MODELLING PHYSICAL ASSET RISK PROFILE USING SYSTEMS THINKING AUGMENTED BY STOCHASTIC AND PROBABILISTIC INFERENCES

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Submitted in fulfilment of the academic requirements for the degree of Doctor of Philosophy in Electrical Engineering

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APRIL 2015

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Dr. Akshay Kumar Saha and Professor Nelson Mutatina Ijumba

As the candidate's supervisor, I agree to the submission of this thesis

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Name: Dr. A.K. Saha Date:……………………………...

Signed: ………………………………….

Name: Prof. N.M. Ijumba Date:……………………………

DECLARATION 1-PLAGIARISM

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DECLARATION 2- PUBLICATIONS

Details of contribution to publications that form part and/or include research presented in this thesis (include publications in preparation, submitted, in press and published and the details of the contributions of each author to the experimental work and writing of each publication) are presented below. I declare that all the publications listed hereunder are my own work. The role of the co-authors in these publications was to provide supervision.

Publication 1:
B.O. Mkandawire, A.K. Saha and N.M. Ijumba, "Stochastic Evaluation of Impact of Power Utility Asset Management Paradigms on Sustainable Energy Supply," *Proceedings of the 11th International Conference on Industrial and Commercial Use of Energy*, 19-20 Aug., Cape Town, South Africa, 2014, pp. 293-301; print ISBN: 978-0-9922041-6-7; DOI: 10.1109/ICUE.2014.6904199 — Publisher IEEE.

Publication 2:
B.O. Mkandawire, A.K. Saha and N.M. Ijumba, "Modelling Impact of Transformer Asset Management Strategies on Costs Using Systems Typologies and Probabilistic Inferences," *Proceedings of the 22nd South African Universities Power Engineering Conference*, 30-31 January, Durban, South Africa, 2014, pp.147-152; print ISBN: 978-1-86840-619.

Publication 3:
B.O. Mkandawire, N.M. Ijumba and A.K. Saha, "Component Risk Trending Based on Systems Thinking Incorporating Markov and Weibull Inferences," *IEEE Systems Journal,* vol. PP, issue 99, 2014; journal paper, DOI: 10.1109/JSYST.2014.2363384.

Publication 4:
B.O. Mkandawire, N.M. Ijumba and A.K. Saha, "Transformer Risk Modelling by Stochastic Augmentation of Reliability-centered Maintenance," *Journal of Electric Power Systems Research*, vol. 119, no. C. pp. 471-477, February 2015; journal paper, DOI: 10.1016/j.epsr.2014.11.005.

Publication 5:
B.O. Mkandawire, N.M. Ijumba and A.K. Saha, "Quantitative Multi-criteria Approach for Power Asset Risk Modelling Using Systems and Parametric Probability Distribution Theories," *IEEE Transactions on Engineering Management* ; journal article under peer review.

Signed: ………………………………..

DEDICATION

To my dear wife Sophia for her support; and to the memory of my beloved dad O'Brien John, for teaching me to cherish the excellence of wisdom and understanding.

PREFACE

This research has been carried out by Burnet O'Brien Mkandawire under the supervision of Prof. Nelson Mutatina Ijumba and Dr. Akshay Kumar Saha in the School of Engineering, the Discipline of Electrical, Electronic and Computer Engineering within the University of KwaZulu-Natal (UKZN). The research project has been partly supported by the Centre for Postgraduate Engineering Studies (CEPS) of South Africa and the High Voltage Direct Current Centre (HVDC) of the UKZN.

This thesis is designed to provide a risk trend monitoring model which can help physical asset managers in the life cycle management processes. Although it presents models with respect to asset management in power utilities, it is envisaged that it is relevant to any firm which depends on the long term performance of its physical assets. The emphasis is on application of systems thinking approach as a means of establishing cause and effect relationships, whereas analytical approaches are employed as a means of collating data that can be used to solve specific problems. This is on the precept that statistical or analytical concepts, in general, may be able to reveal correlation and solve some specific problems, but cannot display causation. Henceforth, just as Kendal and Stuart stated in their work titled 'The Advanced Theory of Statistics', no matter how strong or suggestive a statistical relationship is, it can never establish causation; therefore, our notions on causal typologies must emerge from some theory in the realms outside statistics.

The basic rationale of physical asset management is to optimize the business impact of three key aspects, namely: cost, risk and performance associated with the extension of life of the physical assets or asset systems. In management, problems are emergent in nature — the way small things are compounded to form integrated wholes only becomes evