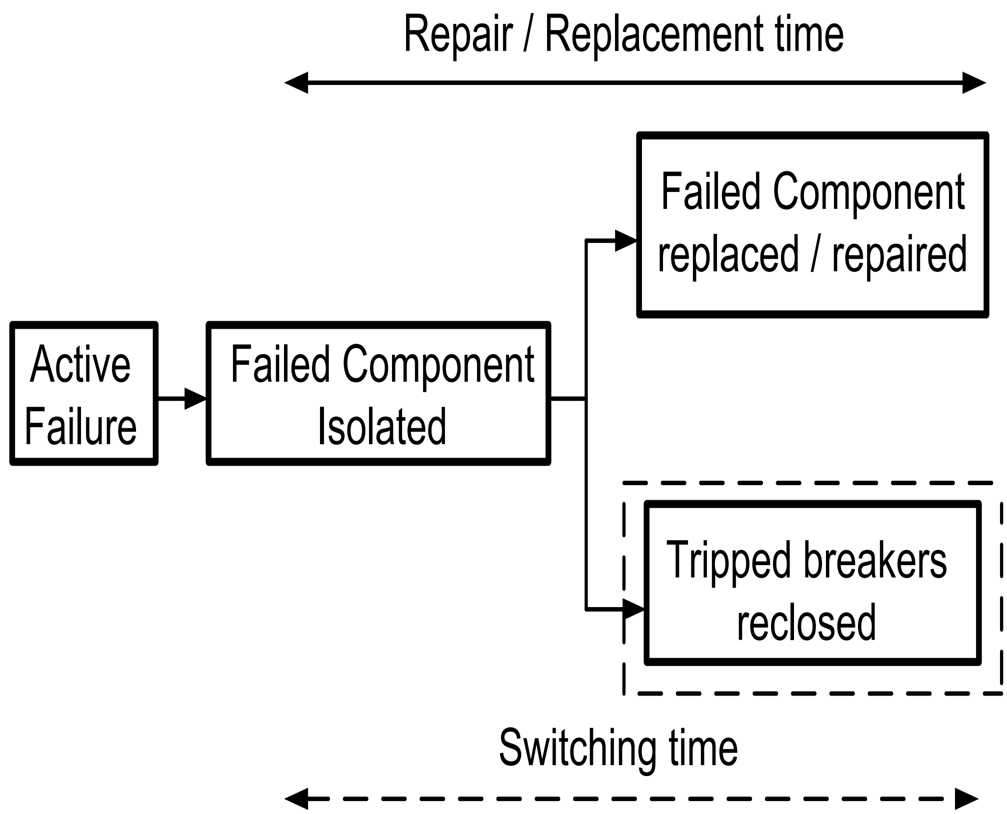


Figure 3.3 Outage time sequence of an active failure

3.3 APPLIED RELIABILITY INDICES

This section presents some basic reliability indices that were used in this thesis as general terms for quantitative measure of reliability. Some of these indices could be evaluated using computer program. They are therefore defined as follows:

3.3.1 Load point indices

Some programs exist for evaluating the following basic reliability indices for each specified load point in a distribution system network:

- Expected failure rate λ (f/yr)
- Average outage duration r (h/f)
- Annual expected outage time U_a (h/yr) and
- Average loss of energy ALOE (kWh/yr)

3.3.2 System performance indices

The basic problem with trying to measure reliability is how to relate the two quantities, frequency and duration [60]. One way of solving this is to use any of the methods for solving system performance indices classified below.

- **System average interruption frequency index (SAIFI) (interruptions/yr)**

$$= \frac{\text{Total number of customer interruptions}}{\text{Total number of customers served}}$$

$$= \sum \frac{\lambda_i N_i}{N_i} \quad \text{-- -- -- -- -- -- -- -- -- -- -- -- -- -- --} \qquad 3.1$$

Where λ_i = the expected failure rate of the load point i and N_i = the number of customers for load point i

- **System average interruption duration index (SAIDI) (h/yr)**

$$= \frac{\text{Sum of customer interruption durations}}{\text{Total number of customers served}}$$

$$= \frac{\sum U_i N_i}{\sum N_i} \quad \text{-- -- -- -- -- -- -- -- -- -- -- -- -- -- -- --} \qquad 3.2$$

Where U_i = the annual expected outage time of load point i

- **Customer average interruption frequency index (CAIFI) (interruption/yr)**

$$= \frac{\text{Total number of customer interruption durations}}{\text{Total number of customers interruptions}}$$

$$= \frac{\sum \lambda i\ N_i}{\sum N_{ai}} \quad \text{-- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- -- --} \qquad 3.3$$

Where N_{ai} = the number of customers affected at load point i

- **Customer average interruption duration index (CAIDI) (h/interruption)**

$$= \frac{\text{Sum of customer interruption durations}}{\text{Total number of customer interruptions}}$$

$$= \frac{\sum U_i N_i}{\sum \lambda_i N_i} \quad ------------------- \quad 3.4$$

- **Customer total average interruption duration index (CATIDI) (h/yr)**

$$= \frac{\text{Sum of customer interruptions}}{\text{Total number of customer interrupted}}$$

$$= \frac{\sum U_i N_i}{\sum N_{ai}} \quad ------------------- \quad 3.5$$

- **Average energy not supplied per customer served (AENS) (KWh/yr)**

$$= \frac{\text{Total energy not supplied}}{\text{Total number of customers served}}$$

$$= \frac{\sum L_o E_i}{\sum N_i} \quad ------------------ \quad 3.6$$

Where $L_o E_i$= Average loss of energy of load point i

- **Average service availability index (ASAI)**

$$= \frac{\text{Customer hours of available service}}{\text{Customers hours of service demand}}$$

$$= \frac{\sum N_i \,.\, 8760 - U_i N_i}{\sum N_i \,.\, 8760} \quad ------------- \quad 3.7$$

Note that CTADI and CAIFI include customers that are interrupted, which implies that each individual customer is only counted once regardless of the number of times their supply is interrupted. This however does not apply to CAIDI where all interruptions for each customer are counted. Moreover, the indices are related according to the following:

$$\text{CAIDI} = \frac{\text{SAIDI}}{\text{SAIFI}} \text{ and } \text{CAIDI} = \frac{\text{CTAIDI}}{\text{CAIFI}}$$

If N_{ai} equals N_i, then SAIFI equals CAIFI. This assumption was made for implementation in some program.

3.4 MAINTENANCE STRATEGIES

Maintenance is an activity undertaken with the purpose of enabling the fulfillment of a desired performance in a component by maintaining its ability to correctly function or return to a previous level of function.

In this work, the maintenance activities have been divided into two different groups according to their aim

- Preventive Maintenance (PM): This is aiming at reducing the probability of the component failing, for example via lubrication, the replacement of faulty components or inspection.
- Corrective Maintenance (CM) aims to restore performance after failure via repair.

It is however important to recognize that there are different definitions and terminology for maintenance concepts.

3.5 CHOOSING AN APPROPRIATE DISTRIBUTION MODEL

There are three main reasons for choosing life distribution model.

(1). There is a physical/statistical argument that theoretically matches a failure mechanism to a life distribution model.

(2). A particular model has previously been used successfully for the same or similar failure mechanism.

(3). A convenient model provides a good empirical fit to all the failure data.

Whatever method used to choose a model, the model should

- “make sense”- for example, don’t use exponential model with a constant failure rate to model a “wear out” failure mechanism.
- pass visual and statistical tests for fitting the data

There are several useful theoretical arguments to help guide the choice of a model. We will consider three of these arguments, they are

- **Extreme value argument**

If component or system failure occurs when the first of many competing failure processes reaches a critical point, then the extreme value theory suggests that the Weibull Distribution will be a good model.

- **Multiplicative degradation argument**

The lognormal model can be applied when degradation is caused by random shocks that increase degradation at a rate proportional to the total amount already present. The following processes are worth considering.

1. Chemical reactions leading to the formation of new compounds
2. Diffusion or migration of ions
3. Crack growth or propagation

These are failure mechanisms that might be successfully modeled by the lognormal distribution based on the multiplicative degradation model. Many semiconductor failure modes are caused by one of these three degradation processes. Therefore, it is no surprise that the lognormal model has been very successful for the following semiconductor wear out mechanisms:

- Corrosion – metal migration
- Electro migration – Diffusion
- Crack growth

- **Fatigue life (Birnbaun –Saunders) Model**

This is based on repeated cycles of stress causing degradation leading to eventual failure. A typical example is crack growth. One key assumption is that the amount of degradation during a cycle is independent of the degradation in any other cycle with the same random distribution.

When this assumption matches well with a hypothesized physical model describing the degradation process, one would expect the Birnbaun – Saunders model to be a reasonable distribution model.

3.6. MODELING OF LIFE DISTRIBUTION FUNCTION

The common application of probability theory, as well as the fundamental issue for this thesis is to predict the lifetime of a component using probability theory. The lifetime of a component or system can be described by a random variable X. The distribution function describes the probability that the lifetime is less than or equal to‘t’.

The fundamental functions for a one – dimensional, continuous, stochastic variable are defined as follows:

One way to describe the characteristics of a one – dimensional continuous variable (X) is to use its distribution function. For a given outcome of X, (x) is the probability P (X≤ x) that X is smaller or equal to x. If this is made for all of x, a function $F_X(x)$ = P (X ≤ x) is obtained, which is defined for all values in the interval -∞ < x < ∞.

Definition 3.6.1 The distribution function for the continuous one – dimensional random variable X is defined by

Fx (x) = P (X ≤ x), -∞ < x < ∞ ------------------------------ 3.8

The distribution function is evaluated as follows:

$F_X(x) = \int_{-\infty}^{x} fx(t)dt$ -------------------------------------- 3.9

If a function fx(x) exists such that equation 3.9 applies, then X is said to be a continuous random variable. The function fx(x) is called the density function for X.

Definition 3.6.2 The density function for the continuous one – dimensional random variable X is defined by: fx (x) = F$'x$ (x) **------------------------------ 3.10**

in every point x where fx (x) is continuous.

The density function describes how the total probability in (3.8) is distributed over the infinite number of possible values of x.

Based on the two functions introduced above, ($f_X(x)$ = F(t) and $f_X(x)$), the lifetime evaluation uses the two functions defined below:

Definition 3.6.3. The reliability function (or the survival probability function) $R_X(t)$, is defined by:

$$R_X(t) = 1 - F_X(t) \quad - - - - - - - - - - - \quad 3.11$$

Definition 3.6.4 The failure rate function (or hazard function) $\lambda_{(t)}$ is defined by:

$$\lambda_{(t)} = \frac{f_X(t)}{R_X(t)} \quad - - - - - - - - - - - - - \quad 3.12$$

An unavailability function, that is, the inverse of availability is consequently given as

$1 - R_X(t) = F_X(t)$.

In addition, there are two measurements that are of specific interest here, being the expected lifetime and the variance **V(x).**

The variance is commonly denoted by $\boldsymbol{\sigma}^2$. The variance measures the distribution of different outcomes for the random variable, and the standard deviation is defined by $\boldsymbol{\sigma} = \sqrt{\mathbf{V(x)}}$. The result is a measure of the distribution that has the same units as the random variable. Let X be the random variable for the length of life of a component or system of components. These characteristics are general and could be used to define any continuous random variable X. However, there are several distribution functions that are widely used for modeling, for example, uniform distribution, normal distribution, lognormal, exponential distribution, Weibull distribution and more. One way of modeling 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.

3.7. EXPONENTIALLY DISTRIBUTED RANDOM VARIABLE

The assumption that the lifetime follows an exponential function is widely adopted. The reason for this is that the resulting failure rate functions imply a constant failure rate. The characteristic functions are presented below.

Definition 3.7.1 An exponentially – distributed random variable $X \in Exp\ (m)$ has the following characteristics for the density and distribution functions respectively:

$$f_X(x) = \begin{cases} 1/m \cdot e^{-x/m} & if\ x \geq 0 \\ 0 & if\ x < 0 \end{cases} \quad ------- \qquad 3.13$$

where m > 0 and

$$F_X(x) = \begin{cases} 0 & \text{if } x < 0 \\ 1 - e^{-x/m} & \text{if } x \geq 0 \end{cases} \quad ------- \qquad 3.14$$

It can be easily deduced that the resulting failure rate function (defined in table 3.1) is constant, meaning that another notation for m is therefore **λ.**

3.8 WEIBULL – DISTRIBUTED RANDOM VARIABLE

The modeling of a system component that is accurate requires distribution functions that will allow different characteristics of the failure rate functions. One of the widely known distribution functions that include several characteristics for the failure rate functions is the weibull function.

Definition; A weibull – distributed random variable X€ Weibull (a,b) has the following characteristics for the density and distribution functions respectively:

$$f_X(x) = \begin{cases} \frac{c}{a}(x/a)^{c-1} e^{-(x/a)^2} & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \qquad 3.15$$

where a and c are positive numbers, and

$$F_X(x) = \begin{cases} 0 & \text{if } x < 0 \\ 1 - e^{-(x/m)^c} & \text{if } x \geq 0 \end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. \qquad 3.16$$

This function has been shown to be useful for example with breakdown strength data. Different values of the parameters a and c provide a band of distributions, and some special cases are: c = 1 which gives the exponential distribution, and c = 2 which gives the Rayleigh distribution.

3.9 FAILURE RATE MODELING FOR THE RCM STUDIES

The method for the modeling of failure rate that are used in this study is to either

(i) assume that the lifetime distribution equals a known distribution with an estimated parameter or

(ii) use data for an actual component and approximate functions for the same component. There are different techniques for approximating data to known functions, two of which are:

- Linear equation fit to data the least square method – where the data is fitted to a function, then the function is transformed into a linear function, and the resulting equation system is solved, or
- Polynomial fit to data where the data is fitted in a least square sense to a polynomial of a defined degree.

At least theoretically, a failure rate function could consequently be shaped into an infinite set of functions. The previous section presented an analysis of how the failure rate function would behave if the lifetime distribution followed the known weibull distribution.

3.10 METHOD OF RELIABILITY EVALUATION.

Presently, there are many techniques for reliability evaluation of Electrical power distribution systems.

Markov Method is generally, accepted to be the most accurate method of analysis [61]. However, the Markov Model becomes cumbersome to apply and in most cases impracticable for very complex systems. To overcome these problems, an approximate method is often employed. This approximate method is based on simple rules of probability. This method according to reference [62] has been shown to yield sufficient accuracy. The difference between it and that of Markov method leads to a computationally efficient technique known as minimal cut-set method. [52, 63]

3.10.1 Minimal Cut-Set Method Implementation.

This method is implemented in Matlab. The algorithm used is the series – parallel implementation of the Binary formulation of the Minimal cut set Method [52, 64].

The advantages of this approach have been extensively treated in the literature. This Method evaluates the load point reliability indices in two steps:

- The first step is to adopt the techniques of the failure modes and effect analysis (FMEA) to determine and list the component outage events which result in an interruption of service at the load point of interest. These are the Minimal Cut-Sets. Most of the available algorithms implement this through the generation of Minimal paths. [52, 65]. A minimal path is a set of system components, when in operation, provides the route for electrical energy transfer from source to the desired load point. No component in the set is used more than once. The minimal-cuts are deduced from the network topology.
- The outage/failures histories of the components as determined and listed above are combined using the reliability evaluation formulae to obtain the reliability indices at the desired load point. All components considered must be identified. These are identified by a number from 1 to k, where k is the total number of components identified in the system.

The reliability data normally required for each component in the network include:

(a) Forced and scheduled failure rates and their average durations.

(b) Switching times of circuit breakers throw – over switches and expected time to replace a blown fuse.

(c) Exposure length of power links such as cables and overhead lines.

3.10.2 The Choice of a Suitable Reliability Analysis Method.

The major problem that is normally faced, when evaluating the reliability of electrical power distribution systems is the determination of all the minimal cut-sets. In the past, some algorithms have been developed to determine the minimal cut-set. However, the uses of these algorithms are restricted by the following:

i. The network may contain unidirectional or bidirectional components.
ii. Nodes or branches are sometimes 100% reliable.
iii. A large number of sub networks of the system have to be considered.

The Binary Formulation of Minimal Cut-Set (BFMCS) method is one of an efficient algorithm that is capable of removing most of these restrictions listed above. This algorithm is based on Boolean algebra and set theory. The advantages of the BFMCS algorithm are listed in [66]. Minimal cut-sets are deduced from minimal paths generated from sources to the desired load point.

Unfortunately, the number of minimal paths grows exponentially with the number of nodes, number of sources and number of network components, relative position of the source to the desired load point and mode of interconnection between nodes.

The computer storage capacity required is usually very large when the BFMCS algorithm is applied to a large and highly connected network.

This will also increase the computation time. To minimize these problems, an algorithm based on graph and set theories is used to deduce the minimal cut-set without generating minimal paths. However, the nodes are assumed to be 100% reliable. This assumption is not useful in a network with pendant nodes. In practice, nodes are not perfectly reliable.

3.10.3 Reliability Evaluation Formulae for Load-Point Indices.

This section presents the formulae that are used in most of the programs for the evaluation of load-point indices. Both forced and scheduled outages are considered.

For N series components:

$$\lambda_s = \sum_{i=1}^{N} \lambda_i \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad 3.17$$

$$\lambda_s^{/} = \sum_{i=1}^{N} \lambda_i^{/} \quad \dots\dots\dots\dots\dots\dots\dots. \qquad 3.18$$

$$U_S = \sum \lambda_i \, r_i \quad \dots\dots\dots\dots\dots \qquad 3.19$$

$$r_s = \frac{\sum \lambda_i r_i}{\lambda_s} = \frac{U_s}{\lambda_s} \quad \dots\dots\dots\dots\dots. \qquad 3.20$$

$$LOE_s = U_s \, . P\, not \ \dots\dots\dots\dots\dots. \qquad 3.21$$

where Pnot = total number of customers x total active power per customer (Kw/Cust.)

These values provide the Customer and power input data.

For the second – order events (overlapping events) representing a parallel reliability system, where 1 and 2 represent the two components that fail.

$$\lambda_{12} = \frac{\lambda_1 \lambda_2 \, (r_1 + r_2)}{1 + \lambda_1 r_1 + \lambda_2 \, r_2} \approx \lambda_1 \lambda_2 (r_1 + r_2)$$

$$= \lambda_1(\lambda_2 r_1) + \lambda_2(\lambda_1 r_2) \quad \dots\dots\dots\dots\dots\dots \qquad 3.22$$

$$r_{12} = \frac{r_{\,1} r_2}{r_1 + r_2} \quad \dots\dots\dots\dots\dots\dots\dots\dots. \qquad 3.23$$

$$U_{12} = \lambda_{12} \, r_{12} \approx \lambda_1 \, \lambda_2 \, r_1 r_2 \quad \dots\dots\dots\dots\dots\dots. \qquad 3.24$$

It should be noted that, there is a difference in the units used for the parameters where average outage duration is given in hours but failure rate is evaluated in failures per year. The following conversion factor for hours/year is therefore required in all formulae including a mix of r and λ, 8760(hours/year).

These equations refer to overlapping events of the same failure type.

Considering the overlapping outages caused by two different failure types (x and y) in a similar manner. There would be four different combinations of overlapping events that would occur, and equation 3.22 would be extended accordingly to:

$$\lambda_{12}^{xy} = \lambda_1^x(\lambda_2^y\, r_1^x) + \lambda_2^x\,(\lambda_1^y r_2^x) + \lambda_2^y r_1^y + \lambda_2^y\,(\lambda_1^x\, r_1^y) \quad \dots\dots\dots\dots\dots. \quad 3.25$$

When several failure types are included, the restoration time will however be complicated.

For one of the four overlapping failure events, the resulting average time would be:

$$r_s^{/xy} = \frac{r_1^x\, r_2^y}{r_1^x\, r_2^y} \quad \dots\dots\dots\dots. \quad 3.26$$

Using equation 3.26 which is for each of the overlapping failure events and equation 3.25 as input in equation 3.20, then the following equation for the restoration time as.

$$r_s^{xy} = \frac{\lambda_1^x\ (\lambda_2^y\, r_1^x)}{\lambda_{12}^{xy}} \cdot \frac{r_1^x r_2^y}{r_1^x r_2^y} + \frac{\lambda_2^x\,(\lambda_1^y r_2^x)}{\lambda_{12}^{xy}} \cdot \frac{r_2^x r_1^y}{r_2^x + r_1^y}$$

$$+ \frac{\lambda_1^x\,(\lambda_2^y\, r_1^x)}{\lambda_{12}^{xy}} \cdot \frac{r_1^x\, r_2^y}{r_1^x + r_2^y} + \frac{\lambda_2^y(\lambda_1^x r_2^y)}{\lambda_{12}^{xy}} \cdot \frac{r_2^x r_1^y}{r_2^x + r_1^y} \quad \dots.. \quad 3.27$$

The following constraint however applies for scheduled maintenance: a component should not be taken out for maintenance if this would cause system failure.

The above constraint leads to the following two exceptions from the earlier equations:

(1) no first-order maintenance outages would occur; this is logical since scheduled maintenance would not be performed on a component if the effect would be the occurrence of a failure event, and

(2) no overlapping failures would occur if the second event is caused by maintenance.

3.11 WAYS FOR CONSTRUCTING THE DEVELOPED MODEL

In an attempt to model the deterioration process in electrical components in order to quantify its remaining life, a Markov model is introduced. To do this, various levels of deterioration are represented in a model through which the remaining life is estimated from the developed model.

An understanding of the basic deterioration process as well as the stresses which have an effect on the process is required for the estimation of the remaining life of any physical electrical components. In addition, the symptoms which accompany the deterioration must be known.

Some basic factors which can affect the occurrence and state of deterioration include the following:

- Level of temperature, voltage and mechanical stress (winding design).
- Cycling rate of the stresses (operating environment)
- Type 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 listed factor can results in a number of deterioration processes, which can cause failure.

3.11.1 Methods for determining the remaining life in electrical component:

Presently, there are three ways of determing the remaining life of distribution component insulation systems

- ✓ Monitoring stresses which are known to cause deterioration and observing the symptoms using inspection and test procedures and estimating the remaining life based on experience.

The first approach may not help in quantifying the remaining life, rather it will only act as a means of making sure that, no situation that is capable of shortening the life span of the component develops.

To determine (predict) the remaining life, one needs to monitor the possible stresses which can lead to insulation failure. With modern insulation systems, if no adverse thermal, mechanical or electrical stresses are present, the remaining life will probably be measured and estimated. Unfortunately, although many of the stresses that shorten insulation life can be measured during normal operation, many other important stresses cannot yet be monitored economically.

The second approach is to watch for any symptoms that indicate deterioration, either with diagnostic tests during normal service or with inspections and tests during outages. Life is then estimated by comparing the severity of the observed symptoms with those seen in the past (ie based on experience). This approach requires considerable expertise, and could require many inspection outages.

The third approach to determining the remaining life of a component insulation system is by modeling the deterioration processes through a homogenous Markov model. This approach is adopted in this thesis.

3.11.2 Developing the Markov Model for the estimation of the remaining life

For the system under study, four states can be identified with reasonable accuracy:

(a) Normal or working state
(b) Minor deteriorating state
(c) Major deteriorating state and
(d) Failure state

In developing this model, we will assume 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 occur as a result of other causes not associated with typical ageing and we will call such a failure a random or poisson outage. If the deterioration process is discovered, preventive maintenance is performed which is expected to restore the system back to the original condition of deterioration (assumed).

Repair maintenance, after either random or deterioration induced failure, will restore the system to a new condition.

All these assumptions are incorporated in the developed state –space Markov model. A model based on discrete parameter (succession of events) is presented.

This system is described through the transition probabilities $P_{(ij)}$ indicating the probability of moving from state i to state j in a given time interval ΔT.

Markov model representing various stages of deterioration that will eventually culminate in failure is presented. This model is presented in figure 3.4.

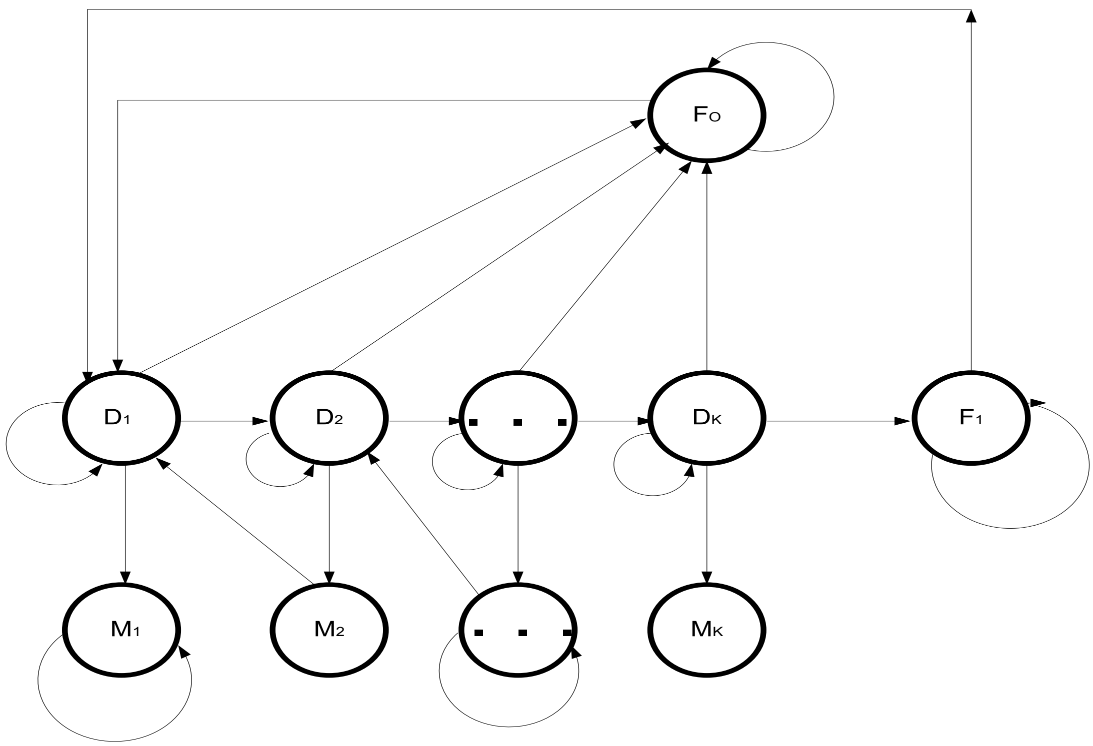


Figure 3.4 Discrete – parameter Markov model for the determination of the remaining life

In the model shown in figure 3.4, $D_1 \ldots D_k$ denote deterioration states, with D_1 being the normal state. $M_1 \ldots M_k$ denote 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 using standard Markov techniques as outlined below:

Transition probability matrix $P = [P_{(i\,j)}]$ is constructed from inspection /observation data 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

$$P = \begin{bmatrix} Q & R \\ O & T \end{bmatrix} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad 3.28$$

where $T = P(F_1 F_1)$ since state F_1 is the last in the state array.

From here, Matrix N, called the 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. $N_{i\,j}$ represents the $i\,j^{th}$ element of N, T_i the sum of the entries in row i of N. $b_{i\,j}$ the $i\,j^{th}$ entry of the matrix B = NR.

- The number $N_{i\,j}$ is the average number of times the process is in the j^{th} transient state if it starts in the i^{th} transient state.
- The number T_i is the average number of steps before the process enters an absorbing state if it starts in the i^{th} transient state.
- The number $B_{i\,j}$ is the probability of eventually entering the j^{th} absorbing state if the process starts in the i^{th} transient state.

It can be shown that the elements of N, $N_{i\,j}$ 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

$$M_i = \sum N_{i\,j} T_j = \sum_j \left(N_{ij} \Delta T \Big/ \sum_{k \neq j} P_{(j,k)} \right) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad 3.29$$

where T_j is the mean time spent in state j.

3.11 3 Methods based on continuous time

In engineering practice, it is often easier to determine transition rates than transition probabilities. A Markov model for the evaluation of the remaining life of insulation based on continuous parameter is shown in figure 3.5.

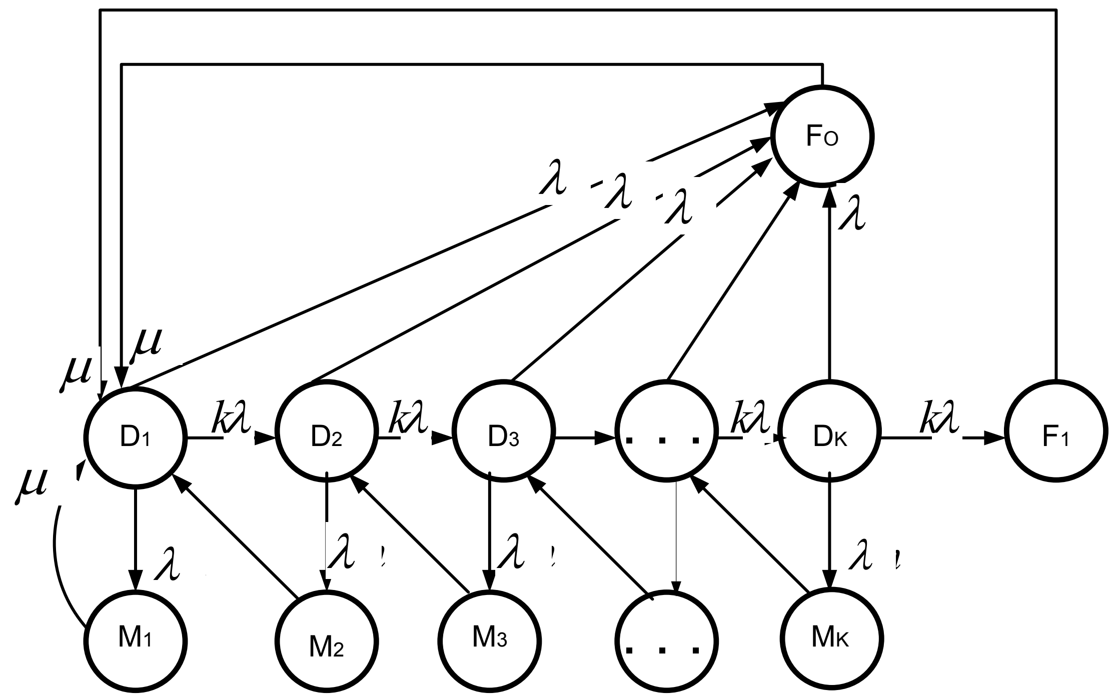


Figure 3.5 Continuous parameter Markov model

3.11.4 Determination of the transition rate parameter

All parameters can be estimated from historical records, except for $\boldsymbol{\lambda}$, the reciprocal of the mean time to failure if no maintenance is carried out.

To obtain the value of $\boldsymbol{\lambda}$, proceed as follows:

- Observe the average time to deterioration failure $\boldsymbol{T_f^*}$. this is the average time between failure events and it can be easily recorded.
- Solve the Markov model for various values of $\boldsymbol{\lambda}$, to obtain the function shown in figure 3.6.
- From this function, determine the values of $\boldsymbol{\lambda}^*$ corresponding to the value of $\boldsymbol{T_f^*}$ recorded earlier.

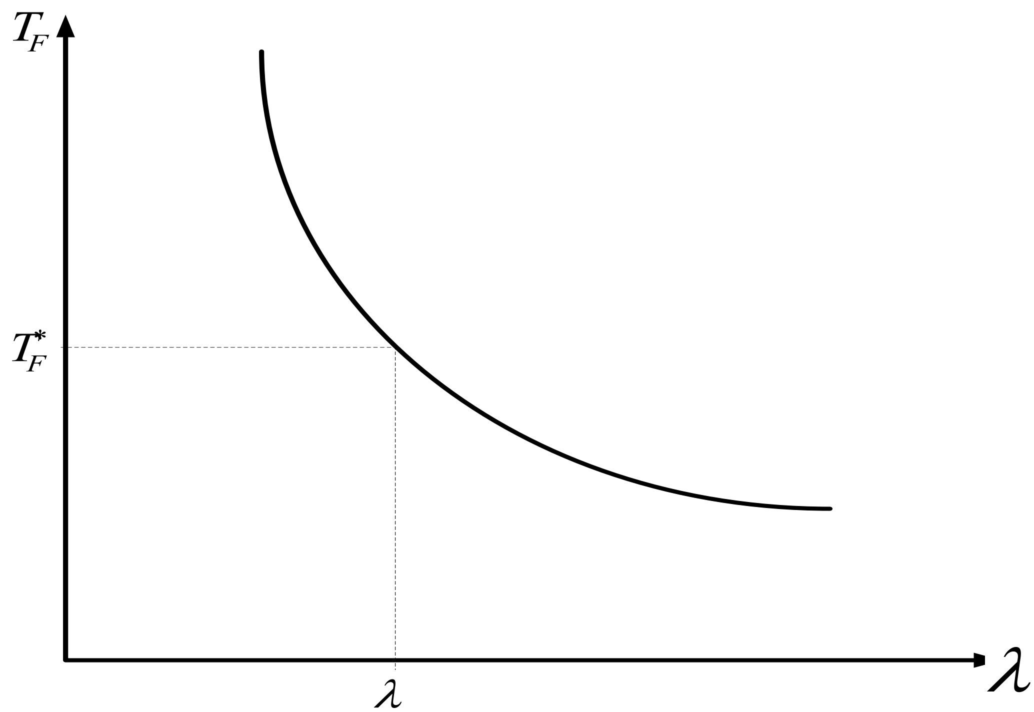


Figure 3.6 Function of the mean time to failure versus failure

To determine the expected time for a component failure, figure 3.5 can now be reduced to figure 3.7 where transition rates are used instead of transition probabilities.

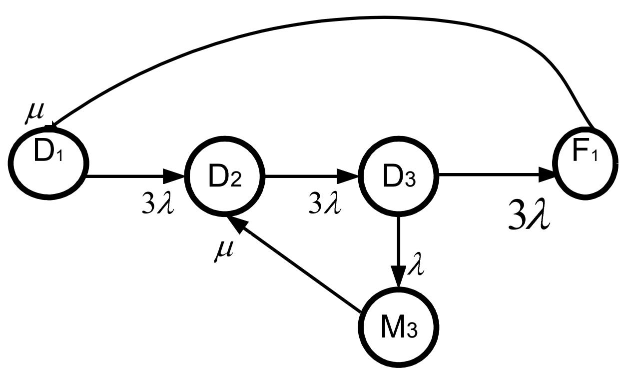


Figure 3.7 Markov model with continuous parameter.

For k = 3, we also denote state $\boldsymbol{D_2}$ by i and state $\boldsymbol{F_1}$ by j. Applying the rules for state combination [67] as illustrated in figure 3.8, we have

$\boldsymbol{\lambda_{is}} = \boldsymbol{3\lambda}$, $\boldsymbol{\lambda_{js}} = \boldsymbol{\mu}$

$$\lambda_{is} = \frac{P_{D1}3\lambda + P_{M3}\mu_M}{P_{D1} + P_{D3} + P_{M3}} \quad 3.30$$

$$\lambda_{Sj} = \frac{P_{D3}3\lambda}{P_{D1} + P_{D3} + P_{M3}} \quad 3.31$$

where P_{D1}, P_{D3} and P_{M3} are the steady–state probabilities of the system states indicated.

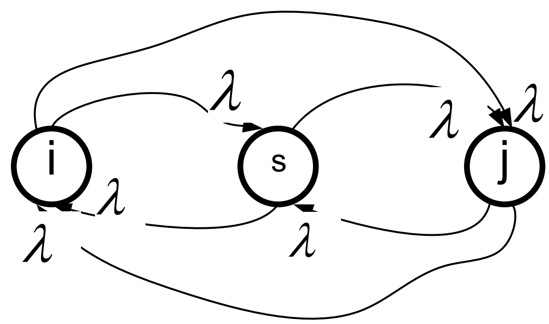


Figure 3.8 Diagram illustrating development of the mean transition time between states i and j.

3.11.5 Determination of steady- state probabilities

The steady - state probabilities needed in equations (3.28 and 3.29) are obtained by solving the equations P.Q = O

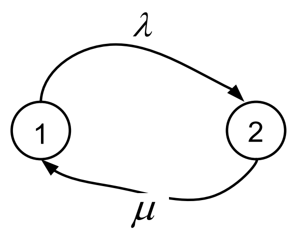
The p_i are the unknown values we wish to find since they are the steady- state probabilities of the system states indicated in figure 3.5. If there are n – states in the state space, there are n such equations in n – unknowns. Unfortunately, this collection of equation is irreducible. We need another equation in order to solve the equations and find the unknowns. Fortunately, since $\{p_i\}$ is a probability distribution, we also know that the normalisation condition holds.

$\sum_{x_i \in S} P_i = 1$ These n +1 equations, can be solved to find the n unknowns $\{P_i\}$

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.

$$Q = \begin{pmatrix} -\lambda & \lambda \\ \mu & -\mu \end{pmatrix}$$



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 3.28 and 3.29 for evaluating λ_{is} and λ_{sj}.

3.11.6 Determination of the mean time to failure (first passage time)

Computing the mean time to failure (first passage time)M_{D2F1}, we 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 P_{si} denote the probability of the first (transferring to state i) and

P_{sj} denote the probability of moving from state S to state j i.e

$$P_{si} = \frac{\lambda_{si}}{\lambda_{si} + \lambda_{sj}} - - - - - - - - \quad 3.32$$

$$P_{sj} = 1 - P_{si} - - - - - - - - - \quad 3.33$$

From the analysis of possible transitions [68] in figure 3.8, we have

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

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

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

$$\boldsymbol{M_{ij}} = \frac{1}{\lambda_{is}} \cdot \frac{1}{1 - P_{si}} + \frac{P_{sj}}{\lambda_{sj}} + \frac{P_{sj}P_{si}}{\lambda_{sj}} \cdot \frac{1}{1 - P_{si}P_{sj}} + \frac{P_{si}}{\lambda_{si}} \cdot \frac{1}{1 - P_{si}} \text{ -------------------- } 3.34$$

Numerical Example Using a Continuous parameter.

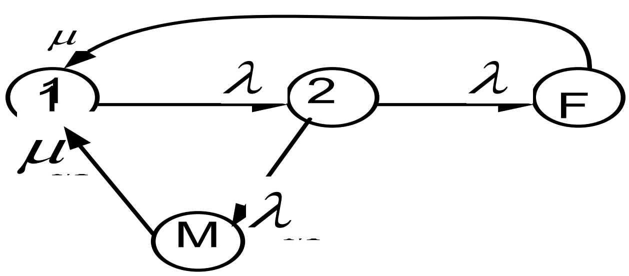


Figure 3.9 A simple maintenance model under deterioration failure

To illustrate the steps outlined in the model, a simple four-state deteriorating component with failure due to deterioration and a maintenance state is solved analytically for a clearer understanding of the model.

From the four-state diagram shown in figure 3.9, the transition probabilities Q are constructed as shown below.

Q represents the intensity matrix or transition probabilities. It is therefore made up of a 4 by 4 matrix having the elements of D_{11},D_{12}, M_{13}, and F_{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:

$D_{11} = -\lambda$ (state transition from state1 to state2 and is negative because is transiting state1 to state2).

$D_{12} = \lambda$ (state transition from state1 to state2, and is positive since the state transition is entry state2).

$M_{13} = 0$, $F_{14} = 0$ (Since there are no transitions between state1 and state3 and state4 respectively). All the entries in the other rows in Q were obtained from figure 3.9 in the same way.

With these transition probabilities, the steady- state probabilities were computed as illustrated in the numerical example.

$$Q = \begin{bmatrix} D_{11} & D_{12} & M_{13} & F_{14} \\ D_{21} & D_{22} & M_{23} & F_{24} \\ D_{31} & D_{32} & M_{33} & F_{34} \\ D_{41} & D_{42} & M_{43} & F_{44} \end{bmatrix}$$

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

Assuming that $\lambda = 0.5,\ \lambda_M = 0.6,\ \mu_M = 22,\ \mu = 4.1$

$$P*Q = \text{) That is } [P_1 \quad P_2 \quad P_M \quad P_F] \begin{bmatrix} -\ .5 & 0.5 & 0 & 0 \\ 0 & -\ .1 & 0.6 & 0.5 \\ 22 & 0 & -\ 2 & 0 \\ 4.1 & 0 & 0 & -\ .1 \end{bmatrix} = 0 \ldots\ldots\ldots \quad 3.35$$

$calculating\ the\ steady -$
$state\ probabilities\ (P_1,\ \ P_2,\ \ P_M,\ and\ P_F)\ from\ the$
$generated\ transition\ probabilities\ and\ the\ normalisation\ condition\ of$
$\sum_{xi \in S} (P_i) = 1, as\ follows$:

From equation 3.33, the following equations are formulated,

$$\left\{\begin{array}{c} -0.5P_1 + 0 + 22P_M + 4.1P_F = 0 \\ 0.5P_1 - 1.1P_2 + 0 + 0 = 0 \\ 0 + 0.6P_2 - 22P_M + 0 = 0 \\ 0 + 0.5P_2 + 0 - 4.1P_F = 0 \end{array}\right\} \quad \ldots\ldots\ldots\ldots\ldots \qquad 3.36$$

From equation 3.34,

$$0.5P_1 = 1.1P_2 \Rightarrow P_1 = \frac{1.1}{0.5}P_2, \quad 0.6P_2 = 22P_M \Rightarrow P_M = \frac{0.6}{22}P_2$$

$$0.5P_2 = 4.1P_F \Rightarrow P_F = \frac{0.5}{4.1}P_2$$

The normalisation equation gives, $P_1 + P_2 + P_M + P_F =$ ………….… 3.37

Substituting for P_1, P_M *and* P_F *in equation* 3.35,

$$\frac{1.1}{0.5}P_2 + P_2 + \frac{0.6}{22}P_2 + \frac{0.5}{4.1}P_2 =$$

$$3.35P_2 = 1 \Rightarrow P_2 = 0.2985$$

$$P_1 = 0.6567, \quad P_M = 0.0081 \quad and \quad P_F = 0.0364$$

With these values, λ_{is} and λ_{Sj} can now be evaluated from these equations:

$$\lambda_{is} = \frac{P_{D1}3\lambda + P_{M3}\mu_M}{P_{D1} + P_{D3} + P_{M3}} \quad and \quad \lambda_{Sj} = \frac{P_{D3}3\lambda}{P_{D1} + P_{D3} + P_{M3}}$$

$o0$

$$\lambda_{is} = \frac{0.6567\ x\ 0.5 + 0.0081\ x\ 22}{0.6567 + 0.298 + 0.0081} = \frac{0.50655}{0.9628}$$

$$= 0.526121728$$

$$\lambda_{sj} = \frac{0.298 \ x \ 0.5}{0.9628} = 0.154756958$$

Also, from equation 3.1, we have

$P_{Si} = \frac{\lambda_{Si}}{\lambda_{si} + \lambda_{sj}}$ and $P_{sj} = 1 - P_{si}$

$$P_{si} = \frac{0.526121728}{0.526121728 + 0.154756958} = 0.772709939$$

$$P_{sj} = \frac{0.154756958}{0.526121728 + 0.154756958} = 0.22729006$$

Substituting these values in equations 3.2 reproduced below:

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

$$M_{ij} = \frac{1}{0.526} \ x \ \frac{1}{1 - 0.7727} + \frac{0.22729}{0.154756958}$$

$$+ \frac{0.22729 \ x \ 0.77271}{0.154756958} \ x \ \frac{1}{1 - 0.22729 \ x \ 0.77271}$$

$$+ \frac{0.77271}{0.5261217} \ x \ \frac{1}{1 - 0.77271}$$

= 17.66 yrs.

3.11.7 Interpretation of the computed result

The value obtained is the estimation of the expected life from a given deterioration state.

In addition to this, the following questions can also be answered:

i. What is the average number of years for the system to transfer from the current state to a failure state?

ii. What is the expected time for the insulation to be in a particular deterioration state?
iii. How many years will it take for the insulation to be in a particular deterioration state for the first time given that it is in a specified state now?
iv. How long, on the average, will each deterioration state last?
v. What is the long range probability of the insulation being in any of the state in figure 3.5?

The model is also capable of allowing, through sensitivity studies of the relatives effects of various other parameter in the process which are controllable e.g. maintenance policy, stress level and operating condition.

With more work, one could compute the probability density functions which we help us answer the duration questions asked for in i to iv.

For now, the results obtained with this model represent the average values of the computed quantities based on the input parameters obtained from observing the statistics of similar transformers.

Computer program using MatLab for the Numerical example.

The computer program using Matlab sequential operations for computing the remaining mean life for the identified distribution component is as illustrated below for the example in figure 3.9.

The program below shows how MatLab solves the model described above.

```
% Computer program for computing the mean time to failure

% calculating the values for first passage time.

lamda = 0.5;

q1 = [-0.5,0,22,4.1;0.5,-1.1,0,0;0,0.6,-22,0;0,0.5,0,-4.1;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 = 0.6569 , P_D2 = 0.2986 ,P_M = 0.0081, P_F = 0.0364

```
mew = 4.1;

mewm = 22;

lamdam = 0.6;

P_D1  = 0.6569;

P_D3 = 0.2986;

P_M3 = 0.0081;

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: 0.5134, lamdasj is: 0.1549,P_si is: 0.7682,P_sj is: 0.2318

vera_1 is: = 8.4020, vera_2 is:= 1.4963, vera_3 is:= 1.3984,vera_4 is:= 6.4541

The mean remaining life of the component is:m_ij = 17.7508.

CHAPTER FOUR

APPLICATION OF THE RCM MODEL TO PHCN NETWORK.

4.1 Introduction

Reliability - centred maintenance has been developed to assist asset managers in maximizing the safety and serviceability of infrastructure facilities within the available budget of making cost - effective maintenance and replacement decisions [69]. The quality of these decisions depends significantly on the accuracy and efficiency of the deterioration models used to predict the time dependent performance and the remaining life of the infrastructure facilities [70]. A deterioration model is defined as a link between measures of facility condition that assess the extent and severity of material damages and other factors that represent facility deterioration, such as age, material properties, applied loads, environmental conditions etc.[71].

Several deterministic and stochastic approaches have been developed to model component deterioration [72]. Deterministic approaches, such as straight – line extrapolation, and multiple regression, have the advantages of being simple to develop and easy to use. However, the existence of deterioration parameters that are not typically observed or measured, subjectivity and inaccuracy of component inspection, and stochastic nature of the deterioration process led to the wide spread of stochastic models. These models are able to capture the physical and inherent uncertainty, model uncertainty, and statistical uncertainty, while predicting the future performance of distribution components [73].

Although the deterioration of distribution components is a continuous and gradual process that may span over decades, discrete ratings or states are commonly used to represent facility conditions. This is because discrete rating systems simplify facility inspection, deterioration modeling, and maintenance optimization [74].

Stochastic models used to predict the deterioration of distribution components can be grouped into two main categories: state – based models and time – based models

State – based models predict the probability that a facility will have a change in its condition state during a fixed time interval and accumulate this probability over multiple intervals. Markov chain models and semi – markov models are the most common example of state – based models.

Time – based models predict the probability distribution of the time taken by a component to change its current condition state to the next lower condition state.

In this thesis, a state - based stochastic deterioration models for the prediction of the remaining life of a distribution transformer is developed.

Distribution transformer was selected because they were found to be one of the critical components in the distribution network studied.

The first section presents the network topology and the data used in identifying the critical components in the model development.

The second and third sections explained the program used for the identification of the critical component and the development of the Markov – chain model for evaluating the remaining life of the identified component so that informed decisions can be taken on the suitability of the continuous operation of the component.

4.2 THE NETWORK TOPOLOGY DESCRIPTION

Electric power is a vital element in any modern economy. The availability of a reliable power supply at a reasonable cost is crucial for economic growth and development of a country. Electric power utilities throghout the world therefore endeavor to meet customer demands as economically as possible and at a reasonable level of service reliability. The determination of what is reasonable level of service reliability has often been based arbitrarily on techniques such as percentage reserve or single contingency evaluation. These traditional methods of evaluation fail to address relevant power systems issues in developing countries.

The main problems faced by electric power utilities in developing countries today is that **the power demand is increasing rapidly wheras the supply growth is constrained by ageing generating plants, scarce resources for constructing new ones and other societal issues.** This has resulted in a need for constructing new additional generating plants and a more economic way of planning and maintaining Electric power distribution assets. System planning and maintenance based on reliability – centred asset management approach will provide an opportunity to justify one of the most vulnerable economic sectors in developing countries.

It is with this objective that distribution network maintenance surveys were conducted in selected service areas of the Power Holding Company of Nigeria (PHCN). The unbundling of NEPA now PHCN had led to the establishment of 18 successor companies from NEPA comprising 6 Generation Companies, one Transmission Company and 11 Distribution Companies [75]. The Lagos zone is now made up of two distribution companies namely Eko distribution Zone with head office at 24/25 Marina, Lagos and Ikeja distribution Zone with head office at Alausa, Opposite MITV, Ikeja. The data used in this thesis is collected from distribution network in Ikeja distribution Zone. Figure 4.1 shows a line diagram of the two distribution companies in Lagos area. This system is considered to be representative model of electric supply systems in many developing Countries.

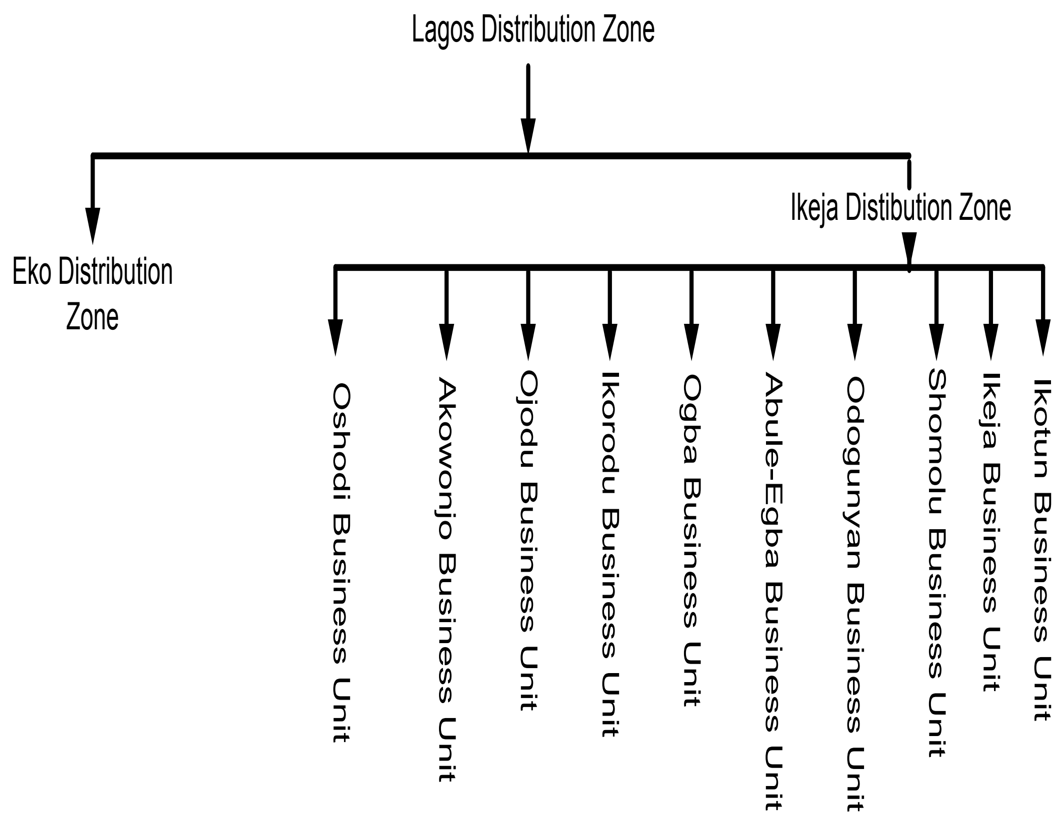


Figure 4.1 Block diagram showing the origin of Ikeja distribution Zone.

The study was centred on Ikeja distribution Zone with particular reference to Abule – Egba Business units that are made up of Industrial, Commercial and Residential customers. This again is shown in Figure 4.2. This unit is made up of ten (10) busbars normally referred to as injection Substations. These injection substations are fed by 4x60MVA, 132/33kV transformers from different substations located within the Zones.

These ten injection substations in turn feed twenty seven 11kV different customer feeders with 647 different load – points.

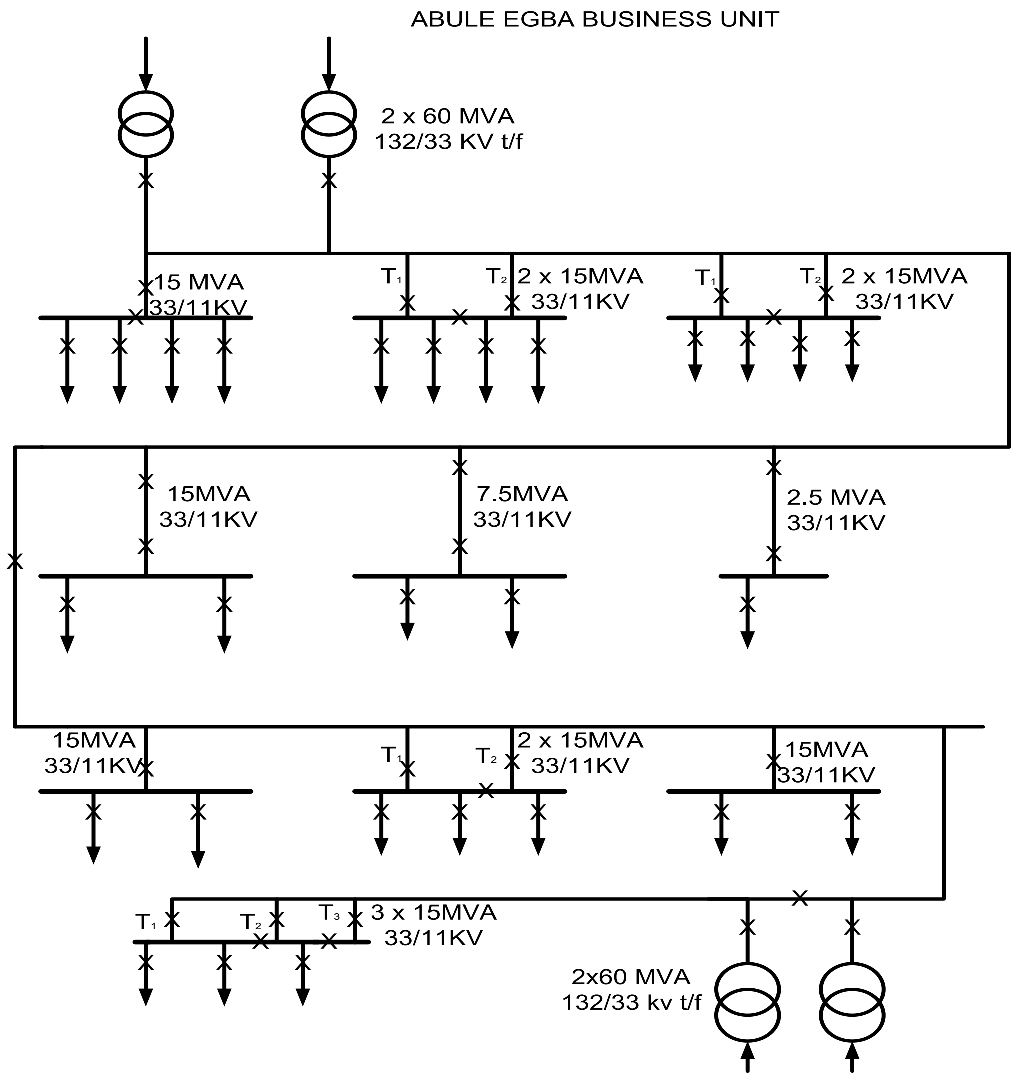


Figure 4.2 Line diagram showing 10 injection substations.

A typical distribution system showing a section of the Ikeja Zones Network feeders is reprsented in a line diagram in Figure 4.3. PHCN called this section Abule-Egba bussiness unit. This unit was created on 1st July 2005; it was carved out of the old Ikeja and Akowonjo (formerly Alimosho) districts.

It covers Ayobo, Igbogila, Ipaja, Majiyagbe, Commands, Ajasa, Amikanle, AIT, Agbado, Ijaye, Abule Egba, Isefun, Iju, and New Oko- oba, Adiyan, Obawole, Oke-Aro, Lambe, Ilupeju, Titun, Beckley Estate, Itoki, Baruwa, Fgba, Lemode and Ajegunle. It shares boundaries with Akowonjo, Ogba, Ojodu and Ota Business unit in Ogun state.

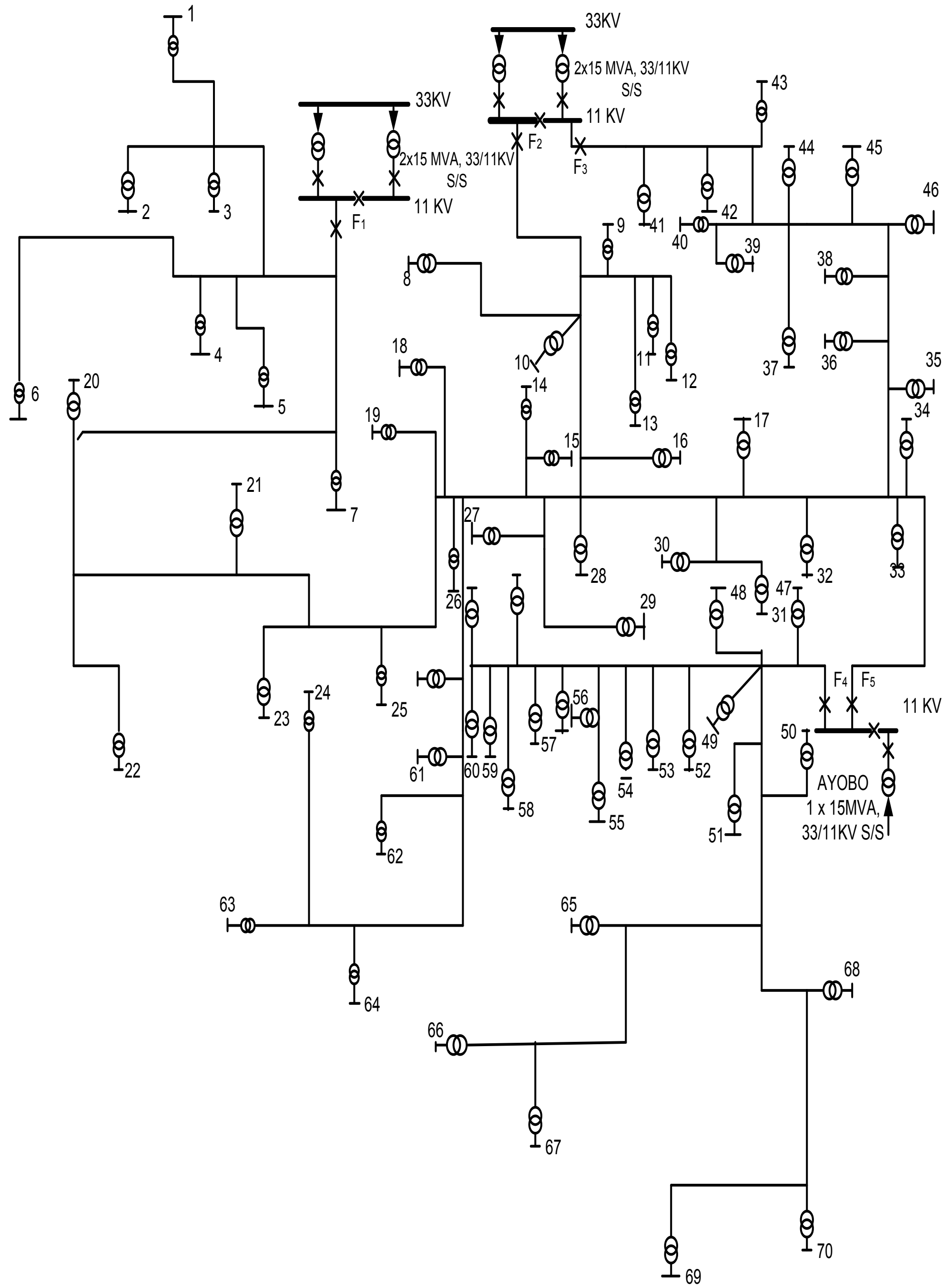


Figure 4.3. A section of the Abule Egba distribution bussiness unit

The raw outage data collected on the entire Business unit was processed and then plotted on histogram in figures 4.5 to 4.8. The feeder with the highest failure rate was selected for a more critical analysis. Figure 4.4 shows the identified feeder that was subjected to more critical analysis.

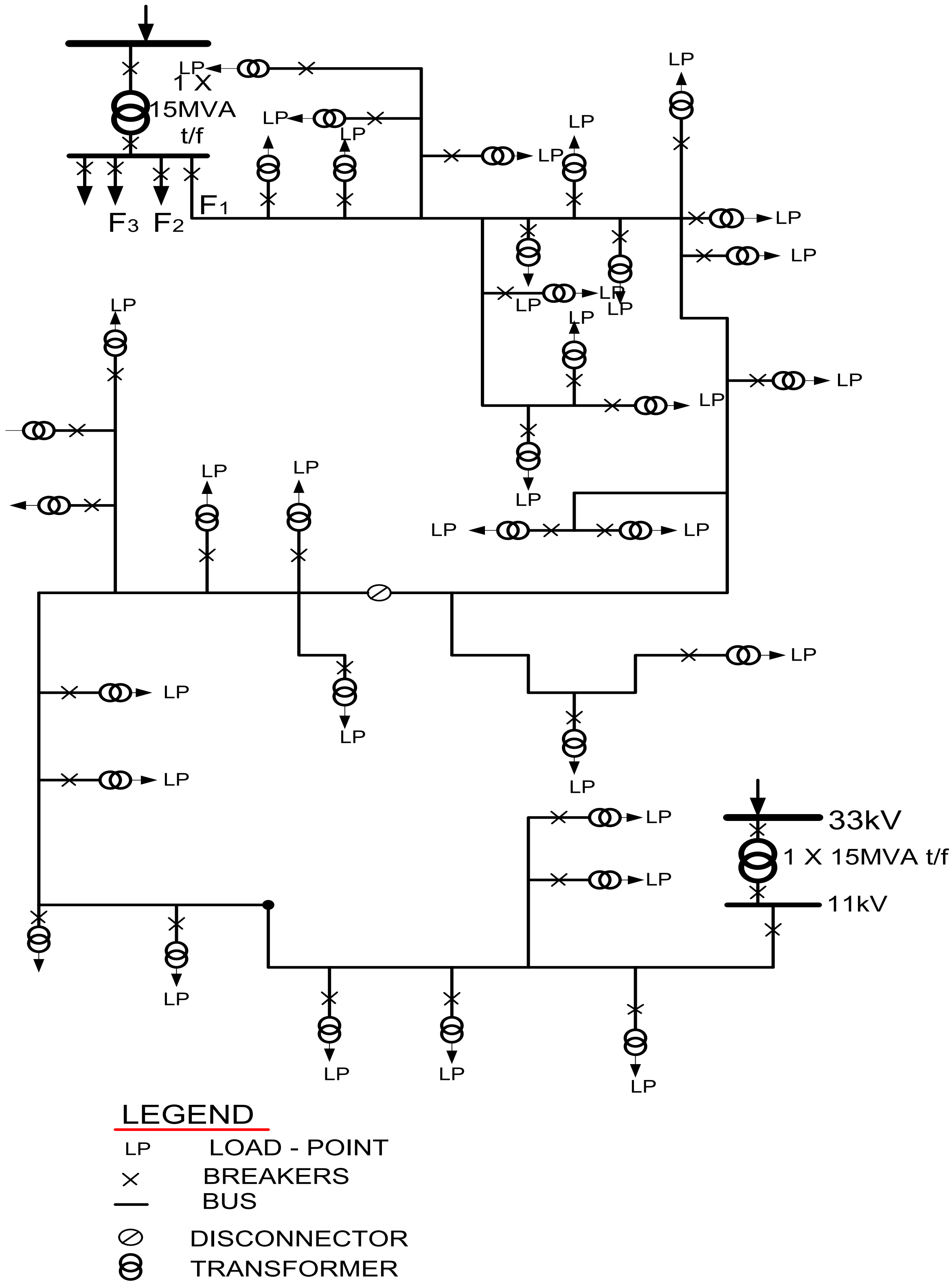


Figure 4.4 A typical customer feeder in Ojokoro injection substation.

In most cases, any distribution network comprises the following:

- Lines conductors (lines, poles and related items).
- Cables (cables, junctions and related items).
- Breakers.
- Transformers.
- Disconnecters (Buscoupler).
- Isolators.
- Fuses and
- Bus bars.

For the purpose of this study, outage data that resulted in system failure because of the failure of any of the listed components above was collected from the outage log book. Only those components found to be critical and which are also impacted by maintenance were analysed.
These data were collated and processed.

4.3 DATA COLLECTION AND PROCESSING

Maintenance of critical equipment is an essential part of power systems. In today competitive power systems, planning for maintenance constitutes an essential part of asset management. However, in most developing countries, this essential part of asset management may receive no attention at all or at best very limited interest from owners of these utilities. The consequences of this would be frequent power interruptions associated with equipment failures/repairs. Computer models therefore remain the most reliable technique for predicting component failure during system operation. It can be used to predict deterioration failure and predict time to complete failure of the component.

The foundation of this process is in the collection of all types of observed failure data. This data set then constitutes the failure sample space. It is the subsequent statistical analysis of the data that will provide valuable insight into the **failure rate and time to failure.** These two are the essential building blocks of any predictive maintenance planning program.

The good data mining techniques to the failure data space can transform the maintenance planning program from a preventive plan into a predictive one that will attempt to arrest system failure before they even occur.

4.3.1 Outage Data Gathering

The starting point for an effective maintenance program using information from failure data is to first decide which data to collect and the method of collecting it. In some organisations, this effort is almost institutionalized; however, in the distribution company of PHCN this critical and all important aspect of maintenance planning is almost non – existent. What is practised here is breakdown maintenance.

4.3.2 Data Analysis Techniques

After a reasonable amount of data has been collected, the data sets to be used for analysis are then obtained after pre – fittering and removal of extraneous events. These events include outage due to scheduled maintenance and those due to load shedding.

We then consider the properties of the aggregate system component outage failure data, deriving simple empirical relationships from the data sets before delving into the statistical analysis of the constituting components.

The data structure has to be well thought out to be able to extract reasonable information from the collected data. The starting point for the statistical analysis is to attempt to gain a better understanding of properties of the raw data usually by imposing the corresponding empirical distribution of each of the component failure data.

This was achieved by constructing a histogram over the sample space. Figures 4.5 to 4.8 shows a typical failure histogram constructed for Abule Egba business unit, containing ten (10) injection substations. The simple histogram immediately gives indication of the dominant failure events and can equally reveal the injection substation or customer feeder that is mostly affected.

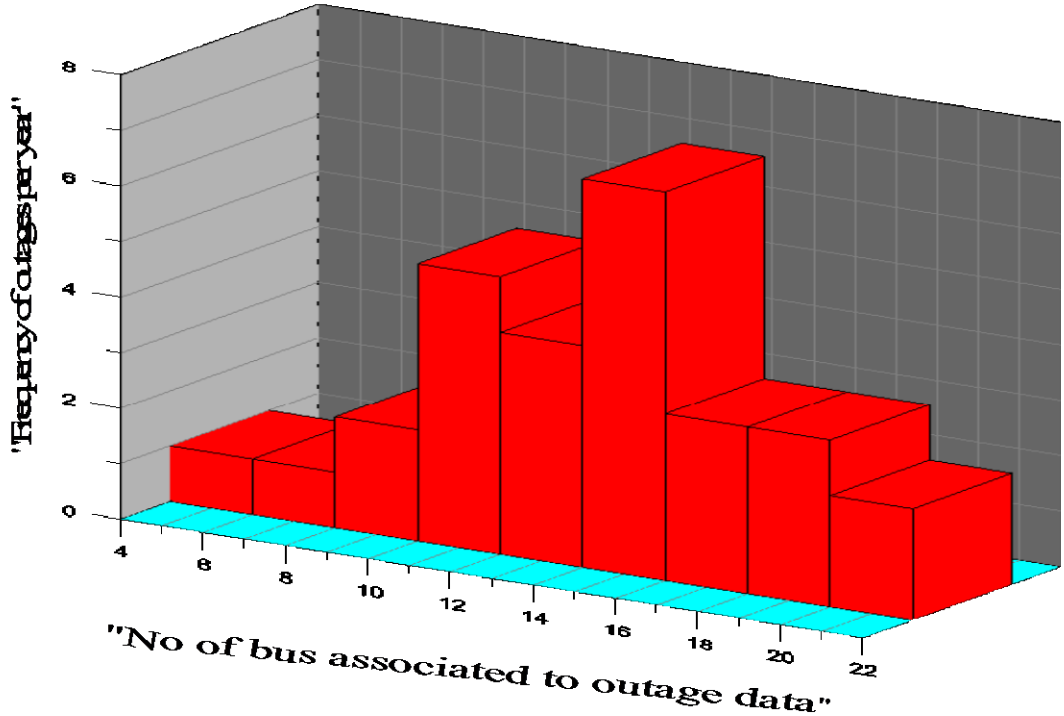


Figure 4.5 Processed 2005 outage data for Abule egba business unit.

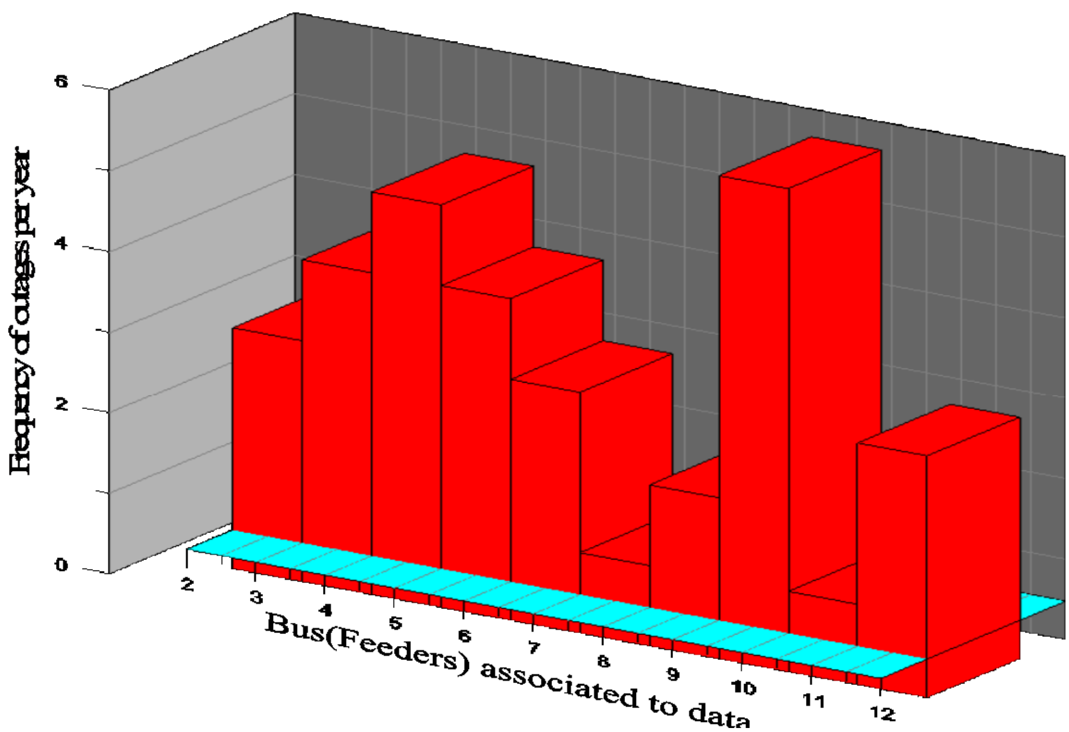


Figure 4.6 Processed 2006 outage data for Abule egba business unit.

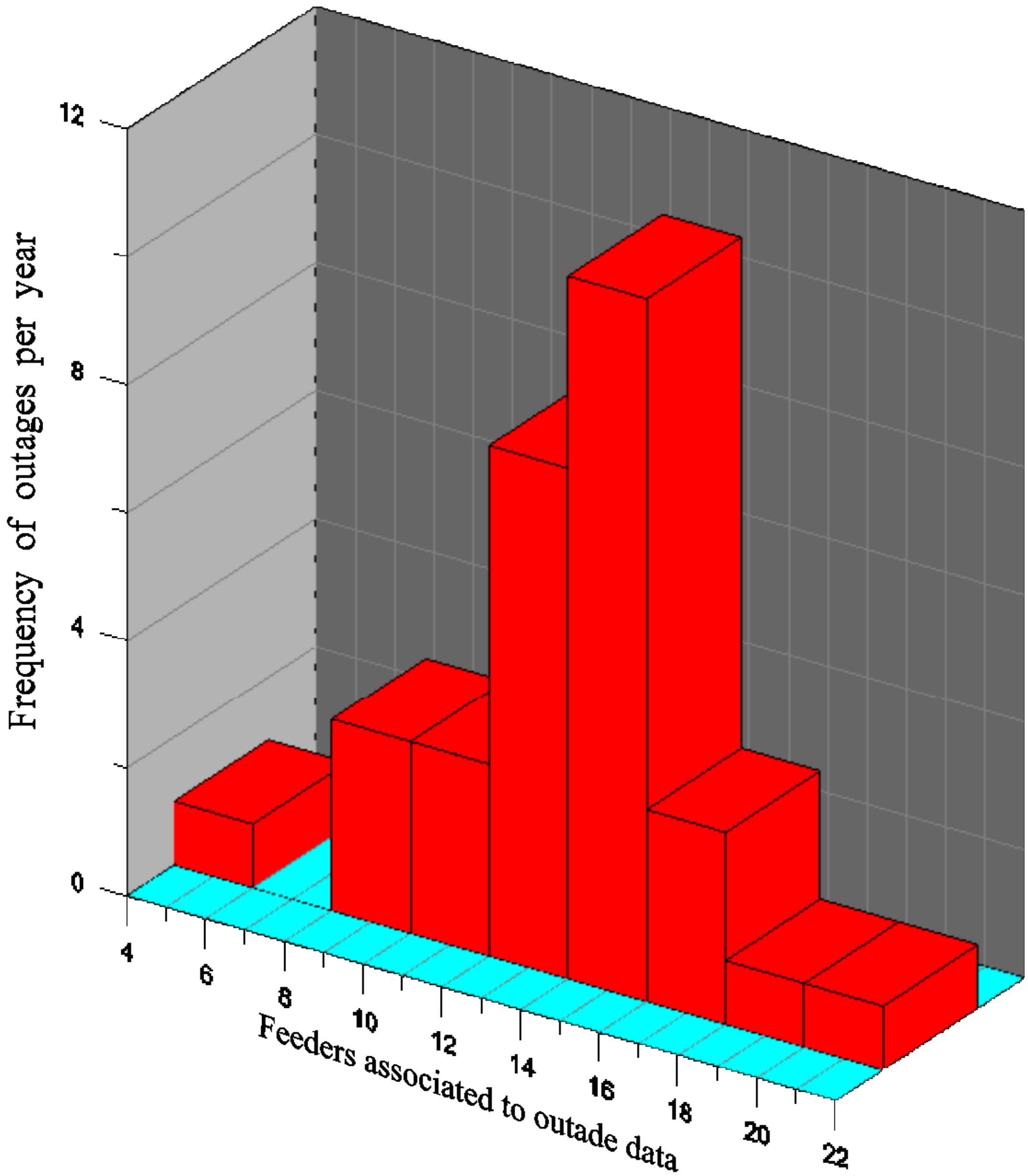


Figure 4.7 Processed 2007 outage data for Abule egba business unit.

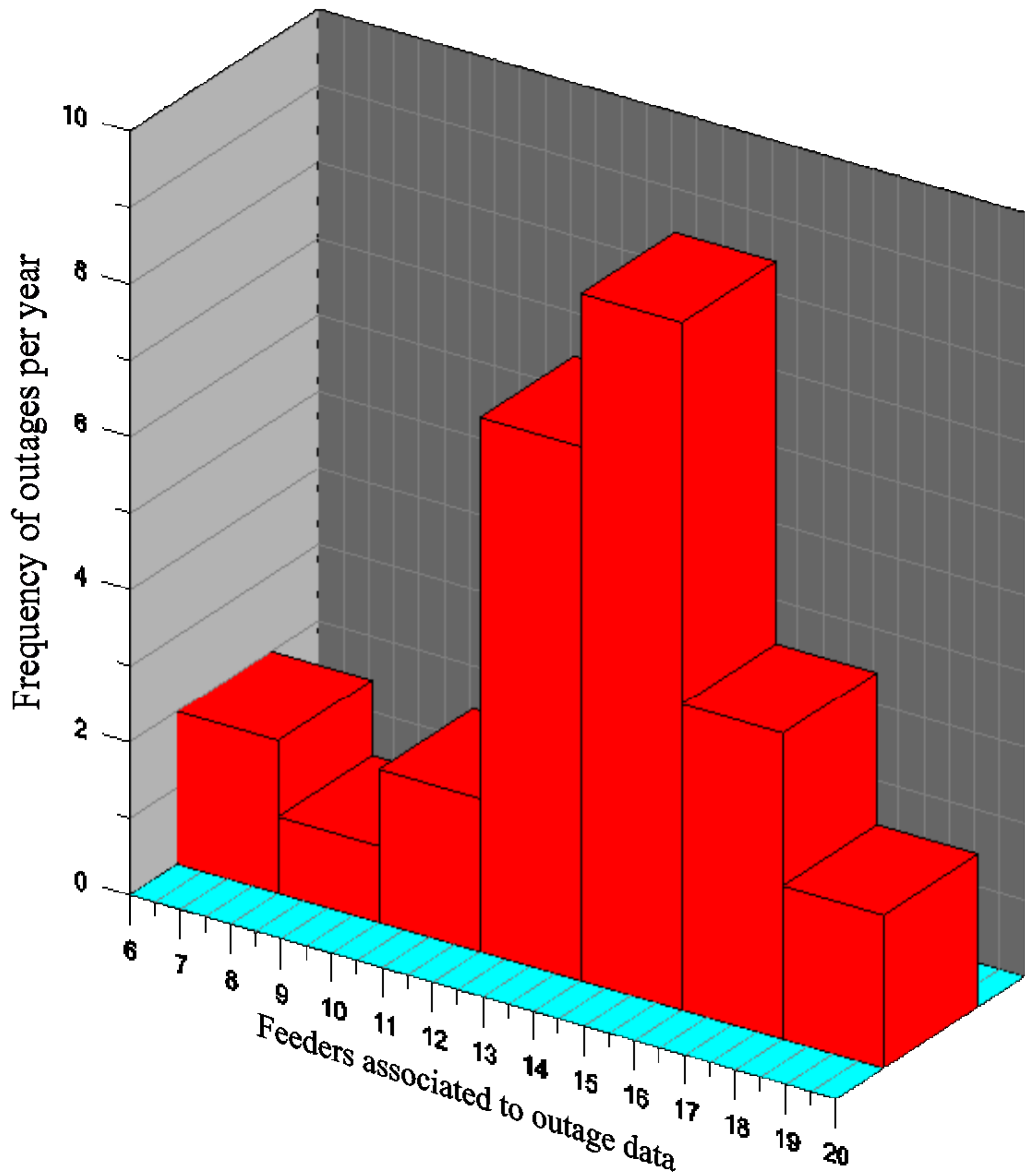


Figure 4.8 Processed 2008 outage data for Abule egba business unit.

Ijaye Ojokoro injection substation containing four customers' feeders was identified from the outage data collected. This was graphically illustrated in the histogram shown in (Figures 4.9 to 4.12). From the analysis of the data collected from this Injection substation, estimates of mean time between failure [MTBF], failure rate [λ] and mean time to repair [MTTR] were determined for the whole Injection substation as well as for each customer's feeders. The performance statistics from the synthesized failure data set for five years 2003 to 2008 is shown in table 4.1a - table 4.1e.

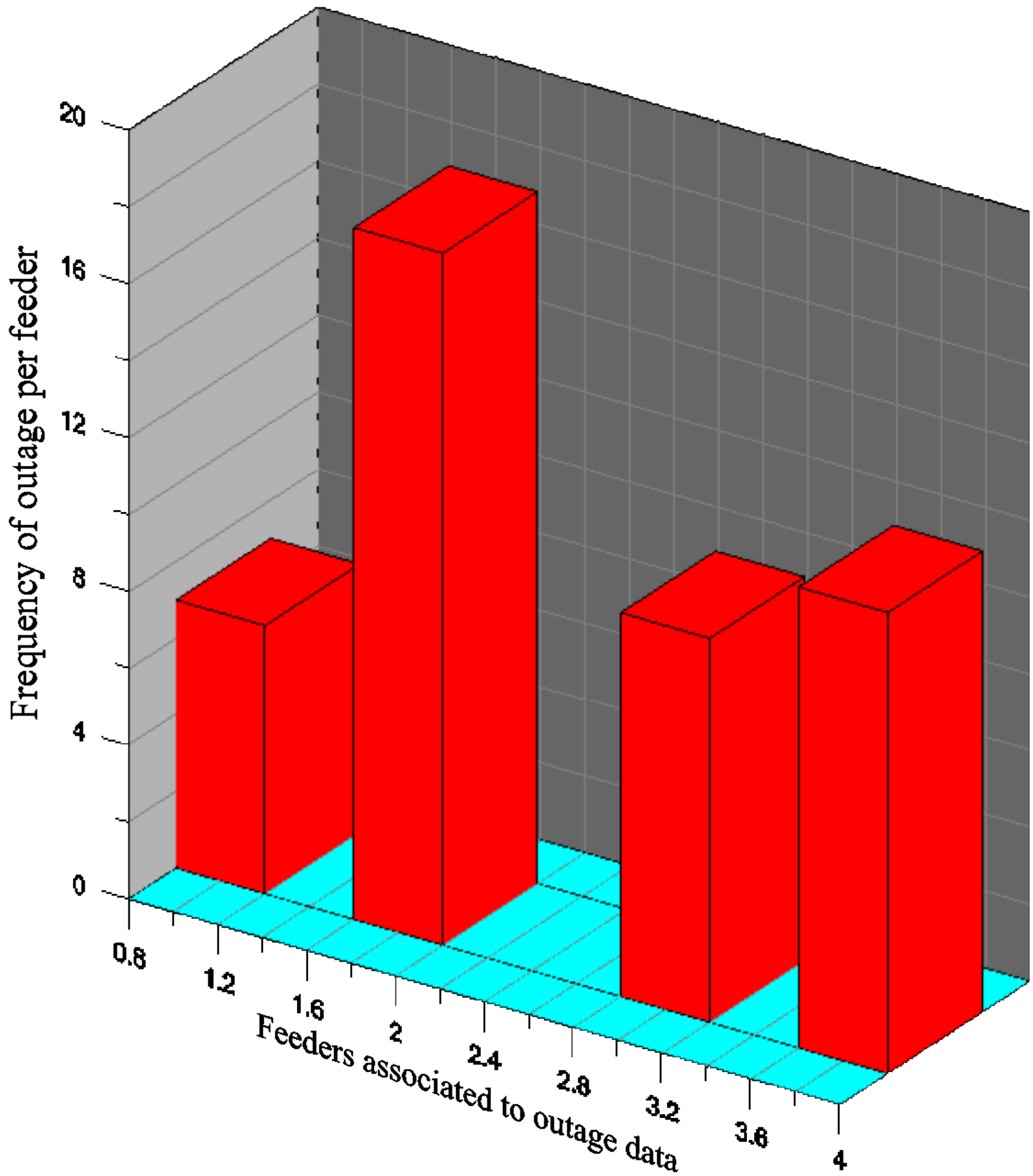


Figure 4.9 Processed Outage data for Ijaye Ojokoro feeders for 2005

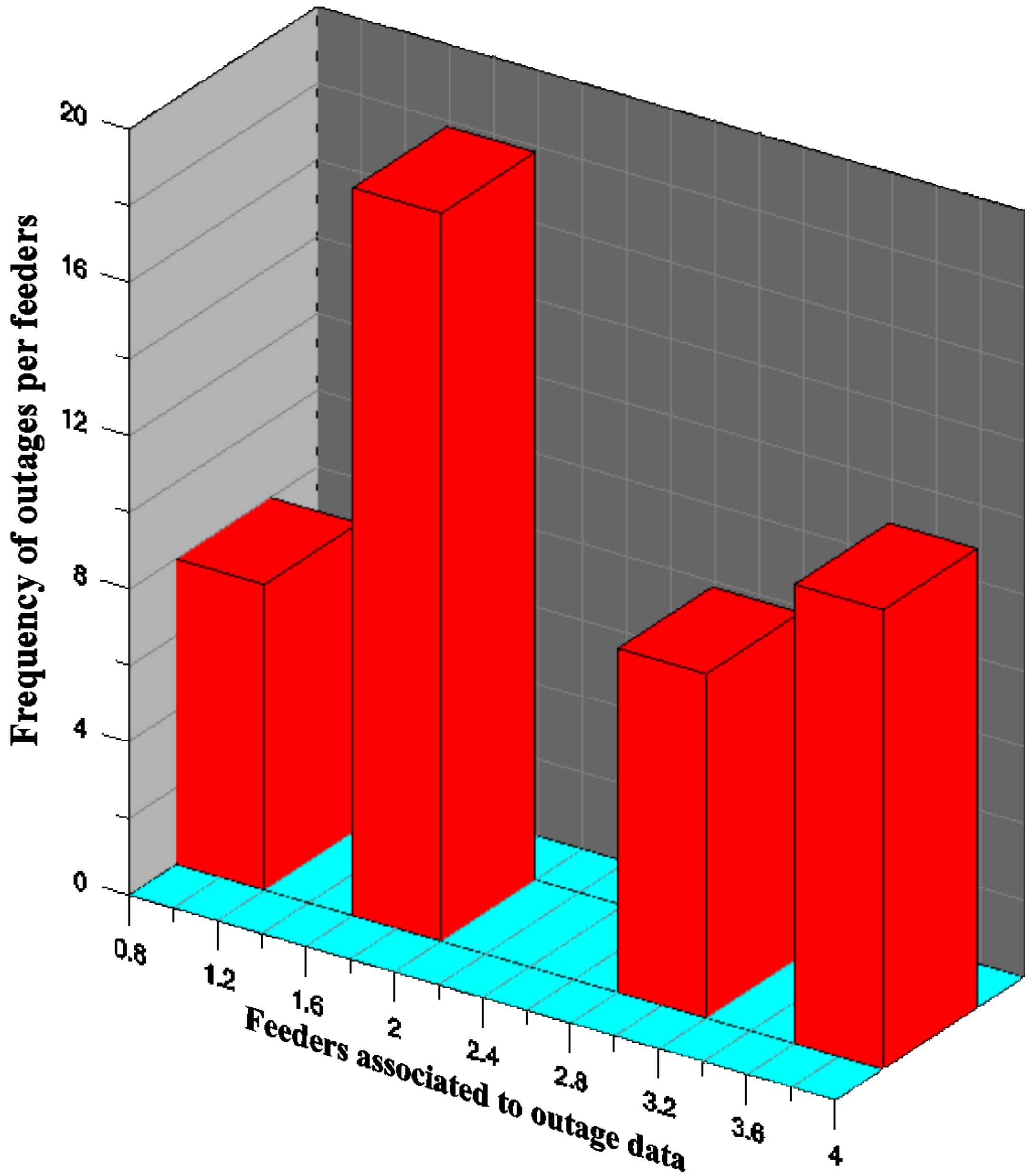


Figure 4.10 Processed outage data for Ijaye Ojokoro feeders for 2006

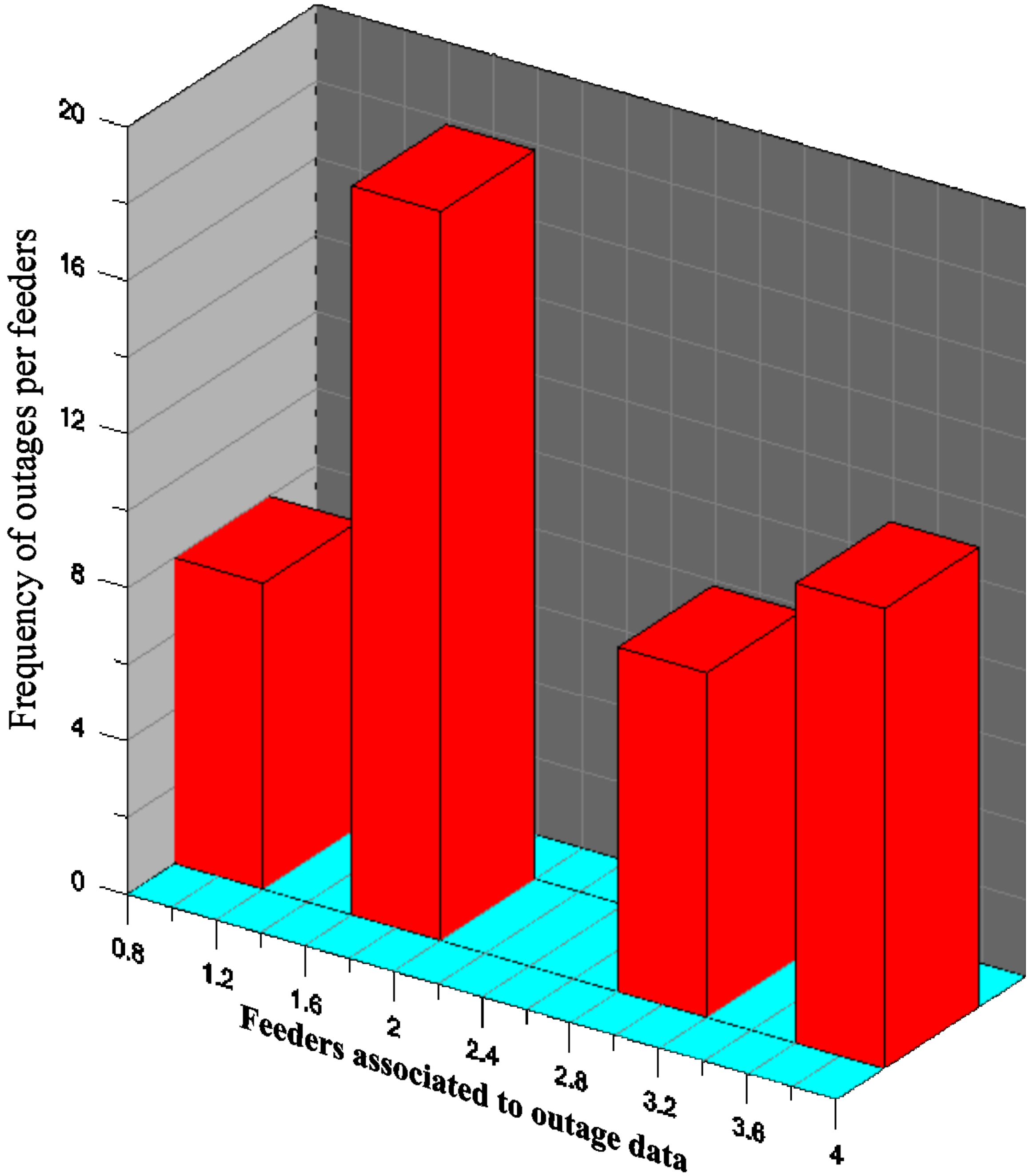


Figure 4.11 Processed outage data for Ijaye Ojokoro feeders for 2007

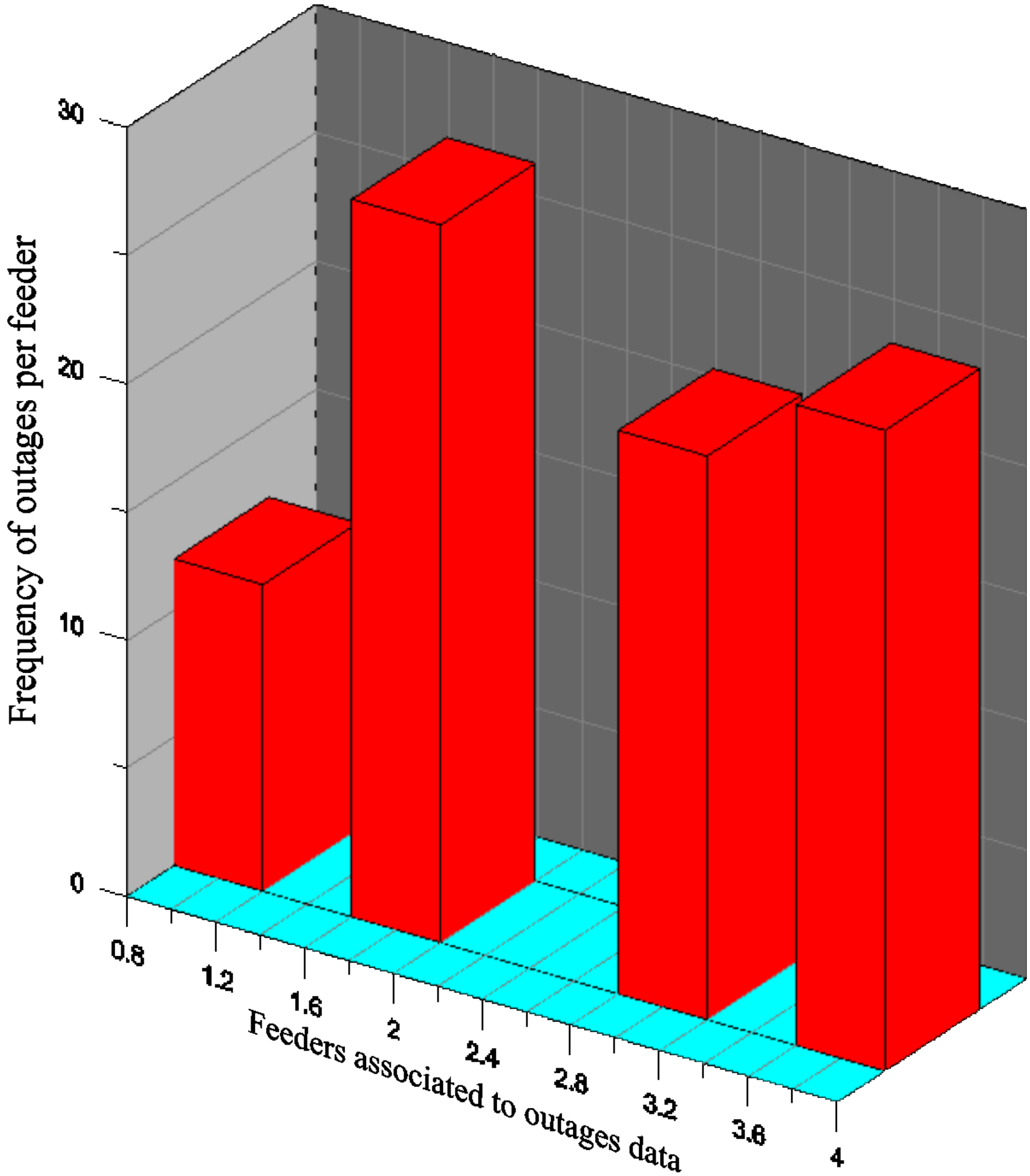


Figure 4.12 Processed Outage data for Ijaye Ojokoro feeders for 2008

Table4.1a Statistical Parameters from Outage Data set for 2004

	F_1	F_2	F_3	F_4	Total Substation
MTBF(days)	3.3	3.1	3.2	3.2	0.97
Failure rate λ Failure/yr	0.304	0.320	0.309	0.310	1.24
MTTR(days)	5.0	5.8	5.1	5.2	0.94

Table4.1b Statistical Parameters from Outage Data set for 2005

	F_1	F_2	F_3	F_4	Total Substation
MTBF (days)	1.6	1.5	2.6	1.6	0.99
Failure rate λ Failure/year	0.63	0.65	0.39	0.64	2.31
MTTR (days)	6.2	6.3	4.2	6.7	0.94

Table4.1c Statistical Parameters from Outage Data set for 2006

	F_1	F_2	F_3	F_4	Total Substation
MTBF (days)	1.7	1.65	2.63	1.69	**0.998**
Failure rate λ Failure/year	0.593	0.606	0.381	0.590	2.17
MTTR (days)	9.7	11.3	6.1	9.5	0.904

Table4.1d Statistical Parameters from Outage Data set for 2007

	F_1	F_2	F_3	F_4	Total Substation
MTBF (days)	2.06	1.65	2.67	1.72	0.998
Failure rate λ Failure/year	0.485	0.608	0.375	0.582	2.05
MTTR (days)	6.67	8.0	5.03	7.84	0.928

Table4.1e Statistical Parameters from Outage Data set for 2008

	F_1	F_2	F_3	F_4	Total for Substation
MTBF (days)	2.17	2.15	3.07	2.31	0.97
Failure rate λ Failure /year	0.461	0.466	0.326	0.432	1.69
MTTR (days)	3.77	3.87	2.85	3.73	0.96

Further analysis of the data indicates that 26% in 2004, 28% in 2005, 28% in 2006, 30% in 2007, and 28% in 2008 of all the yearly outages in the substation occurred in feeder two(F_2). From the data analysis, esimates of MTBF, Failure rate (λ) and MTTR can be determined for the whole substation as well as each of the respective feeders. This is shown in tables 4.1a to table 4.1e above.

These pieces of information help the asset manager to focus more attention on feeder two to find out the component/components that is (are) responsible for the high rate of failure in that feeder.

With this kind of information, we then began to probe deeper into the working of the components that made up the network of feeder two (F_2). Maybe it is a customer induced failure or maybe the constituting components are ageing or of different make, etc. In order to gain useful insight on what is going on in feeder two (F_2), we then further analyze the failure data on this particular feeder alone.

The analysis of the failure data collected on this critical feeder when plotted on histogram shows that the four main components of the distribution system that present the greatest challenge to uninterrupted operation of power at this level include line conductor, distribution transformers and cable. This plot is shown in figure 4.13a to figure 4.13c. From this plot transformer was identified as the highest contributor to customer's electric power interruption.

Taking into consideration the cost implication, effective decisions can then be made on the type of maintenance policy to be adopted in order to improve the power supply reliability to the customers.

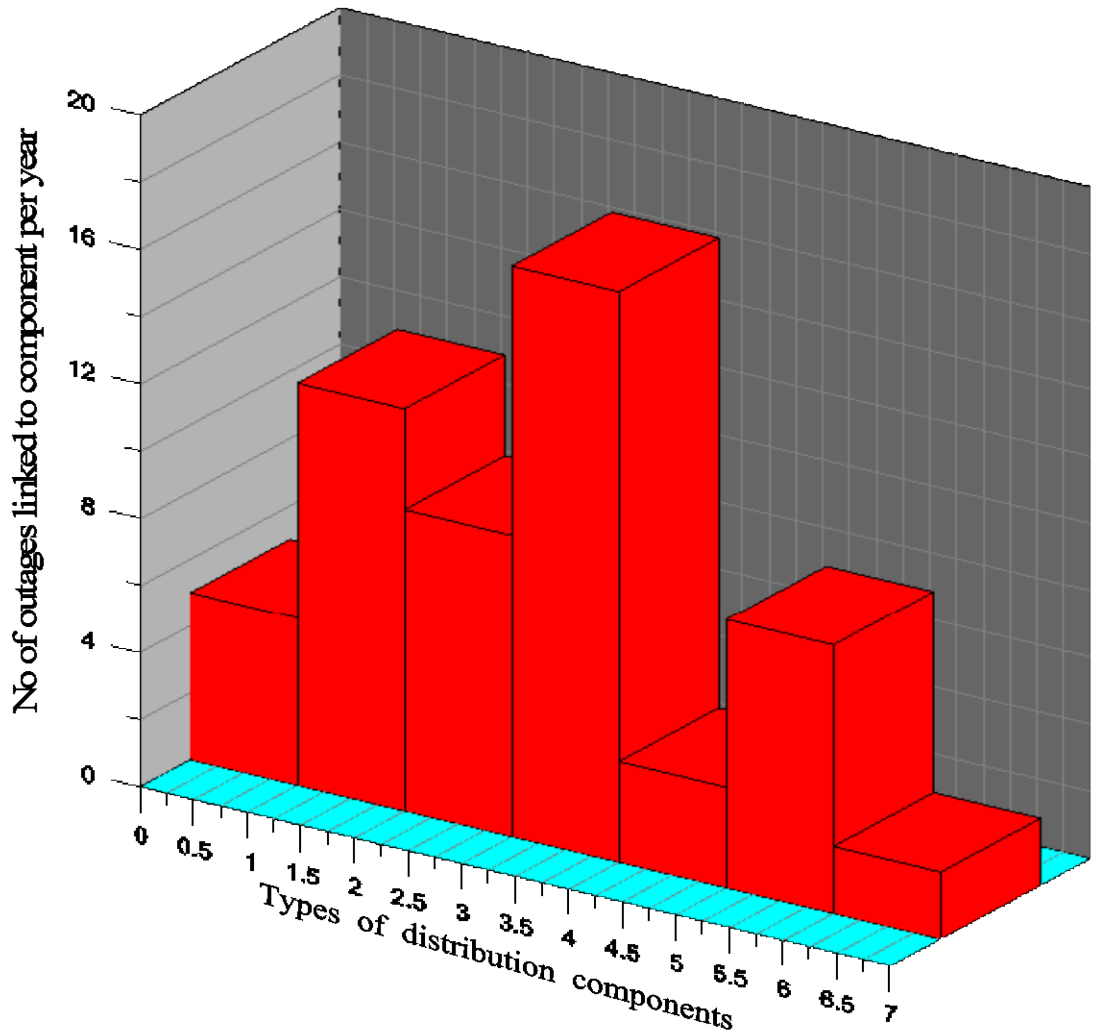


Figure 4.13a, Processed failure data for critical feeder (2005)

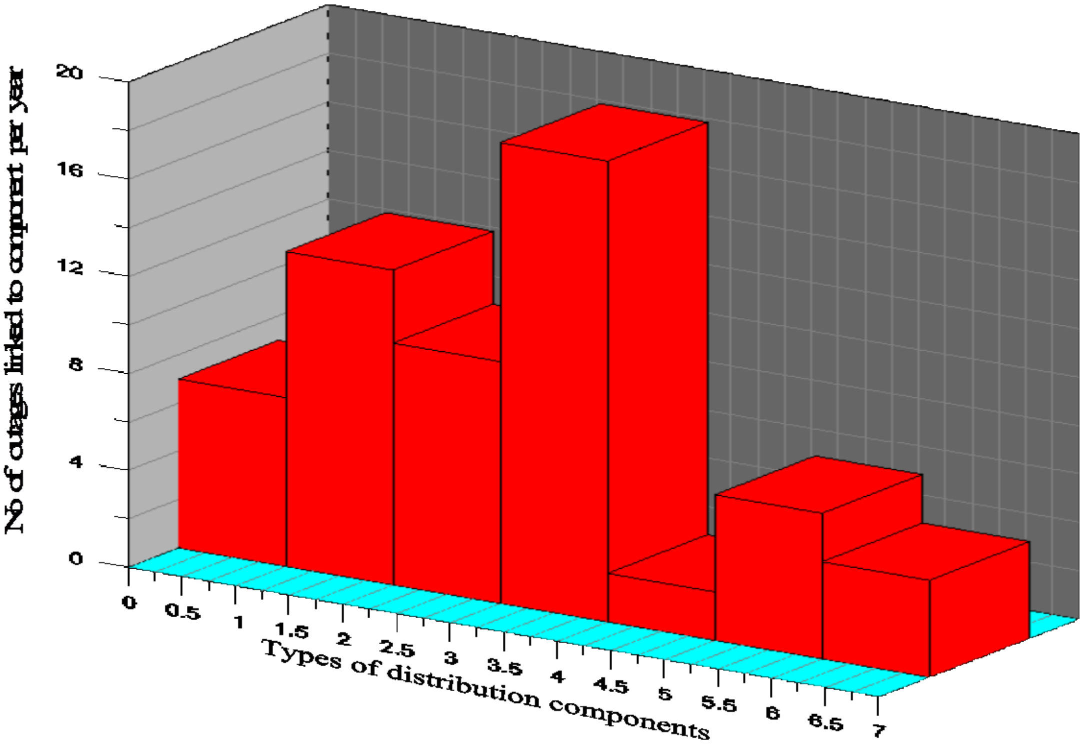


Figure 4.13b, Processed failure data for critical feeder (2006)

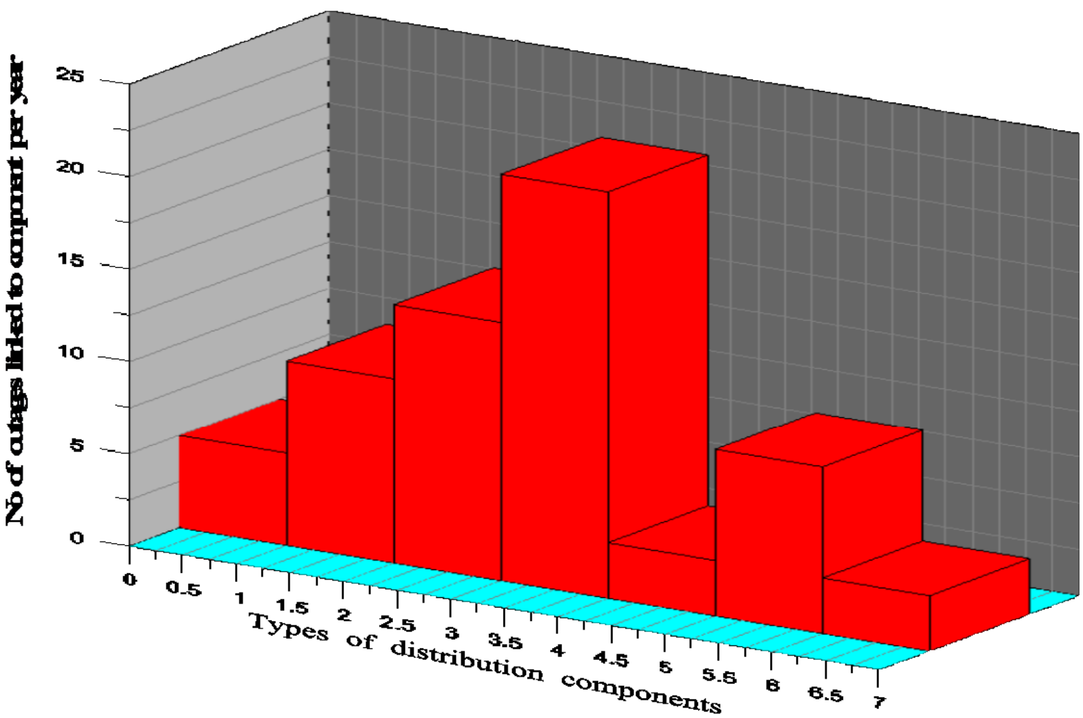


Figure 4.13c, Processed failure data for critical feeder (2007)

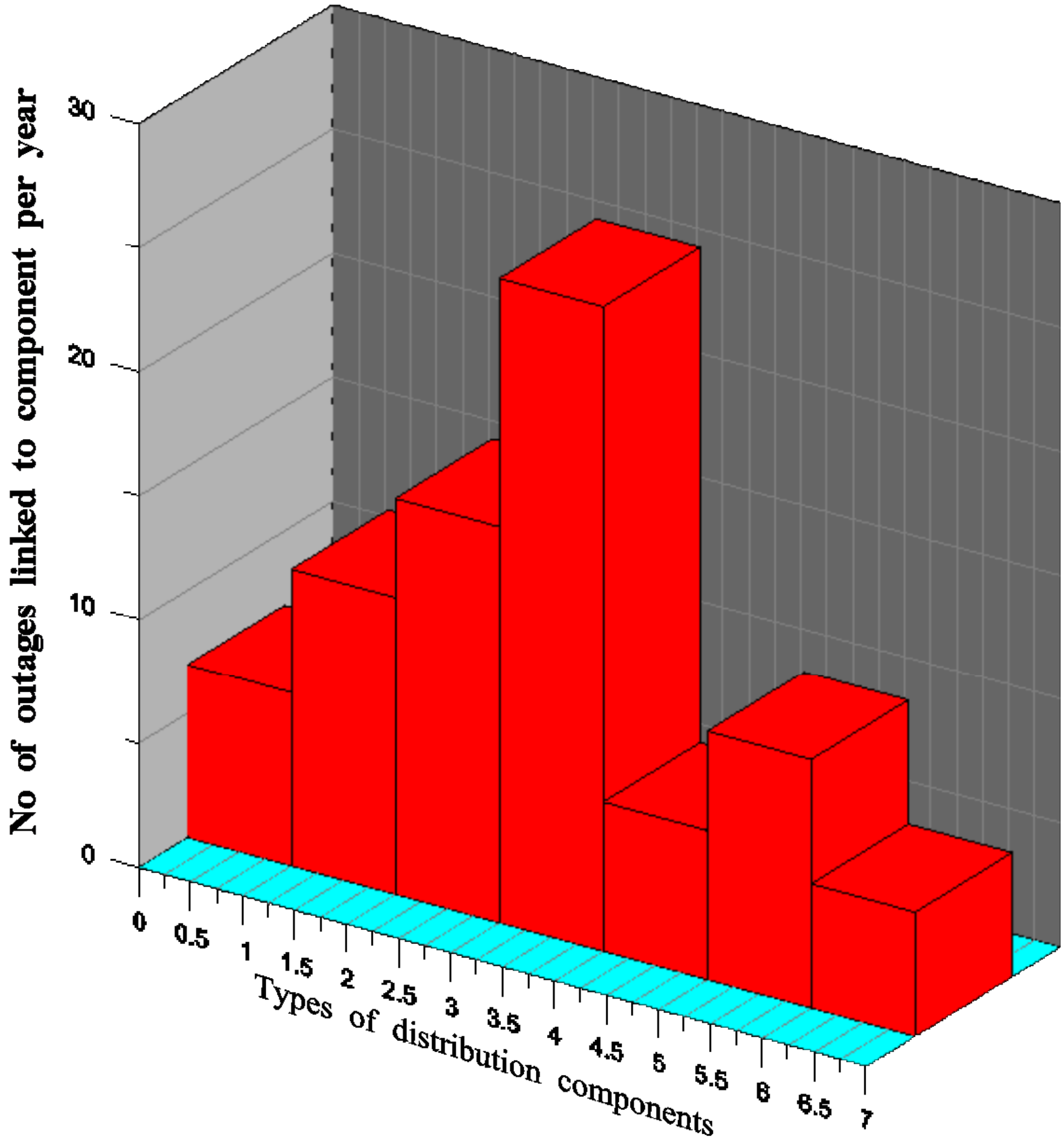


Figure 4.13d, Processed failure data for critical feeder. (2008)

4.4 MODELING OF FAILURE AND REPAIR PROCESSES

In this section, five years of outage information from one of the PHCN business unit in Ikeja Zone Distribution Company in Nigeria are analyzed to test assumptions about failure rate and repair duration models. The data included 9500 faults after excluding those occurring as a result of load shedding due to insufficient generation.

Faults in distribution system are usually modeled as a Homogeneous Poisson Process (HPP) [76], [77]. 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 have the effect of improving it. Upgrading maintenance practices should improve system reliability, and declining maintenance budgets, all other things being equal, should result in deterioration.

Appropriate models of the failure and repair processes can be obtained by analyzing historical utility outage data.

Systematic approaches for analysis of repairable systems are available in the literature [78], [79]. Using these methods, the ageing of transformer that was found to be the highest contributor to sustained outage was explored while analysizing the reliability data of Abule-Egba business unit distribution feeders.

The most basic statistic that can be extracted from the failure data is the measure of center for the variable under consideration. It is also called the sample mean. This is the arithmetic average of the n failure observations.

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} \quad \text{.................... ....} \quad 4.1$$

where n = number of observations in the sample space,

x_i = number of aggregate failure/day,

y_i = time between failure on the system components, and

z_i = time taken to repair failed components.

Using the sample mean, we can easily estimate

$\bar{x}$ = λ as the mean number of failure occurrence per given time,

$\bar{y}$ = Mean time between Failure (MTBF) and

$\bar{z}$ Mean time to repair (MTTR).

For a system that has a good maintenance record, this simple analysis can be performed on different components that perform the same function and very easily the group of feeders that are prone to failure can be identified.

An important statistical issue of interest is one that concerns carrying out some basic tests on the collected data.

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 $T_1, T_2 \dots \dots \dots . T_m$ are a set of chronologically arranged outage times, the Laplace test statistic is calculated as

$$U_L = \frac{\left[\frac{1}{m-1}\sum_{i=1}^{m-1} T_i\right] - \frac{1}{2}T_m}{T_m\sqrt{\frac{1}{12(m-1)}}} \quad \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots . \quad 4.2$$

The conclusions drawn from the test are:

- $U_L = 0$ Indicates lack of trend. We then assume HPP.
- $U_L > 0$ Indicates that interarrival time trends are increasing, indicating system deterioration with time
- $U_L < 0$ Indicates that interarrival 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 $U_L < -1.96$.

For the five year's outage data collected on the system under consideration, $U_L = 2.33$, indicating that at 95% confidence level, the system reliability is deteriorating with time. The existence of a trend requires the need for 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 now be determined

The **second step** in the data analysis is to test if the times –between – faults (tbfs) are independent. This can be evaluated using the serial correlation coefficient of the tbf data. The tbf data is independent if the correlation coefficient is 0, has perfect positive correlation if it is 1.0, and has perfect negative correlation if it is -1.0.

The definition of linear correlation used here assumes that each set of data has exactly n samples. The linear correlation (referred to in the statistical literature as Pearson's r) is obtained from

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. \quad 4.3$$

where $\bar{x} = \frac{1}{n}\sum_{i=1}^{n}(x_i)$ and $\bar{y} = \frac{1}{n}\sum_{i=1}^{n}(y_i)$

Since the observed sample values are random, the calculated value of r is also random. When n is large (say, greater than 500), the distribution of r is approximately Gaussian.

The serial correlation coefficient for the data collected from the PHCN distribution systems used for the example data has a value of 0.388, indicating that the tbfs are largely independent. Strong evidence of correlation, positive or negative, would require a model incorporating interaction among faults.

CHAPTER FIVE

TRANSFORMER INSPECTION AND MAINTENANCE

5.1 Introduction:

Failure of power transformers can greatly affect power delivery.

The "remaining life" of power apparatus and maintenance cost are two most important aspects which affect the maintenance policies. There is a number of maintenance strategies already reported in most literatures [80]. The conclusion drawn from the literature is that distribution component's service availability and replacement cost should be balanced so as to get an optimal maintenance strategy. Incipient sign of failures not attended to, will have a long-term accumulated effect, which is capable of causing major failures if a commensurate maintenance action is not taken. The "remaining life" of distribution component's model concept using Markov Proceses developed in this thesis is already discussed in detail in chapter three. Based on this concept, a maintenance model for one of the critical component identified in the system under consideration is presented

We will address the transformer failure statistics over the last 5 years, and why major losses involving oil-cooled transformers continue to occur on frequent basis. Research shows [81] that the magnitude of these losses has increased significantly since the advent of deregulations of the power sector. From the literature [82], the advanced reasons are:

- Increased equipment utilization,
- deferred capital expenditures and
- reduced maintenance budget.

To make matters worse, world power consumption is increasing, and load on each ageing transformer continues to grow.

5.2 CAUSES OF TRANSFORMER FAILURE

For this power component investigated, the leading cause of transformer failures is "Insulation failure". This category includes substandard or defective installation, insulation deterioration, and short circuits, with voltage surges, lightning and line faults excluded.

Table 5.1 lists the number of failures for each cause of failure.

The risk involved in a transformer failure is of two types:

- The frequency of failure and
- The severity of failure.

A description of each cause of failure in table 5.1 is given below.

Table 5.1 Number of failures for each cause of failure.

Causes of failure	Number of failures
Insulation failure	28
Design/Material/Workmanship	27
Unknown	17
Oil Contamination	9
Overloading	5
Fire/Explosion	1
Line Surge	4
Improper Maintenance/Operation	6
Loose Connection	2
Lightning	2
Moisture	1
Total	97

Insulation Failure-: This failure was the leading cause of failure in the distribution network considered. This category excludes those failures where there was evidence of lightning or a line surge. The following four factors were discovered to be responsible for insulation deterioration:-

Pyrolosis (heat), Oxidation, Acidity, and Moisture. But moisture is reported separartely. The average age of the transformers that failed due to insulation was 15 years.

Design/ Manufacturing Errors – This group includes conditions such as ; loose or unsupported leads, loose blocking , poor brazing, inadequate core insulation, inferior short-circuit strenght, and foreign objects left in the tank. During the investigation, this is the second lead cause of transformer failures.

Oil Contamination – This refers to those cases where oil contamination can be established as the cause of failure. This includes slugging and carbon tracking.

Overloading- This category pertains to those cases where actual overloading could be established as the cause of the failure. It includes only those transformers that experienced a sustained load that exceeded the nameplate capacity.

Fire / Explosion- This category pertains to those cases where a fire or explosion outside the transformer can be established as the cause of the failure. This does not include internal failures that resulted in fire or explosion.

Line surge: This includes switching surges, voltage spikes, line faults/flashovers, and other abnormalities. This significant portion of transformer failures suggests that more attention should be given to surge protection, or the adequacy of coil clamping and short circuit strength.

Maintenance/Operation

Inadequate or lack of maintenance was a major cause of transformer failures, when overloading, loose connections and moisture are included. This includes disconnected or improperly set controls, loss of coolant, accumulation of dirt and oil, and corrosion. Inadequate or no maintenance has to bear the blame for not discovering incipient troubles that could have been corrected if maintenance was carried out.

Loose connections: These include workmanship and maintenance in carrying out electrical connections. One major problem is the improper mating of dissimilar metals, although this has decreased recently. Loose connections could be included in the maintenance category.

Lightning: Failure due to lightning is now fewer in number than previous studies carried out in this areas. Unless there is confirmation of a lightning strike, a surge type failure is categorized as “line surge”.

Moisture: The moisture category includes failures caused by leaky pipes, leaking roofs, water entering the tanks through leaking bushings or fittings, and confirmed presence of moisture in the insulating oil. This could be included in the inadequate maintenance category.

Transformer Ageing

In table 5.1, we did not add “age” as a cause of failure. Ageing of insulation system reduces both the mechanical and dielectric-withstand strength of the transformer. As the transformer ages, it is subjected to faults that result in high radial and compressive forces. As the load increases, with system growth, the operating stresses increase. In an ageing transformer failure, typically the conductor insulation is weakened to the point where it can no longer sustain mechanical stresses of a fault. Turn-to-turn insulation then suffers a dielectric failure, or a fault causes a loosening of winding clamping pressure, which reduces the transformer’s ability to withstand future short-circuit forces.

Table 5.2 displays the distribution of transformer failure by age

The age of transformers deserves special attention, because the world went through significant industrial growth in the post world war II era, causing a large growth in base infrastructure industries, especially the electric utilities [83]. World energy consumption grew from 1 trillion to 11 trillion KWhr, in the decades following the war [84]. Most of these equipment are now in the ageing part of their life cycle.

Table 5.2 List of the distribution of transformer failures by age.

Age at Failure	No of Failures
0 to 6 years	8
7 to 11 years	6
12 to 16 years	12
17 to 21 years	12
Over 21 years	24
Unknown	35

5.3 TRANSFORMER MAINTENANCE MODEL.

A general probabilistic model of the impact of maintenance on reliability proposed in this work is applied on transformer in figure 5.1. The model represents the deterioration process in a distribution transformer using discrete stages. In figure 5.1, deterioration process of a transformer is approximated by three discrete stages: D_1, D_2, and D_3. At each state, oil is inspected to determine its condition. After the inspection, oil condition is determined by some defined criteria as indicated in [85]. The criteria categorize oil condition into three groups as follows:

Condition C_1 means - Satisfactory

Condition C_2 means – Should be reconditioned for further use.

Condition C_3 means – Poor condition, dispose and replace.

Maintenance action is assigned corresponding to the oil condition. If oil condition is C_1, nothing is done. If oil condition is C_2 or C_3, two options are available and are assigned with different probabilities: oil filtering or oil replacement.

If for example, the present stage is D_2 with oil condition C_2, the probability of oil filtering will be higher than oil replacement. On the other hand, if the present state is D_2 with oil condition C_3, the probability of oil replacement will be higher. After maintenance, the device will have three options, going to state D_1, D_2 or D_3. The probability of transferring to other states depends on the present state and the maintenance strategy adopted.

Further, the maintenance process is divided into three levels,

(1) Do nothing

(2) Basic Maintenance and

(3) Replacement.

Once the suggested maintenance action is taken, the subsequent condition of the transformer is determined.

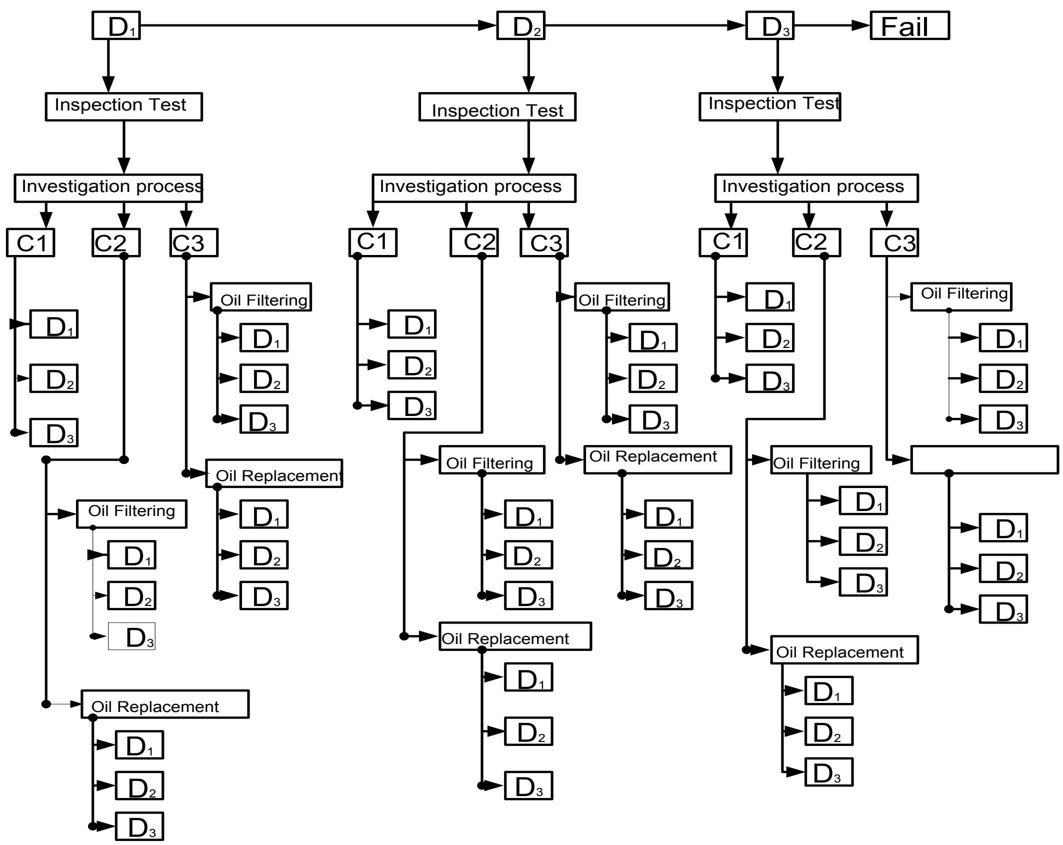


Figure 5.1 Transformer Maintenance Model

The model takes results from various inspection and maintenance tasks and the frequency of performing the tasks is input and it gives the failure rates as output. The changes in the "mean time to failure" indicator can be observed by considering different inspection and maintenance actions. This model can help asset managers in obtaining optimum maintenance intervals such that both the transformer availability and the total cost are balanced.

Various inspection tests and maintenance actions performed during maintenance task of a transformer are shown in table 5.3 and table 5.4 respectively.

Table 5.3 Transformer maintenance tasks

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 voltage frequency.
Deterioration process	Insulation paper in the winding, oxidation of oil.
Particles produced by ageing process	Sludge, water, fiber, Gases (CO, CO2 etc), Furfural, partial Discharge.
Failure mode	- Themal 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.

- Stated limits for Service- Aged oils for Transformers. [86]

This is shown in table 5.4.

Table 5.4 Rated limit for values of transformer oil for voltage class.

Test and Method	Transformer (Value for Voltage Class		
	69 KV and below	69 – 230KV	230 KV and above
Dielectric strength,^ KV minimum 1mm gap* 2mm gap*	 23 40	 28 47	 30 50
Dissipation factor (power factor) 25^0c,% maximum 100^oc,% maximum	 0.5 5.0	 0.5 5.0	 0.5 5.0
Interfacial tension, mN/m Minimum	25	30	32

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

*Alternative measurements of 0.04in and 0.08in respectively for gaps.

5.3.1 Model parameters

Table 5.5 shows the list and definition of the parameters that are used in transformer maintenance model.

Notice that model parameters 1 and 3 can be approximated from historical data of oil condition of a physical transformer. These parameters are given, whereas, parameter 2, which is the inspection rate of each stage can be varied to achieve high reliability with minimum cost. Therefore, this parameter is of paramount importance in determining the impact of maintenance on transformer analysis.

The sensitivity analysis of inspection rate of each stage could also be implemented on the model in figure 5.1. Other model parameters such as cost parameter could also be included.

The analysis covers two aspects:

- Mean time to the first failure, and
- All associated costs (failure, maintenance and inspection costs respectively).

The simulation results from Matlab for this model are presented under results and discussion.

Table 5.5 List of model parameters and definitions

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 transfering from any oil condition to a given stage. • The probabilities of filtering or replacing the oil and • Probabilities of transfering to each stage after maintenance.

5.4 EQUIVALENT MATHEMATICAL MODELS FOR TRANSFORMER MAINTENANCE.

Two equivalent models are used to simplify the transformer maintenance model shown in figure 5.1. The equivalent models have three discrete stages representing the deterioration processes. We assume that decision is taken at the end of every inspection. Decision for maintenance and inspection rate of each stage is considered to be an equivalent repair rate.

Let y_1 = mean time in state 1(year),

y_2 = mean time in state 2(year)

y_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).

5.4.1 Perfect Maintenance Model

It is assumed that in the initial state, the transformer is in good working condition that needs no maintenance. More–over it is assumed that maintenance will always improve the device to the previous state; this means that the repair rate of state 2 will improve the device to state 1 and repair rate of state 3 will improve the device to state 2. This type of model is shown in figure 5.2.

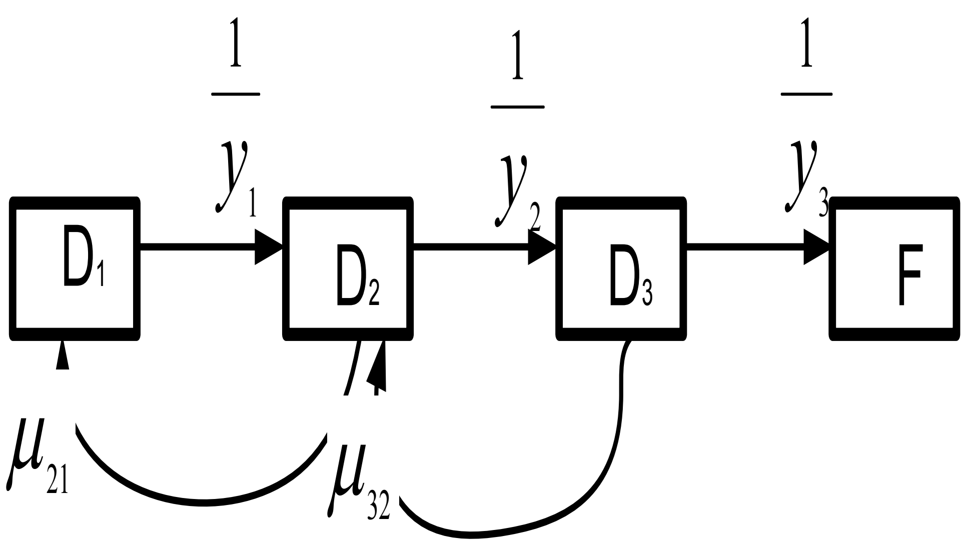


Figure 5.2 Perfect Maintenance Model

5.4.1 Imperfect Maintenance model

This model type is slightly different from the model in figure 5.2. Transition rate from state 1 to 3 is introduced (λ_{13}) to describe an imperfect inspection of state 1. This Model accounts for the probability that inspection of state 1 might cause the system to transit to state 3. This Model is therefore the equivalent Model for transformer maintenance Model in figure 5.1 since it accounts for a transition of state 1- 3 in figure 5.3. This equivalent Model will be used in predicting the remaining life of the transformer using the first passage time and steady-state probability calculation programme developed. The model for this is shown in figure 5.4 below.

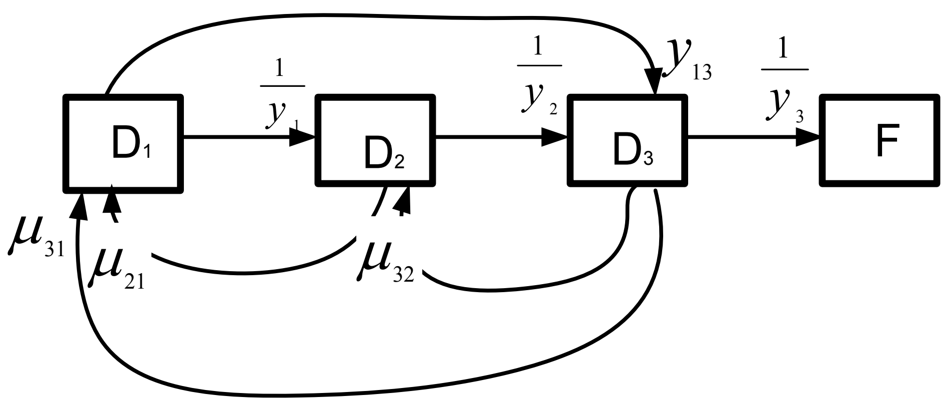


Figure 5.3 Imperfect Maintenance Model

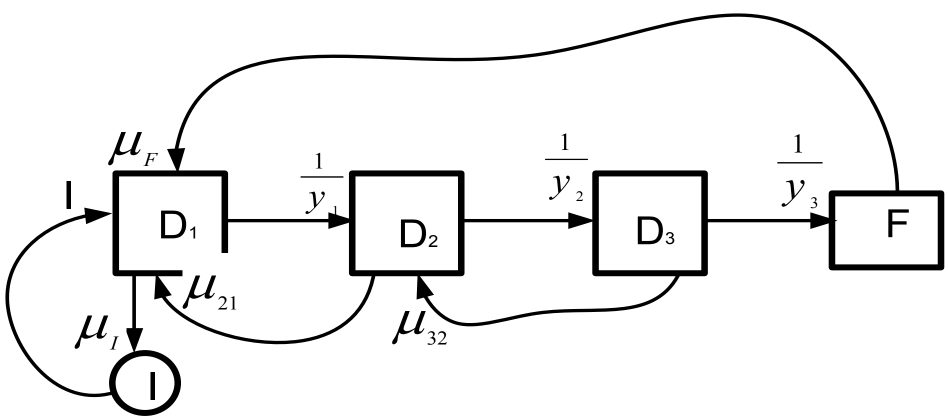


Figure 5.4 Inspection Model

5.4.2 Inspection Tests

Various inspection tests are considered in developing the proposed model.In particular; the following tests were considered in developing this proposed model. Oil-filled transformers are considered in this study. The underlisted items form the basis for the inspection tasks in this model.

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

The condition of the transformer can be obtained by comparing the measured values with the working stardard. In the case of the transformer oil, table 5.4 could be regarded as the working standard.

5.4.3 Investigation

Information out of the inspection tests is used to determine the condition of the device followed by the necessary maintenance action and rate of the next inspection.

5.4.4 Maintenance Action

1) **Do nothing**

The transformer is in satifactory condition and no maintenance is needed. The probability that the system is set back to same stage is relatively high.

2) **Basic Maintenance**

This maintenance action increases the probability of going back to the previous stage

3) **Replacement**

Replacement of damaged components brings the system back to its original stage i.e. its initial stage.

5.5 SENSITIVITY ANALYSIS OF INSPECTION RATE ON MEAN TIME TO FIRST FAILURE (MTTFF)

Mean time to first failure is the expected number of operating times that elapsed before the failure of transformer when started from initial stage. The sensitivity analysis is expected to provide information of how the transformer operating time changes when the inspection rate of each stage changes. We shall let

i_1 = inspection rate of D_1 (per year),

i_2 = inspection rate of D_2 (per year),

i_3 = inspection rate of D_3 (per year).

The transformer maintenance model and its parameters showed in annex 2.1 are then simulated using Relex software. The simulation results of the relationship of each inspection rate and MTTFF are shown in figures 5.5a-c and 5.6a-c respectively.

The observations that could be drawn from these simulation results are:

1. In figure 5.5a, the MTTFF is seen to decrease with i_1. This is associated with the assumption of exponential distribution of time spent in each stage. The assumption of exponential distribution implies constant failure rate. This becomes very important in stage D_1. This implies that the inspections, which will result in going back to $D_{1,}$ will not improve the time to failure in D_1. However, those that will lead to D_2 and D_3 will result in deterioration. This means that, if we assume an exponential distribution for stage 1, maintenance at this stage will not be necessary.
2. In figure 5.5b, it was observed that MTTFF increases at a decreasing rate with i_2 and then remains constant afterwards
3. In figure 5.5c, MTTFF and i_3 were observed to possess positive linear relationship.

The next stage of simulation is to modify the model in figure 5.1 by representing state 1 by three sub-unit in order to nullify the assumption of exponential distribution. Although each sub-unit is exponentially distributed, the overall D_1 is not and hence will experience deterioration.

The simulation results of the relationship of each inspection rate and MTTFF based on this arrangement are shown in figures 5.6a – 5.6c.

In fig 5.6a, MTTFF is observed to increase rapidly when i_1 is correspondingly increased and then decreases slightly at high i_1.

The simulation results as shown in figure 5.6b and 5.6c gave the same observation as that obtained in figure 5.5b and 5.5c.

The simulation results suggest that inspection rate of D_1 could help in prolonging MTTFF. In addition, carrying out inspection of D_2 beyond a certain value will have a little or no impact on reliability.

Figure 5.5c however, indicates that transformer life-time will be longer with an improved inspection rate at stage D_3.

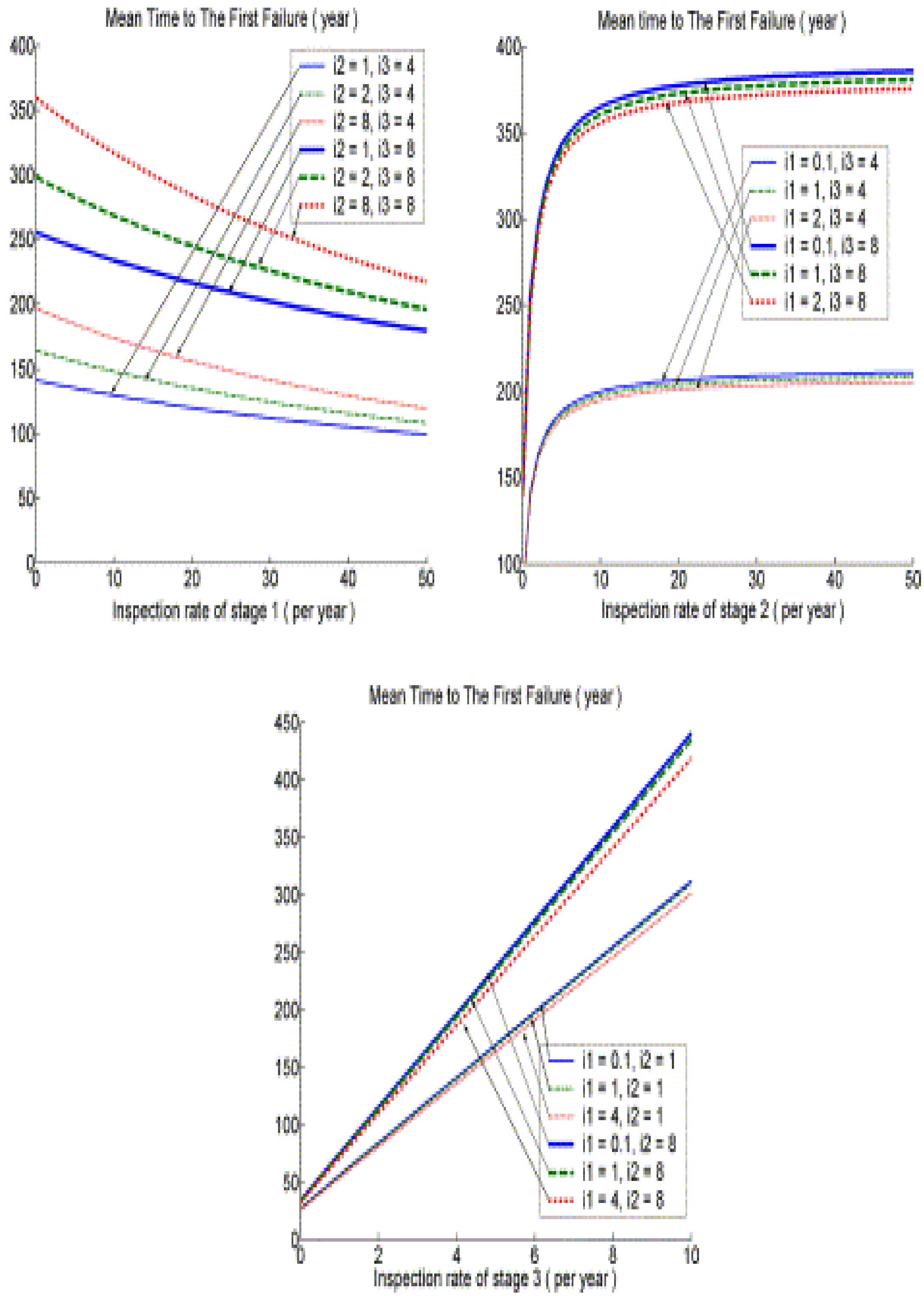


Figure 5.5a – c the relationship between inspection rate and MTTFF.

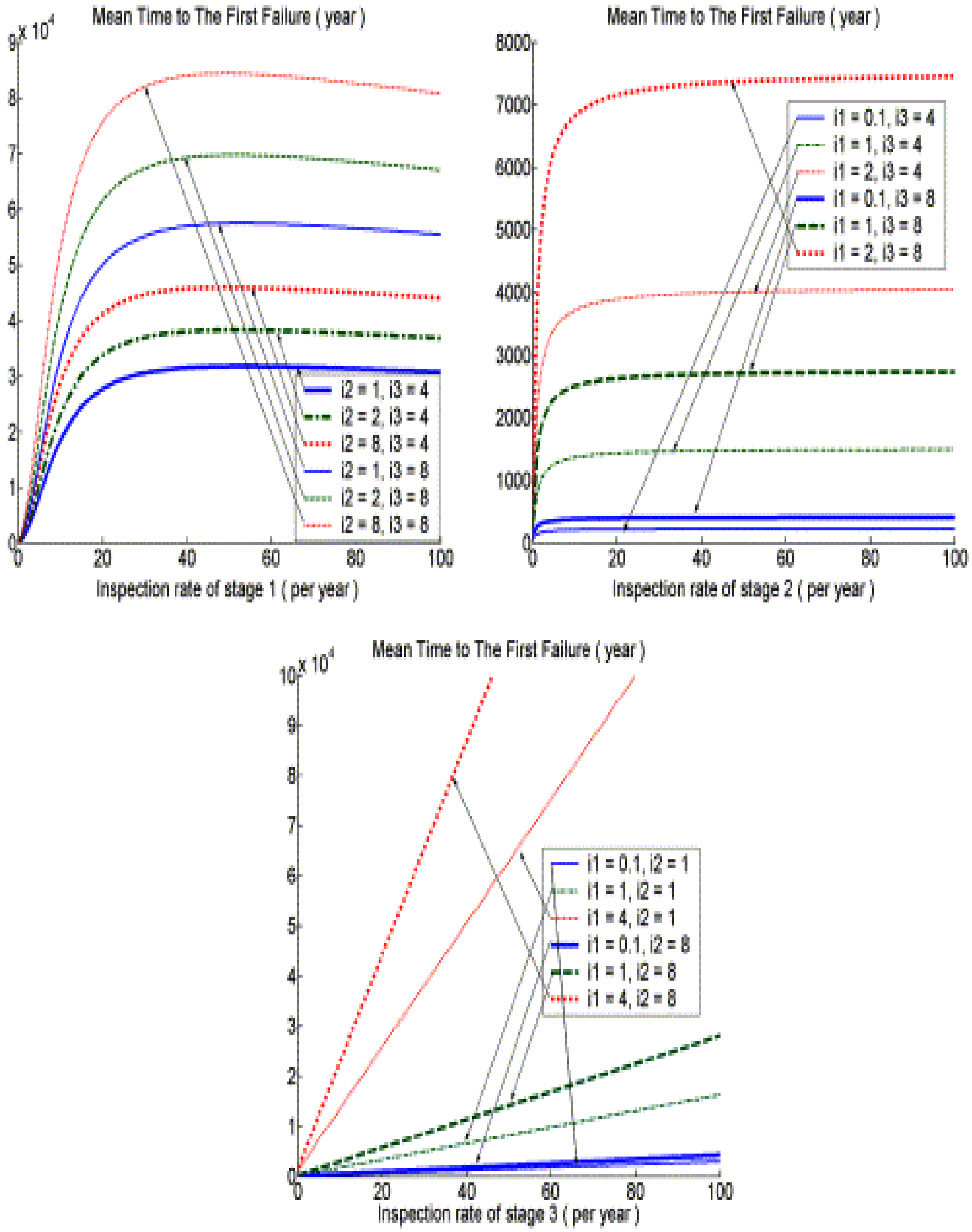


Figure 5.6 a – c the relationship between inspection rate and MTTFF when state1 is represented by three sub-units.

5.6 ANALYSIS OF THE MEAN TIME TO THE FIRST FAILURE

Using the first passage time calculation [86], the MTTFF equations were derived. With these equations, the simulation results obtained in figure 5.5 and figure 5.6 will be explained. The analysis is based on the equivalent mathematical models of both perfect and imperfect maintenance models.

5.6.1 Perfect maintenance model

The MTTFF is calculated using the method shown in equations 3.30 – 3.32.

Let T_o = life time without maintenance and

T_E = prolonged life time with maintenance.

$\lambda_{12} = \frac{1}{y_1}$ Transition rate from D_1 to D_2,

$\lambda_{23} = \frac{1}{y_2}$ Transition rate from D_2 to D_3,

$\lambda_{3F} = \frac{1}{y_3}$ *transition rate from* D_3 *to* F.

Then, we have $T_o = y_1 + y_2 + y_3$ (without maintenance) …………… 5.1

Considering the case of components that are maintainable,

$$T_E = \frac{\mu_{21}}{\lambda_{12}\lambda_{23}} + \frac{\mu_{32}}{\lambda_{23}\lambda_{3F}} + \frac{\mu_{21}\mu_{32}}{\lambda_{12}\lambda_{23}\lambda_{3F}} \quad \text{-------------------------} \quad 5.2$$

For the perfect maintenance model, the prolonged life time is the summation of all possible combinations of ratios between maintenance rate of the current stage and failure rate of the current and previous stages.

Since T_E can only be positive in this model, inspection and maintenance will always extend the equipment life time.

If the repair rate of each stage is high relative to the transition rate of that stage and the previous stage ($\mu_{31} \gg \lambda_{12},\ \mu_{32} \gg \lambda_{23}\lambda_{3F}$), the life-time before failure of the device will be high.

5.6.2 Imperfect Maintenance Model

The MTTFF is calculated A3 using the first passage time technique.

This gives $MTTFF = \dfrac{T_o + T_E}{1 + {\lambda_{13}}/{\lambda_{12}} + {\lambda_{13}\mu_{21}}/{\lambda_{12}\lambda_{23}}}$ --------------- 5.3

This results in $MTTFF = \frac{\mu_{21}\mu_{31}+\mu_{21}\mu_{32}+\mu_{21}\lambda_{13}+\mu_{32}\lambda_{12}}{\lambda_{12}\lambda_{23}\lambda_{3F}} + \frac{\mu_{21}}{\lambda_{12}\lambda_{23}} + \frac{\mu_{31}}{\lambda_{23}\lambda_{3F}} + \frac{\mu_{31}}{\lambda_{12}\lambda_{3F}} +$
$\frac{\mu_{32}}{\lambda_{23}\lambda_{3F}} + \frac{\lambda_{13}}{\lambda_{12}\lambda_{3F}}$ …………………………………… 5.4

The relationships of inspection rate of each stage and MTTFF are explained in the following:

5.6.3 Simulation Result Analysis and Discussion

1. **Inspection rate of stage1**

It is possible that inspection and maintenance will reduce MTTFF at very high inspection rate of stage1 (high inspection in stage1 will increase λ_{13}, thus, denominator may be large). This will increase the failure rate from stages 1 to 3, therefore, MTTFF may decrease. This suggestion is verified by the simulation result in figure5.6a.

2. **Inspection rate of stage2**

High inspection rate of stage2 will increase the repair rate from stages2 to 1(μ_{21}). Let's assume that this repair rate is very high,

$MTTFF = \frac{1+ y_3(\mu_{31}+\mu_{32}+\lambda_{13})}{\lambda_{13}}$ -------------------------------- 5.5

This shows that MTTFF will increase to a constant value. This again is verified by the simulation result in figure5.6b

.

3. **Inspection rate of stage3**

High inspection rate of D_3 will increase the repair rate from stage 3 to 2 (μ_{32}) and also repair rate of stages 3 to 1 (μ_{31}). These rates are linearly related to MTTFF; therefore, the lifetime will increase linearly with inspection rate of stage3. This again is verified by the simulation result in figure5.6c.

CHAPTER SIX

ESTIMATING THE REMAINING LIFE OF THE IDENTIFIED DISTRIBUTION TRANSFORMER.

6.1 Introduction

Asset management is one of the hottest topics on everyone's mind. Asset management is not something new. Infact asset management has been with us since inception of creation.

The problem is that we have been making decisions about assets without the benefit of having thought of a formal strategy regarding asset maintenance, repair and replacement before hand. We have relied heavily on the frequency of occurrences of unplanned and unscheduled repair events to drive our thought process.

In many situations, decisions regarding equipment maintenance, repair or replacement have been made in the heart of a crisis, ususally at the time when piece of critical equipment has failed and requires immediate attention.

Most often, due to lack of planning, managers had to rely on a personal account of an event or history of failures to justify costly and untimely maintenance or replacement decisions.

Even with well-documented equipment repair and maintenance history records, we find ourselves planning for the future by looking in the rearview mirror.

We have lacked a process that would provide information that could be used to esimate the remaining useful life of an asset and allow us to optmize our decisions about deploying resources in the most effective and efficient manner.

Asset management is about decision-making. It is a disciplined, deliberate, and systematic approach to making informed decisions about assets. Asset management is a cost of doing business and also a great liberator.

By defining and then focussing on the core mission of the system and the level of service, we become free to prioritize our level of maintenance effort vis-avis our assets. We can then focus on those assets that are critical to our mission and give less attention to those that are less critical.

6.2 ASSET'S LIFE CYCLE

Asset management is broader than just maintaining and repairing an asset. It represents one of the many stages in an asset's lifecycle. Figure 6.1 illustrates the stages involved in asset management lifecycle.

Performing maintenance and repair activities represent only one of several stages of an asset's life cycle. However, maintenance and repair activities represent about 90% of the asset's life cycle [87]. Figure 6.2 illustrates this.

So, it makes sence for us to emphasize proper planning, scheduling and executing maintenance and repair activities. This is where operators and managers spend the greatest amount of their time. The heart of asset management involves doing the right things and doing them the right way to extend the useful life of an asset.

Asset management, therefore, is a forward-looking, rather than rear-view mirror process. It is a disciplined understanding of deploying resources in a manner that focussed on extending the remaining useful life of an asset.

An effective asset management program forestalls equipment failure and prolongs the useful life of the asset. It ensures that critical assets will continue to meet the required level of performance throughout the life of the system.

A well- defined asset management program focuses manager's attention on what matters most (the critical components that are necessary to meet the required level of performance today and in the near future.).

It ensures that critical assets will continue to meet the required level of performance throughout the life of the system.

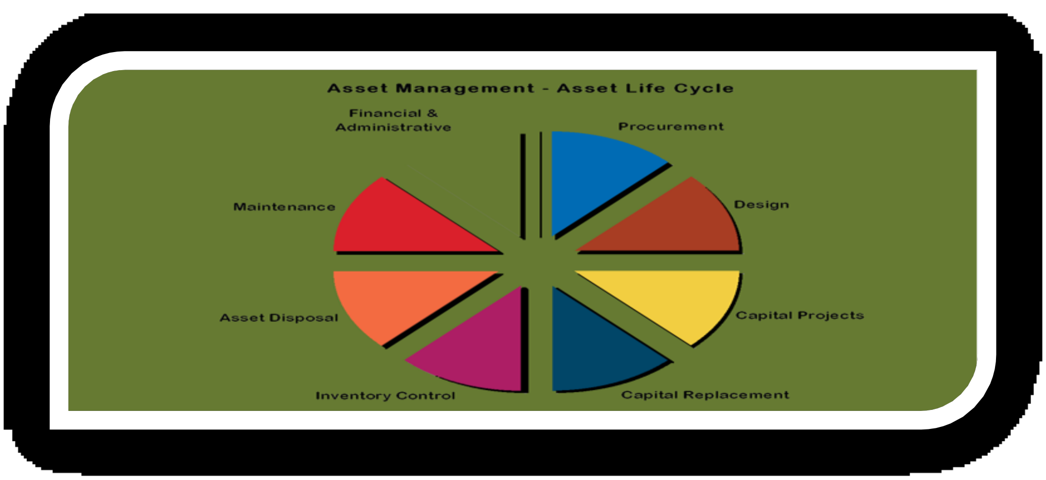


Figure 6.1 Stages in the asset management lifecycle [88].

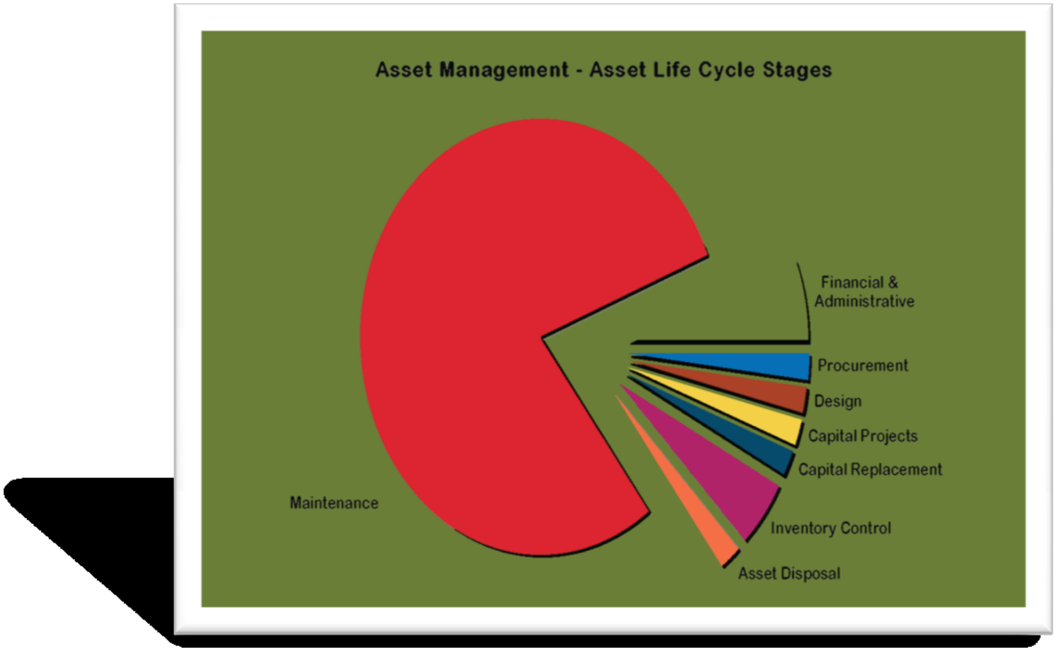


Figure 6.2 Asset life cycle with about 90% maintenance stage [88].

6.3 TECHNIQUES FOR ASSET MANAGEMENT OF TRANSFORMERS

6.3.1 Introduction

Transformer as an asset is generally considered as the most important power equipment in asset managements. This is due to the huge investments in both power and distribution transformers as well as the importance of transformers as one of the major factors that affect the system reliability. The un-planned outages of the transformers due to unexpected failures are always catastrophic in many cases.

Asset management activities of transformer are numerous and researchers tackle them from different points of view. Maintenance plans and condition monitoring techniques are samples of the general asset management activities that can be applied to any transformer, circuit breaker, high voltage capacitors, etc. However, each asset management activity differs from equipment to equipment. For example, condition monitoring techniques applied to transformers are different from those applied to circuit breakers or high voltage capacitors even though some of these techniques may have some similarities.

The block diagram in figure 6.3 shows the transformer main asset management activities. The transformer main asset management can be classified into the following activities:

(1) Condition monitoring (CM) and condition assessment (CA) techniques

(2) Performing maintenance plans.

(3) Ageing, health, and end of life assessments.

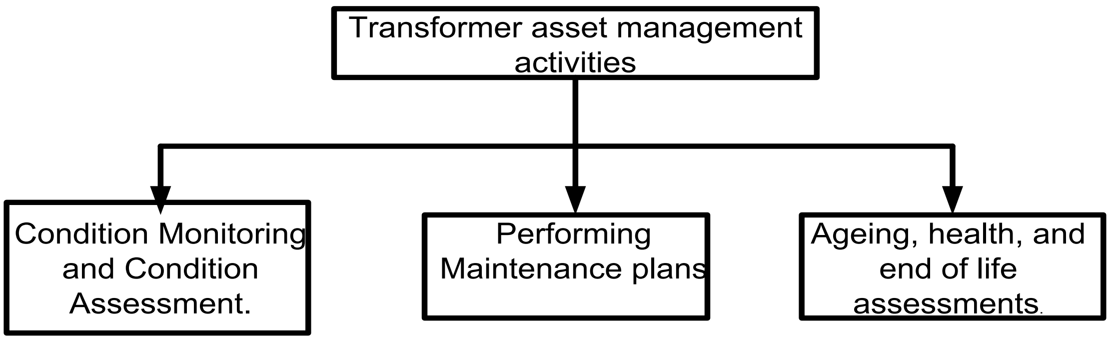


Figure 6.3 Transformer asset management activities

6.3.2 CM and CA techniques

Condition monitoring technique of a transformer is concerned with the application and development of special purpose equipments/methods that are involved in monitoring the condition of a parameter in the transformer and its data acquisition while CA means the development of new techniques for analyzing this data to predict the trends of the monitored transformer and evaluate its current performance. CM focuses mainly on the detection of incipient faults inside the transformer that are created from the gradual deterioration of the transformer. Some of these faults may however be detected during routine maintenance. Other faults may cause different kinds of problems before the routine maintenance cycle. For this reason, the ability to have detailed information on the state – of – health of the transformer prior to carrying out maintenance work was not available. Also, the diagnosis of many incipient fauts in the transformer was, in many cases, unavailable especially with those faults occurring after the routine maintenance cycle [89].

Benefits of CM

- It reduces the maintenance costs due to its ability to detect faults early,
- It limits the probability of complete failures,
- It identifies the root causes of the realization of the CM techniques such as extra added cost to the system due to the added monitoring and communication equipments,
- It also increases the complexity of the control and communication system because of the need for new and high speed processing systems for data processing and decision making as well as the need for suitable memory storage for data base knowledge.

The monitored data and the incipient faults detected by the CM system should be analyzed so as to have information about the state / condition of the

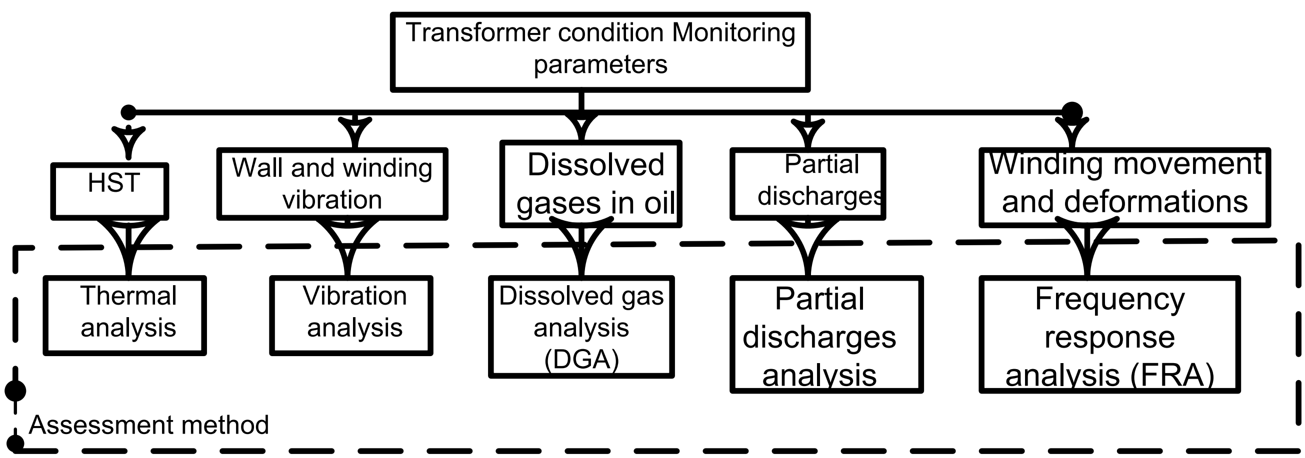


Figure 6.4 Transformer condition monitoring and assessment techniques

transformer. This analysis is done using the CA of the transformer. Transformer CM can be divided into five main categories: figure 6.4 shows the main categories of transformer CM and the corresponding CA techniques.

The various CA techniques outlined in figure 6.4 will be discussed briefly.

6.3.3 Condition assessment by thermal analysis

This can be used to detect the inception of any fault in the transformer. Most of the faults cause change in the thermal behaviour of the transformer. Abnormal condition can be detected by analyzing the transformer hot spot temperature (HST). The most common abnormal condition of the transformer that can be detected by thermal analysis is the overload. For a continuous maximum HST more than 110^{0C} [90], transformer life is affected greatly. HST can be predicted by the use of two techniques: The first technique uses Artificial Neural Network (ANN) to predict the HST [91]. The second method develops a thermal model to predict the thermal behaviour of the transformer [92].

6.3.4 CA by vibration analysis

The use of vibration signals in assessing the transformer health is a new technique compared with other methods of transformer condition assessment. The transformer vibration consists of core vibrations, winding vibrations, and on – load –tap – changer vibrations [93]. These generated vibrations propagate through the transformer oil until they reach the transformer walls, through which they can be collected via vibration sensors. The condition of the core and windings can be assessed using the vibration signature of the transformer tank [94]. Vibration analysis is a very powerful tool for assessing the condition of the on-load tap changer [95].

6.3.5 Condition Assessment by partial discharge analysis.

Partial discharges (PDs) occur when the electric field strength exceeds dielectric breakdown strength of a certain localized area, in which an electrical discharge or discharges partially bridge the insulation between conductors. The dielectric properties of the insulation may be severely affected if subjected to consistent PD activity over a long period of time. This may lead to complete failure if the PD activity is not corrected. [96]. PD can be detected and measured using piezo-electric sensors, optical fiber sensors [97], and Ultra High Frequency (UHF) sensors [98]. PD measurement was used extensively for the condition assessment of the transformer insulation due to the fact that large numbers of insulation problems start with PD activity [99].

6.3.6 Condition Assessment by disolved gas analysis (DGA).

At normal operating temperatures, both distribution and power transformers generate different gases. The concentration of these gases increases in the presence of fault such as thermal, partial discharge, and arcing faults [100]. During internal faults, oil produces gases such as hydrogen (H_2), methane (CH_4), and ethane (C_2H_6), while cellulose produces methane (CH_4), hydrogen (H_2), carbon monoxide (CO), and carbon dioxide (CO_2). Each fault type produces certain gases from the above – mentioned gases [101]. Analysizing transformer oil for these key gases by chromatography helps to know the fault type, and location [102]. Thermal faults such as sustained overloads and high HST produce many gases. Low temperature decomposition of mineral oil produces relatively large quantities of hydrogen (H_2) and methane (CH_4), and trace quantities of ethylene (C_2H_4) and ethane (C_2H_6).

These incipient faults affect the reliability of the transformer very much if not detected and treated early. The paper insulation system may be damaged due to local high temperature hot spots if the thermal faults are left untreated. Moreover, the paper insulation properties decreased notably for sustained PD or arcing faults. The degradation of the paper insulation can be detected using the ratio of CO_2/CO dissolved in transformer oil, which represents the tensile strength of the paper insulation.

6.3.7 Condition assessment by frquency response analysis

When a transformer is subjected to high fault currents, the windings are subjected to severe mechanical stresses causing winding movement, deformations, and in some cases severe damage. Deformation results in relative changes to the internal inductance and capacitance of the winding which can be detected externally by frequency response analysis (FRA) method [103]. Winding damage detection can be accomplished by comparing the fingerprints of a good winding (or the calculated response using a transformer equivalent circuit) with the fingerprints of a damaged winding. Changes in fingerprints can be used to estimate the degree of winding damage and its location [104].

6.3.8 New developments in condition monitoring and condition assessment.

With new development in sensors technology and communication systems, one or more parameters can be monitored at the same time [105]. Presently, new online cm and CA systems that monitor more than one parameter in the transformer are commercially available. Many parameters in the transformer can be monitored online using these new systems such as HST, dissolved gases, and oil temperature. Advanced technology sensors are used for parameter measurements in these new CM systems. All data measured are then collected using data acquisition subsystem to be analyzed and to provide interpretation for the operator. Recently, intelligent systems are used for data analysis and interpretation such as multi-agent systems [106]. Research revealed that these new CM systems provide fast and accurate interpretation to any problem in the transformer.

6.4 PERFORMING MAINTENANCE PLANS

Maintenance plans performance is the second transformer asset management activity. Transformer outage has harmful effects on the system and can be assumed as one of the most castrophic outages, especially for high rating power transformers. Accordingly, maintenance of the transformers should be planned carefully to avoid harmful outages.

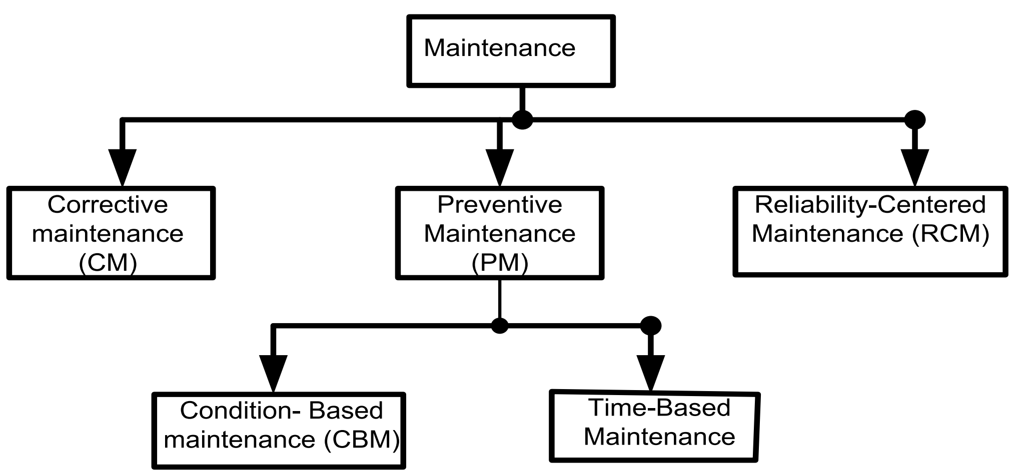


Figure 6.5 Classification of maintenance activities

According to figure 6.5, the maintenance types can be classified into corrective maintenance, preventive maintenance, and reliability centered maintenance.

6.4.1 Reliability-Centered Maintenance (RCM) On Transformer

The fundamental goal of RCM is to preserve the function or operation of a system with a reasonable cost [107]. RCM can be defined as a mix of more than one maintenance strategies in an optimized manner in order to reduce the system risk. For a successful RCM plan, the degree of risk of each fault should be identified in order to define the optimum maintenance actions [108], the risk index can be found as follows:

Risk = probability of failure x consequences of index …………… 6.1

The main items in the implementation of RCM according to (6.1) are the prioritization of the failure modes according to their consequences on the system and modeling the probability of failure [108]. The consequences index of each failure mode can be determined by the analysis of the history of failure or by experience. RCM starts with collecting data about the transformer failures to model the failure modes in a probabilistic form. The information about the consequences of each failure can be collected from the past experience of the skilled engineers. The information collected about consequences of failures together with the probability of each failure is used to calculate the risk index of each failure. The failure modes that have low risk indices can be treated by preventive maintenance such as CBM or TBM with optimum maintenance interval based on the maintenance cost [109]. This type of maintenance is assumed as the most recent maintenance strategy. More power utilities are converting from the regular TBM into RCM.

The main aim of the asset management is to maximize the benefits of the asset. The benefits are maximized from the asset by performing suitable CM techniques as well as performing good maintenance plan to maximize the usage, reducing the outage time, and increasing the lifetime of the asset. The lifetime issue as well as predicting the remaining life of the transformer will be discussed using the developed model in the next section.

6. 5 PARAMETERS FOR PREDICTING DISTRIBUTION TRANSFORMER

The value of λ used for estimating the remaining life for the distribution transformer was obtained as follows:

For the case when the deterioration states can be observed, we assumed that the mean times T_i between the deterioration states are all the same and equal to T_d. In this case, it would be sufficient to observe the times between normal state and the first deterioration state and then compute λ from $\lambda = \frac{1}{kT_d} \dots \dots \dots \dots$ 6.2

Similarly, for the case when deterioration states cannot be observed but can be experimentally identified, the average time to failure for the case of no maintenance policy is obtained from the Markov calculation using Relex software. The value of λ was therefore obtained as follows:

1) The observed average time to deterioration failure T_F.This is also the average time between failure events which were recorded from the outage data obtained from the system selected.
2) Solving the Markov Model for the case of no maintenance policy, for the various values of λ obtained from 1 above (see annexes 2.20 to 2.30).
3) The result obtained is plotted using MatLab as show in figure 6.6.

The Markov program for the plot is as shown below.

```
% plot of the simulated failure rate of the markov model.

   % For deteriorating system without maintenance.

lamda =[0.01:0.005:0.11];

z = 1./lamda;

plot(lamda,z,'g*',lamda,z,'r-'),grid, set(gca,'XTick',

[0.01:0.01:0.11],'YTick', [0:10:100]), xlabel('Failure rate'),

ylabel('Mean time to failure'),...

title('Function of the mean time to failure versus failre rate')
```

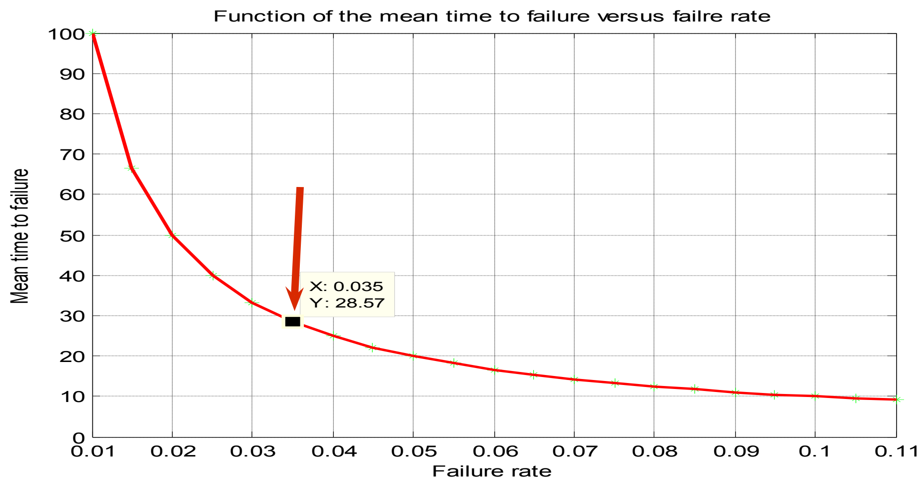


Figure 6.6 Function of mean time to failure versus failure rate

Considering a distribution transformer type for which we want to determine the mean remaining life of the transformer oil insulation which has been found in the deterioration state D_2. For this, we consider three states of deterioration as shown in the Markov model below.

These oil conditions are categorized as:

1) Oil in good working condition (D_1).
2) Oil required reconditioning before use (D_2).
3) Oil in poor condition and will require replacement or it will fail.(D_3 orF)

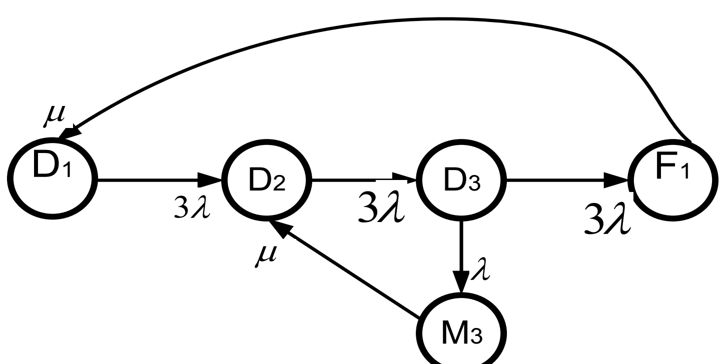


Figure 6.7 Markov model with continuous parameter.

Note therefore that k = 3, referring to figure 3.5, state D2 is denoted by i and state F by j. When the rule of states combination is applied, the following equations are obtained:

$\lambda_{is} = k\lambda = 3\lambda$, ……………………….. 6.3

$\lambda_{js} = \mu$

$$\lambda_{is} = \frac{P_{D1}3\lambda + P_{M3}\mu_M}{P_{D1} + P_{D3} + P_{M3}} \quad \ldots\ldots\ldots\ldots\ldots\ldots. \qquad 6.4$$

$$\lambda_{Sj} = \frac{P_{D3}3\lambda}{P_{D1} + P_{D3} + P_{M3}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots.. \qquad 6.5$$

where the probabilities P_{D1} , P_{D3} and $P_{M3,}$ are the steady – state probabilities of the system states. Using the system states, the transition matrix was constructed with the parameters obtained from the outage of the system selected.

The mean time to first failure of the transformer can now be predicted using the program developed in this thesis following the underlisted steps.

6.6 DETERMINATION OF THE STEADY STATES PROBABILITIES

Using the 5 – state Markov process (figure 6.8), the intensity matrix (Q) is generated from the state transition diagram as illustrated below:

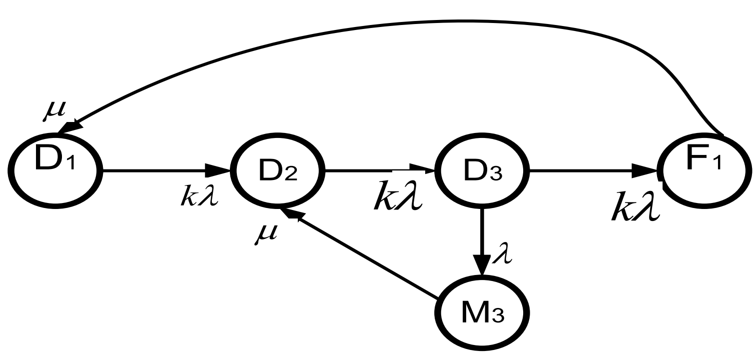


Figure 6.8 Markov model for generating intensity matrix

From figure 6.8, the intensity matrix (Q) was generated as shown below:

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

$\lambda = 0.1$, μ = 5.1, μm = 36, λm = 0.9.

$$Q = \begin{bmatrix} D_{11} & D_{12} & D_{13} & M_{14} & F_{15} \\ D_{21} & D_{22} & D_{23} & M_{24} & F_{25} \\ D_{31} & D_{32} & D_{33} & M_{34} & F_{35} \\ D_{41} & D_{42} & D_{43} & M_{44} & F_{45} \\ D_{51} & D_{52} & D_{53} & M_{54} & F_{55} \end{bmatrix},$$

$$Q = \begin{bmatrix} -3\lambda & 3\lambda & 0 & 0 & 0 \\ 0 & 3\lambda & -3\lambda & 0 & 0 \\ 0 & 0 & -(3\lambda - \lambda_m) & \lambda_m & 3\lambda \\ 0 & \mu_m & 0 & -\mu_m & 0 \\ \mu & 0 & 0 & 0 & -\mu \end{bmatrix}$$

$$[P_{D1}, P_{D2}, P_{D3}, P_{M3}, P_{F1}] \begin{bmatrix} -\ .3 & 0.3 & 0 & 0 & 0 \\ 0 & -\ .3 & 0.3 & 0 & 0 \\ 0 & 0 & -\ .2 & 0.9 & 0.3 \\ 0 & 42 & 0 & -\ 6 & 0 \\ 6.1 & 0 & 0 & 0 & -\ .1 \end{bmatrix} =) \ldots\ldots \qquad 6.6$$

$P_{D1} + P_{D2} + P_{D3} + P_{M3} + P_{F1} = 1$ …………………… 6.7

The steady state probabilities stated in section 6.5 are obtained by solving the equations P.Q = O

The p_{D1}, P_{D2}, P_{D3}, P_{M3} and P_{F1} are unknown, they are the values we wish to find since they are the steady- state probabilities of the system states indicated in figure 6. If there are n – states in the state space, there are n such equations in n – unknowns. Unfortunately, this collection of equation is irreducible. We need another equation in order to solve it and find the unknowns. Fortunately, since $\{p_i\}$ is a probability distribution, we also know that the normalisation condition holds.

$\sum_{x_i \in S} \boldsymbol{P_i} = \mathbf{1}$. With these n + 1 equations, we can solve to find the n unknowns. $\{P_i\}$ which is equals P_1 to P_n steady-state probabilities is now represented by P_{D1}, P_{D2}, P_{D3}, P_{M3} and P_{F1} respectively.

Calculating the steady – state probabilities (P_{D1}, P_{D2}, P_{D3}, P_{M3} *and* P_{F1}) from the generated transition probabilities and the normalisation condition of $\sum_{xi\epsilon S}(P_i)$ = 1, are obtained as follows:

$$\left(\begin{array}{c} -0.3P_{D1} + 0 + 0 + 0 + 5.1P_{F1} = 0 \\ 0.3P_{D1} - 0.3P_{D1} + 0 + 36\mathrm{P}_{M3} + 0 = 0 \\ 0 + 0.3P_{D2} - 1.2P_{D3} + 0 + 0 = 0 \\ 0 + 0 + 0.9P_{D3} - 36P_{M3} + 0 = 0 \\ 0 + 0 + 0.3P_{D3} + 0 - 5.1P_{F1} = 0 \\ \mathrm{P}_{D1\,+}\,\mathrm{P}_{D2+}\,\mathrm{P}_{D3+}\,\mathrm{P}_{M3+}\,\mathrm{P}_{F1} = 1 \end{array}\right) \quad \ldots\ldots\ldots. \qquad 6.8$$

Using the MatLab program, the steady-states probabilies were computed as shown below:

% computing the steady state probabilities,using Matlab program.

A = [-0.3,0,0,0,5.1;0.3,-0.3,0,36,0;0,0.3,-1.2,0,0;0,0,0.9,-36,0;0,0,0.3,0,-5.1;1,1,1,1,1];

B = [0;0;0;0;0;1];

x1 = A\B

P_D1=x1(1,1); P_D2=x1(2,1); P_M=x1(3,1); P_F=x1(4,1); P_F=x1(5,1)

P_D1 = 0.1644, P_D2 = 0.6575,p_D3 = 0.1644,P_M3 = 0.0041,P_F = 0.0097.

6.7 DETERMINATION OF MEAN TIME TO FIRST FAILURE

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

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

A Matlab program developed in this thesis was used for the determination of the mean time to first failure. The failure rates, maintenance rate, repaire rate and the steady-state probabilities obtained in equations 6.5 and 6.6 were now used as inputs for this program.

A Markov model has been used for estimating the remaining life of distribution transformer used in a selected Utility. The recent trend for most asset managers in power system utilities is to reduce capital spending, and one area that is being scrutinized by most managers is in the area of capital expenditures on power transformers. This model will aid asset managers to take quality decisions for carrying out maintenance of one of the most vital components of the power distribution network . So far, a mathematical formulation of the approximated transition time from any deterioration state to failure state (expected remaining life) capable of answering other questions that will help asset managers take informed decisions has been presented.

The computer program computes the remaining expected life of the distribution transformer based on the deterioration conditions of the transformer oil. The deterioration process of a transformer is approximated by three discrete stages: D_1, D_2, and D_3. At each stage, oil is inspected to determine its condition. After the inspection , oil condition is determined by some criteria indicated earlier. The criteria categorized oil condition into three groups as indicated before. The influence of this inspection on taking informed decisions on the nature of the maintenance policy was fully explored in the simulation model. The extent of the computer program is to compute the mean life to transformer failure based on the failure, maintenance and repair rates generated from the outage data of the groups of transfomers under investigations. These parameters are used as inputs to this program. The computation of the estimated mean time to failure for the model in figure 6.8 with the input parameters obtained from the outage data of the PHCN system under consideration is shown below. The effects of the variable parameters which are controllable were also assessed throgh sensitivity studies.

```
% Computer program for computing the mean time to failure

% calculating the values for first passage time.

lamda = 0.1;

mew = 5.1;

mewm = 36;

lamdam = 0.9;

P_D1  = 0.1644;

P_D3 = 0.1644;

P_M3 = 0.0041;

P_total = 0.3329

lamdais = 3*lamda

Osa_1 = P_D1 * lamdais;

Osa_2 = P_M3 * mewm;

lamdasi = (Osa_1 + Osa_2)/P_total;

disp('lamdasi is:')

lamdasi

lamdasj = (P_D3*3*lamda)/(P_D1+ P_D3+ P_M3);

disp('lamdasj is:')

lamdasj

P_si = lamdasi/(lamdasi+lamdasj);

disp('P_si is:')
```

```
P_si

P_sj = (1-P_si);

disp('P_sj is:')

P_sj

vera_1 = (1/(lamdais))*(1/P_sj);

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/lamdasi)*(1/(1-P_si));

disp('vera_4 is:')

vera_4

m_ij = vera_1+vera_2+vera_3+vera_4;

disp('The mean remaining life of the component is:')

m_ij
```

P_total = 0.3329, lamdais = 0.3000,lamdasi = 0.5915,lamdasj = 0.1482

P_si = 0.7997,P_sj = 0.2003,vera_1 = 16.6423, vera_2 = 1.3519,

vera_3 = 1.2874,vera_4 = 6.7498.

The mean remaining life of the component is = 26.0314 years

6.8 SENSITIVITY ANALYSIS OF FAILURE RATE ON ESTIMATED REMAINING LIFE OF DISTRIBUTION TRANSFORMER

The equation for the mean transition time from the first deterioration state to the major deterioration state is given as $\lambda_{is} = \frac{P_{D1}3\lambda + P_{M3}\mu_M}{P_{D1} + P_{D3} + P_{M3}}$, when maintenance rate μ_M is held constant while changing the frequency of failure(λ), the program was implemented, the result obtained from the program developed indicates the followings:

That as the failure rate intensity increases, the MTBF decreases and the mean remaining life of the transformer decreases as well. This agrees with the developed model. From the model, λ_{is} is directly proportional to (λ), and λ_{is} is inversely proportional to m_ij (mean remaining life of the transformer). The graphical illustration of the result obtained from the program are shown in figure 6.10a-c. The result obtained from the computer program when sensitivity analysis was performed on the model were illustrated graphically in figures 6.10b – c.

```
% Computer program for computing the mean time to failure
% calculating the values for first passage time
   lamda =0.1:0.05:1.5;mew = 5.1;
mewm = 36;
lamdam = 0.9;
P_D1  = 0.1644;
P_D3 = 0.1644;
P_M3 = 0.0041;
```

```
P_total = 0.3329

lamdais = 3*lamda

Osa_1 = P_D1 * lamdais;

Osa_2 = P_M3 * mewm;

lamdasi = (Osa_1 + Osa_2)/P_total;

disp('lamdasi is:')

lamdasi

lamdasj = (P_D3*3*lamda)/(P_D1+P_D3+P_M3);

disp('lamdasj is:')

lamdasj

P_si = lamdasi./(lamdasi+lamdasj);

disp('P_si is:')

P_si

P_sj = 1 - P_si;

disp('P_sj is:')

P_sj

vera_1 = (1./P_sj).*(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./lamdasi).*(1./(1-P_si));

disp('vera_4 is:')

vera_4

m_ij = vera_1+vera_2+vera_3+vera_4;

disp('The mean remaining life of the component is:')

m_ij

plot(lamda,m_ij,'g*',lamda,m_ij,'r-'),

grid,set(gca,'XTick',[0.1:0.1:1.5],'YTick',...

 [0:3:26]),xlabel('Failure rate'),ylabel('Estimated Mean time to
transformer failure'),...

title('Sensitivity analysis of failure rate on estimated remaining life')
```

The results obtained from the computer program are the esimated transformer lifespan at varying failure rate, assuming all other variable parameters are held constant (for example maintenance rate(μ_m)). These results are plotted as shown in figure 6.9. This plotted graph is fitted to 8th degree polynomial. The resulting graph and its residual plots are shown in figures 6.10a and 6.10b. These verified the degree of accuracy of the obtained solution.

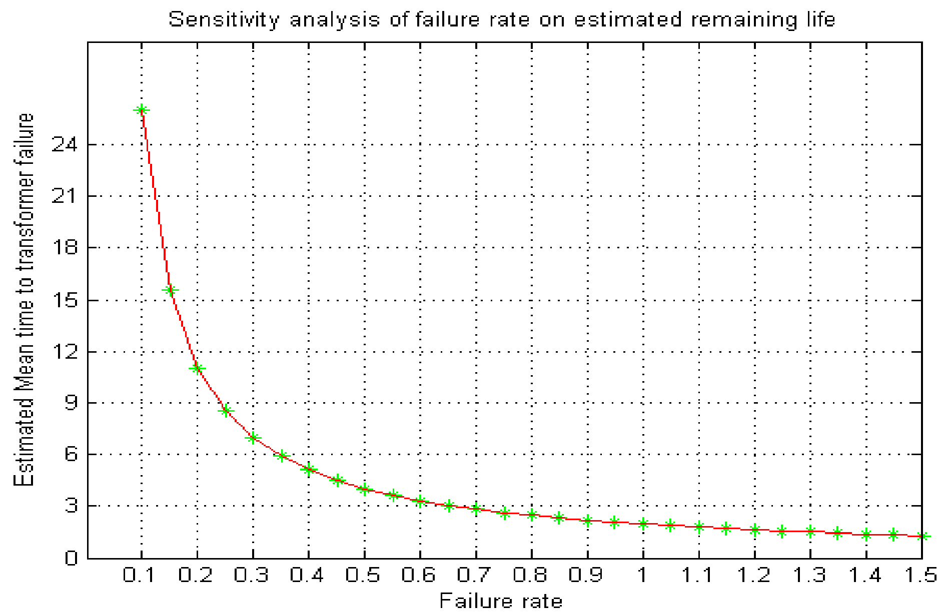


Figure 6.9 Estimated transformer lifespan at varying failure rate.

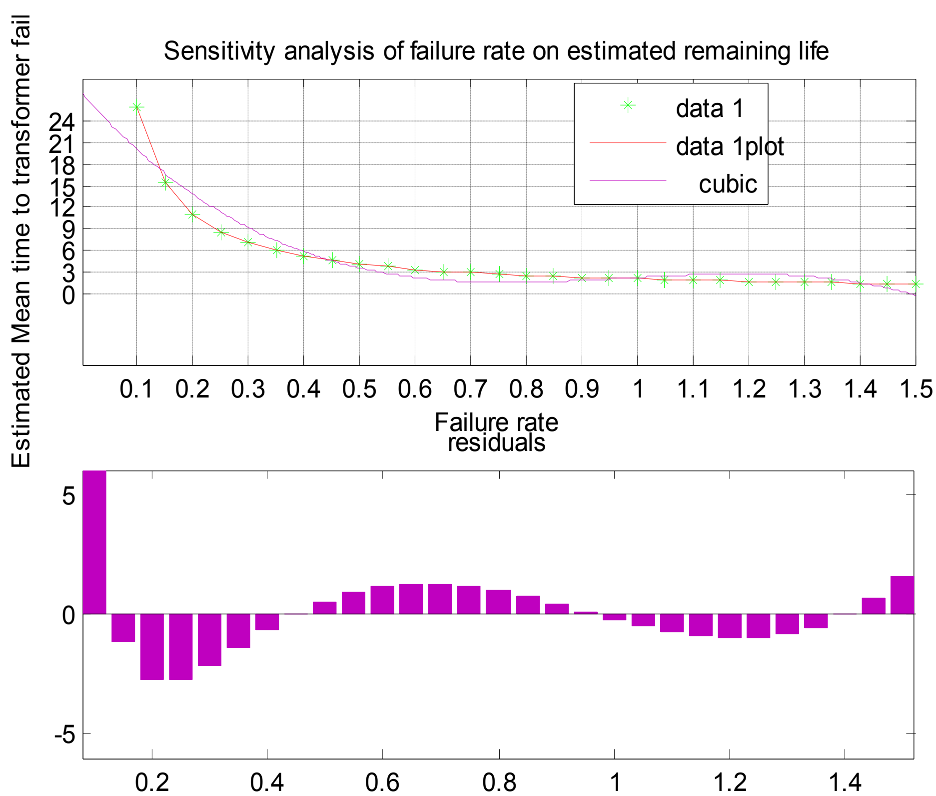


Figure 6.10a-b sensitivity data fitted to 8th degree polynomial and its corresponding Norm residuals

The next step was to hold the failure rate (λ) constant and vary the maintenance rate(μ_m), the remaining life of the distributed transformer insulation was again computed, and the computer program for performing this operation is shown below.

```
% Computer program for computing the mean time to failure

% calculating the values for first passage time

lamda =0.1;

mewm =06:06:80;

lamdam = 0.9;

P_D1  = 0.1644;

P_D3 = 0.1644;

P_M3 = 0.0041;

P_total = 0.3329;

lamdais = 3*lamda;

Osa_1 = P_D1 * lamdais;

Osa_2 = P_M3 * mewm;

lamdasi = (Osa_1 + Osa_2)/P_total;

lamdasj = (P_D3*3*lamda)/(P_D1+P_D3+P_M3);

P_si = lamdasi./(lamdasi+lamdasj);

P_sj = 1 - P_si;

vera_1 = (1./P_sj).*(1./lamdais);

vera_2 = P_sj./lamdasj;
```

```
vera_3a = (P_sj.*P_si)./lamdasj;

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

vera_3 = vera_3a.*vera_3b;

vera_4 = (P_si./lamdasi).*(1./(1-P_si));

m_ij = vera_1+vera_2+vera_3+vera_4;

[mewm', m_ij']

plot(mewm,m_ij,'g*',mewm,m_ij,'r-');grid
in;set(gca,'XTick',[06:06:80],'YTick',...

    [18:1.5:39]),xlabel('Mean duration of maintenance
strategy[mewm]'),ylabel('Mean time to first failure'),...

    title('Result of sensitivity analysis when other variable are held
constant except mewm')
```

The results obtained were plotted and the graphical representation that shows the sensitivity of this variation with the computed remaining life of the component (distributed transformer) is shown in figure 6.11. This graph shows that the maintenance rate (μ_m) is directly proportional to the computed remaining life of the component under consideration. The linear relationship between the maintenance rate and the computed remaining life becomes more pronounced when the computed values are fitted usng Matlab tool to 3rd degree polynomial. The goodness of fit is also displayed in the bar chart plot shown in figures 6.12a and 6.12b. The value obtained from norm (the square root of the sum of the squares of the residuals) indicated a very good fit.

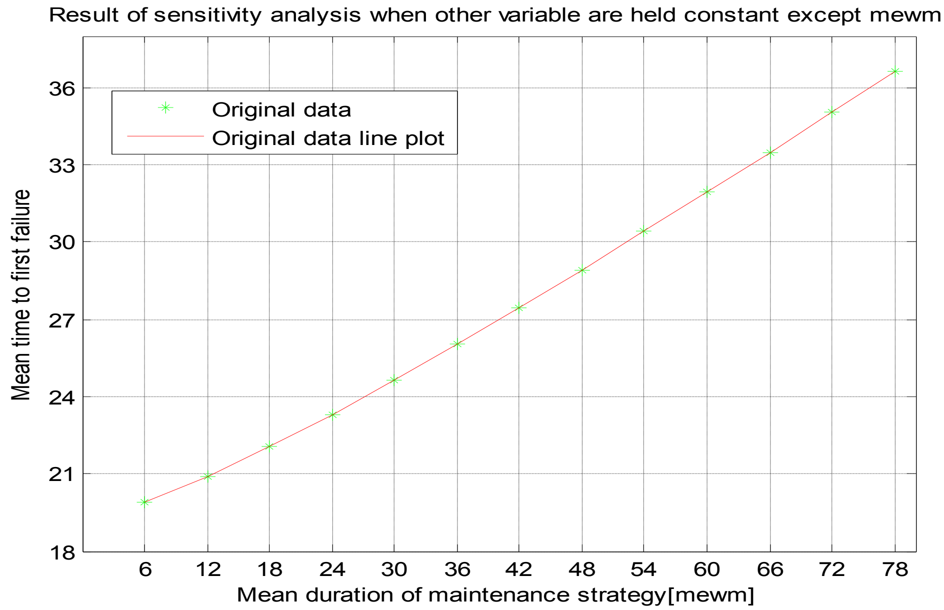


Figure 6.11 Plot of the result of the sensitivity analysis when other variables are held constant except μ_m.

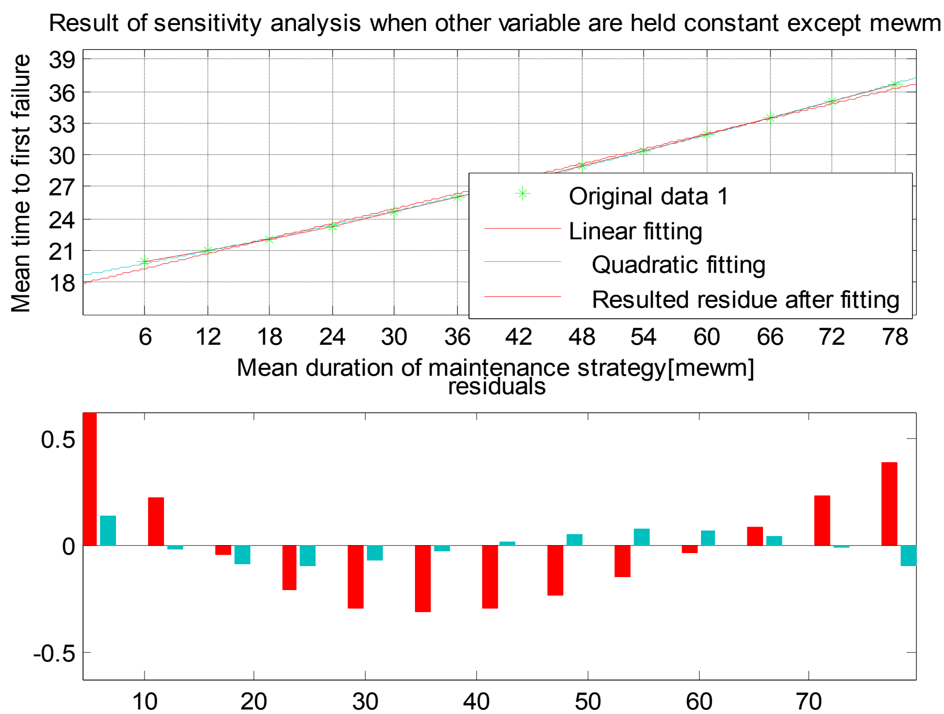


Figure 6.12a-b sensitivity data fitted to 3[th] degree polynomial and its corresponding Norm residuals

6.9 DISCUSSION AMD ANALYSIS OF RESULTS

The following observations can be made from the simulation results

The simulation result suggests that an effective maintenance occurs at small inspection rate of D_1 and high inspection rate of D_2 and D_3. The sensitivity analysis of inspection rate on MTTFF based on the simulation results of figure 5.1 is discussed as follows:

1. **Inspection rate of stage1**

It is possible that inspection and maintenance will reduce MTTFF at very high inspection rate of stage1 (high inspection in stage1 will increase λ_{13}, thus, denominator may be large). This will increase the failure rate from stage 1 to 3, therefore, MTTFF may decrease. This suggestion is verified by the simulation result in figure 5.6a.

2. **Inspection rate of stage2**

High inspection rate of stage2 will increase the repair rate from stage2 to 1(μ_{21}). Let's assume that this repair rate is very high,

$$MTTFF = \frac{1 + y_3(\mu_{31} + \mu_{32} + \lambda_{13})}{\lambda_{13}}$$

This shows that MTTFF will increase to a constant value. This again is verified by the simulation result in figure 5.6b.

3. **Inspection rate of stage3**

High inspection rate of D_3 will increase the repair rate from stages 3 to 2 (μ_{32}) and also repair rate of stages 3 to 1 (μ_{31}). These rates are linearly related to MTTFF; therefore, the lifetime will increase linearly with inspection rate of stage3. This again is verified by the simulation result in figure 5.6c.

Simulation results from Matlab are shown and from the above analysis, are verified by mathematical equations of the equivalent model.

The model developed for estimating the remaining life of deteriorating component that was derived using the methodology of first passage time calculation explains the simulation result obtained in figures 5.6a to 5.6c

A Markov model has been introduced for estimating the remaining life of the oil insulation of a distribution transformer. A mathematical model as well as a computer program for computing the expected transition time from any deterioration state to failure state (expected remaining life) has been presented. The result obtained was also represnted graphically so as to determine its sensitivity with different failure rates and maintenance rates when other parameters are held constant.

This model would also allow assessment by way of sensitivity studies of relative effects of various other parameters in the process which are controllable, for example maintenance policy and impact of loading.

That as the failure rate intensity increases, the MTBF decreases and the mean remaining life of the transformer decreases as well. This agrees with the developed model. From the model, λ_{is} is directly proportional to (λ), and λ_{is} is inversely proportional to m_ij (mean remaining life of the transformer). The graphical illustration of the result obtained from the program as shown in figure 6.9 confirms this proposition. The computer program for the sensitivity analysis and the result obtained as well as the graghical representation verified the mathematical formulation in the model.

CHAPTER SEVEN

SUMMARY OF FINDINGS, CONCLUSION AND RECOMMEDATIONS

7.1 SUMMARY OF FINDINGS

- In this work, an effective Maintenance planning program using statistical analysis of failure data as well as deciding which failure data are relevant using Laplace test analysis and Serial Correlation Coefficient techniques has been presented.
- Various estimates of sample mean from failure data such as λ, MTBF and MTTR etc, which are tools for reliability analysis yield immediate insight into the group of distribution feeders or components that are prone to failures.

  This will aid in the selection of the critical components that possess the highest risk index to the system reliability.
- Some failures could be tolorated when selecting appropriate maintenance strategy during normal operation of the system. RCM methodology requires that extensive mitigation plans need to be put in place for other types of system failure so that they do not occur at all, and if they do, their risk (probability of failure x consequences index) would have been optimized.
- A probabilistic maintenance model that links maintenance and reliability for describing the impact on reliability of gradually deteriorating equipment with periodic inspections that can lead to various possible maintenance strategies has been developed.
- Simulation results obtained from Transformer Maintenance Model with Relex software are shown and this is verified by mathematical equations of the equivalent model. The analysis of the simulation results suggests that inspection is only introduced to determine the stage of the device deterioration

- A Markov Model for estimating the remaining life of the electrical insulation of transformer had been developed.
- A Matlap program based on mathematical formulation of the expected transition time from any deterioration state to the failure state (expected remaining life) has been presented. The M – files of this program were created using the developed mathematical equations.
- The program was applied to a distribution transformer identified as critical component in the Abule-Egba business unit considered in this thesis.
- 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. It is a fact of life that prediction (forecast) stand on a firmer ground if it is relative rather than absolute

7.2 ACHIEVEMENTS

We have been able to achieve the following objectives

a) A probabilistic Maintenance Model that link maintenance and reliability had been developed and simulated on a MatLab platform.
b) A Markov Model for predicting the remaining life of Electrical insulation of transformer had been developed.
c) A Matlap program based on mathematical formulation of the expected transition time from any deterioration state to the failure state (expected remaining life) has been implemented.
d) The program was applied to a distribution transformer identified as critical component in one of the PHCN Utility.
e) RCM application studies have been performed by analysing (i) real distribution systems (Abule-Egba Business unit), (ii) outage data statistics evaluation, (iii) experience from supply interruptions, (iv) critical component identification and (v) the effect of taking informed decision based on the results obtained from the computer program applied to the distribution transformer.

7.3 CONCLUSIONS

A propabilistic maintenance model that link maintenance and reliability for describing the impact on reliability of gradualing deteriorating equipment with periodic inspections that can lead to various possible maintenance strategies has been developed. Furthermore, a Reliability-Centred Maintenance model for utility asset management capable of predicting the nature and time of maintenance action to ensure continuity of supply had been developed. The procedure for the development of this model is unique in the sense that it is a departure from the conventional heuristic approach. It deployed statistical analysis of some operational data and incorporated Markov's model based techniques to make valid predictions on the time and type of maintenance action to guarantee reliability.

A MatLab's m-files based on a new mathematical formulation were developed and a computer program based on this m-file was implemented for predicting the remaining life of distribution trasformers' insulation. Simulation results from MatLab program are shown and these verified the simulation results obtained from the transformer maintenance model that was implemented on Relex 2009 platform. The analysis of the simulation results suggests that inspection is only introduced to determine the stage of the device deterioration.

This model was applied to a distribution transformer located in Abule-Egba business unit network of the PHCN considered in this thesis.

7.4 RECOMMEDATION

In coming to the conclusion of this work, the problem statement outlined in the introduction has been addressed in greater detailed. It therefore seems appropriate to end the work by identifying and highlighting some of the special difficulties encountered in an attempt to achieve the primary objective of this work. The system that is being analysized is the Electric power distribution system. It is a well know fact that this system behave randomly and therefore it is essential to use probability methods in combination with deterministic description so that the developed model will not be too complicated.

It was however realised during the work that the main challenges are not only technical. The system is required to be operated and maintained in a cost-effective way and still be reliable. This in turn requires strategies that place the technical and economic issues side by side, in order to develop a total model for informed asset management decisions.

7.4.1 Difficulties encountered

The main difficulties are as follows:

- Locating supporting input data that can generate enough detailed information and cover a long period of time for reliability evaluation from a Utility such as Nigeria PHCN.
- It was almost impossible to generate data on maintenance cost and maintenance budget from a utility that do not have any maintenance policy.
- The major challenges facing the RCM are the data needed about failure modes and their consequences on both the transformer itself and the system. This data includes recorded information from many operating transformers about their failure modes and failure consequences.
- Not all the problems have been solved; this leads to the next section, recommendation for future work.

7.5 FUTURE RESEARCH WORK

All the problems have not yet been solved, for future work the following recommendations are proposed:

i. For the model developed to be used in the computation of probability density functions that will help to answer the question on duration, more work need to be done. With this present model, only the mean time to failure could be computed.

ii. There is need for more work in the area that relate to the determination of the various transition rates used in the model and precise definition of various deterioration states.

iii. There is an urgent need to maintain maintenance data center for the country's power utility that could be updated daily.

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Annex 2.1

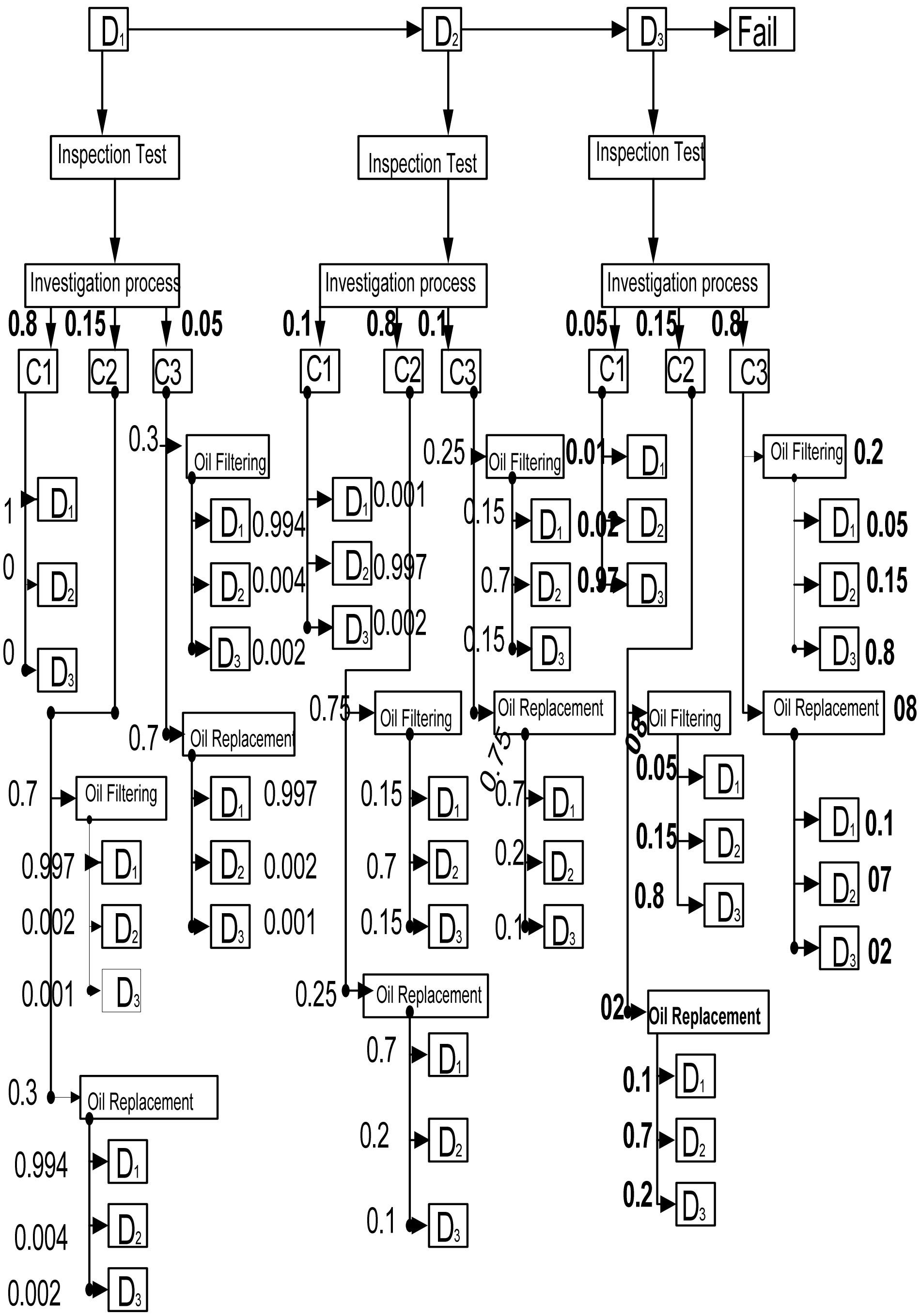

Figure 5.1 Transformer Maintenance Model

ANNEX- 3.1 -- OUTAGE DATA FOR THE YEAR 2004 (F1)

S/N	Failure times in (Hrs.)	Outage Duration (Hrs)
1	10	10
2	26	16
3	44	18
4	57	13
5	72	15
6	83	11
7	99	16
8	120	21
9	132	12
10	148	16
11	165	17
12	180	15
13	193	13
14	206	13
15	223	17
16	237	14
17	248	11
18	262	14
19	278	16
20	292	14
21	309	17
22	324	15
23	340	16
24	349	9
25	364	15
26	370	6
27	385	15
28	404	19
29	417	13
30	426	9
31	441	15
TOT	7204	441

$\lambda 1$ = Mean X = 441/24

= 18.375/31

= 0.593

MTBF1 = 1/λ1 = 1.7

MTTR1 = Mean Y = 7204/24

= 300.16/31

9.7

LEGEND

F1 = Feeder One

ANNEX 3.2 --OUTAGE DATA FOR THE YEAR 2004 (F2)

S/N	Failures times in (Hrs.)	Outage Duration (Hrs.)
1	13	13
2	29	16
3	41	12
4	56	15
5	72	16
6	84	12
7	103	19
8	119	16
9	133	14
10	146	13
11	161	15
12	177	16
13	188	11
14	199	11
15	217	18
16	229	12
17	243	14
18	256	13
19	272	16
20	287	15
21	301	14
22	317	16
23	333	16
24	340	7
25	357	17
26	365	8
27	377	12
28	393	16
29	408	15
30	423	15
31	439	16
TOT	7078	439

UL = 4.5

$\lambda 2 = 439/24 = 18.29/31 = 0.59$

$MTBF2 = 1/\lambda 2 = 1.69$

$MTTR2 = 7078/24 = 294.9/31 = 9.51$

ANNEX 3.3 --OUTAGE DATA FOR THE YEAR 2004 FOR FEEDER3 (F3)

S/N	Failures times in (Hrs.)	Outage Duration (Hrs.)
1	12	12
2	16	4
3	29	13
4	38	9
5	49	11
6	57	8
7	72	15
8	77	5
9	85	8
10	91	6
11	100	9
12	106	6
13	119	13
14	128	6
15	137	9
16	140	3
17	148	8
18	158	10
19	173	15
20	188	15
21	196	8
22	206	10
23	214	8
24	218	4
25	227	9
26	230	3
27	244	14
28	250	6
29	260	10
30	268	8
31	283	15
TOT	4519	283

$\lambda 3 = 283/24 = 11.79/31 = 0.3803$, UL = 3.4, MTT = 0.3803

MTBF3 = $1/\lambda 3 = 2.63$, MTTR3 = 4519/24 = 6.07

ANNEX 3.4 --0UTAGE DATA FOR THE YEAR 2004 FOR FEEDER4 (F4)

S/N	Failures times in (Hrs.)	Outage Duration (Hrs.)
1	12	12
2	33	21
3	46	13
4	62	16
5	76	14
6	90	14
7	108	18
8	124	16
9	137	13
10	151	14
11	166	15
12	178	12
13	189	11
14	206	17
15	222	16
16	235	13
17	249	14
18	263	14
19	280	17
20	295	15
21	308	13
22	326	18
23	342	16
24	348	6
25	365	17
26	371	6
27	386	15
28	404	18
29	421	17
30	434	13
31	451	17
TOT	8429	451

UL =
3.4

$\lambda 4 = 451/24 = 18.79/31$

$= 0.606$

$MTBF4 = 1/\lambda 4$

$= 1.65$

$MTTR = 8429/24 = 351.2/31 = 11.3$

ANNEX 3.5 --OUTAGE DATA FOR THE YEAR 2005 FOR FEEDER1 (F1)

S/N	Failures times in (Hrs)	Outage times (Hrs.)
1	14	14
2	30	16
3	46	16
4	59	13
5	60	1
6	62	2
7	66	4
8	72	6
9	78	6
10	93	15
11	109	16
12	123	14
13	138	15
14	153	15
15	167	14
16	177	10
TOT	1447	177

$\lambda 1 = 177/24$ UL = 2.3

$= 7.375/16$

$= 0.461$

MTBF1 = $1/\lambda 1$

$= 2.17$

MTTR1 = 1447/24

$=60.29/16$

$= 3.77$

ANNEX 3.6 -- OUTAGE DATA FOR THE YEAR 2005 FOR FEEDER2 (F2)

S/N	Failures times in (Hrs.)	Outage Duration (Hrs)
1	16	16
2	31	15
3	42	11
4	58	16
5	60	2
6	64	4
7	70	6
8	77	7
9	85	8
10	100	15
11	113	13
12	130	17
13	142	12
14	152	10
15	167	15
16	179	12
TOT	1486	179

UL = 1.8

$\lambda 2 = 179 / 24$
$= 7.458/16$
$= 0.466$

MTBF = $1/ \lambda 2$
$= 2.17$

MTTR = 1447/24
= 60.29/16
= 3.77

ANNEX 3.7 --OUTAGE DATA FOR THE YEAR 2005 FOR FEEDER 3 (F3)

S/N	Failures times in (Hrs.)	Outage duration (Hr)
1	9	9
2	18	9
3	29	11
4	39	10
5	43	4
6	45	2
7	56	11
8	65	9
9	69	4
10	80	11
11	89	9
12	99	10
13	103	4
14	108	5
15	119	11
16	125	6
TOT	1096	125

ul = 2.6

$\lambda 3 = 125/24$
$= 5.208/16$
$= 0.326$

MTBF3 $= 1/\lambda 3$
$= 3.072$

MTTR3 $= 1096/24$
$= 45.666/16$
$= 2.85$

ANNEX 3.8 -- OUTAGE DATA FOR THE YEAR 2005 FOR FEEDER 4 (F4)

S/N	Failures times in (Hrs.)	Outage Duration (Hrs.)
1	15	15
2	31	16
3	44	13
4	59	15
5	63	4
6	68	5
7	75	7
8	79	4
9	83	4
10	95	12
11	104	9
12	119	15
13	132	13
14	144	12
15	155	11
16	166	11
TOT	1432	166

UL =1.7

$\lambda 4 = 166/24$
$= 6.9166/16$
$= 0.432$

MTBF4 $= I/\lambda 4$
$= 2.31$

MTTR = 1432/ 24
= 59.667/16
= 3.73

ANNEX 3.9 --OUTAGE DATA FOR THE YEAR 2006 FOR FEEDER 1 (F1)

S/N	Failures times in (Hrs.)	Outage Duration (Hrs.)
1	14	14
2	24	10
3	37	13
4	52	15
5	70	18
6	83	13
7	98	15
8	113	15
9	130	17
10	148	18
11	162	14
12	177	15
13	198	21
14	216	18
15	228	12
16	244	16
17	259	15
18	273	14
19	288	15
TOT	2814	288

UL 3.03

$\lambda 1 = 288/24$
$= 12/19$
$= 0.63$

MTBF1 = $1/\lambda 1$
$= 1.6$

MTTR1 = 2814/24
= 117.25/19
= 6.2

ANNEX 3.10 --OUTAGE DATA FOR THE YEAR 2006 FOR FEEDWE 2 (F2)

S/N	Failures times in (Hrs.)	Outage Duration (Hrs.)
1	13	13
2	26	13
3	41	15
4	53	12
5	71	18
6	85	14
7	100	15
8	116	16
9	135	19
10	151	16
11	165	14
12	182	17
13	200	18
14	217	17
15	236	19
16	250	14
17	264	14
18	280	16
19	296	16
TOT	2881	296

UL 4.6

$\lambda 2 = 296/24$
$= 12.3/19$
$= 0.65$

MTBF2 = $1/\lambda 2$
$= 1.5$

MTTR2 = 2881/24
= 120/19
= 6.3

ANNEX 3.11 --OUTAGE DATA FOR THE YEAR 2006 FOR FEEDER 3 (F3)

S/N	Failures times in (Hrs.)	Outage Duration (Hrs.)
1	7	7
2	17	10
3	23	6
4	37	14
5	46	9
6	58	12
7	71	13
8	76	5
9	87	11
10	98	11
11	112	14
12	118	6
13	130	12
14	138	8
15	146	8
16	156	10
17	164	8
18	170	6
19	179	9
20	188	9
TOT	2021	188

UL = 2.3

$\lambda 3 = 188/24$
$= 7.83/20$
$= 0.392$

MTBF = $1/\lambda 3$
$= 2.6$

MTTR3 = 2021/24
= 84.21/20
= 4.2

ANNEX 3.12 -- OUTAGE DATA FOR THE YEAR 2006 FOR FEEDER 4 (F4)

S/N	Failures times in (Hrs.)	Outage Duration (Hrs)
1	14	14
2	27	13
3	44	17
4	60	16
5	75	15
6	90	15
7	104	14
8	121	17
9	139	18
10	155	16
11	167	12
12	184	17
13	201	17
14	217	16
15	235	18
16	247	12
17	260	13
18	277	17
19	293	16
20	307	14
TOT	3217	307

UL = 5.2

$\lambda 4 = 307/24$
$= 12.79/20$
$= 0.64$

MTBF4 = $1/\lambda 4$
$= 1.6$

MTTR4 = 3217/24
= 6.7

ANNEX 3.13 -- OUTAGE DATA FOR THE YEAR 2007 FOR FEEDER 2 (F2)

S/N	Failures times in (Hrs.)	Outage Duration (Hrs.)
1	14	14
2	24	10
3	30	6
4	40	10
5	55	15
6	65	10
7	81	16
8	93	12
9	105	12
10	114	9
11	122	8
12	129	7
13	134	5
14	150	16
15	162	12
16	178	16
17	193	15
18	209	16
19	222	13
20	237	15
21	244	7
22	261	17
23	275	14
24	279	4
25	293	14
26	299	6
27	314	15
TOT	4322	314

UL = 3.8

$\lambda 2$ = 314/24

= 13.08/27

= 0.485 MTTR2 = 4322/24 = 6.67

MTBF2 = 1/$\lambda 2$

= 2.06

ANNEX 3.14 -- OUTAGE DATA FOR THE YEAR 2007 FOR FEEDER 4 (F4)

S/N	Failures times in (Hrs.)	Outage Duration (Hrs.)
1	14	14
2	24	10
3	30	6
4	40	10
5	54	14
6	67	13
7	84	17
8	108	24
9	123	15
10	131	8
11	142	11
12	154	12
13	168	14
14	177	9
15	184	7
16	208	24
17	225	17
18	245	20
19	263	18
20	277	14
21	296	19
22	312	16
23	321	9
24	339	18
25	350	11
26	364	14
27	377	13
TOT	5077	377

UL = 1.2

$\lambda 4 = 377/24$
$= 15.708$
$= 0.5818$

MTBF4 = $1/\lambda 4$
$= 1.72$

MTTR4 = $5077/24$
$= 211.54/27$
$= 7.84$

ANNEX 3.15 -- OUTAGE DATA FOR THE YEAR 2008 FOR FEEDER 1 (F1)

S/N	Failures times in (Hrs.)	Outage Duration (Hrs.)
1	4	4
2	9	5
3	12	3
4	18	6
5	30	12
6	40	10
7	52	12
8	64	12
9	73	9
10	82	9
11	88	6
12	99	11
13	104	5
14	111	7
15	115	4
16	125	10
17	135	10
18	142	7
19	147	5
20	155	8
21	161	6
22	171	10
23	176	5
24	179	3
25	184	5
26	188	4
27	191	3
28	197	6
29	207	10
30	219	12
31	226	7
TOT	3704	226

UL = 1.8

$\lambda 1 = 0.32$, MTBF1= 3.3, MTTR1 = 5.0

ANNEX 3.16 --OUTAGE DATA FOR THE YEAR 2008 FOR FEEDER 2 (F2)

S/N	Failures times in (Hrs)	Outage Duration (Hrs.)
1	6	6
2	10	4
3	27	17
4	36	9
5	45	9
6	54	9
7	63	9
8	74	11
9	85	11
10	95	10
11	103	8
12	109	6
13	118	9
14	126	8
15	132	6
16	140	8
17	149	9
18	156	7
19	162	6
20	170	8
21	176	6
22	185	9
23	188	3
24	194	6
25	199	5
26	204	5
27	207	3
28	214	7
29	220	6
30	231	11
31	237	6
TOT	4319	237

UL = -1.34

$\lambda 2 = 0.32$, MTBF2 = 3.14 MTTR2 = 5.8

ANNEX 3.17 OUTAGE DATA FOR THE YEAR 2008 FOR FEEDER 3 (F3)

S/N	Failures times in (Hrs.)	Outage Duration (Hrs.)
1	5	5
2	10	5
3	17	7
4	24	7
5	32	8
6	41	9
7	50	9
8	59	9
9	68	9
10	79	11
11	87	8
12	98	11
13	110	12
14	113	3
15	119	6
16	129	10
17	137	8
18	142	5
19	151	9
20	157	6
21	166	9
22	175	9
23	183	8
24	187	4
25	191	4
26	194	3
27	200	6
28	206	3
29	213	7
30	225	12
31	230	5
TOT	3798	230

UL = 2.0

$\lambda 3 = (230 / 24)/31 = 0.309$ MTBF3 = $1/\lambda 3 = 3.23$, MTTR3 = 5.1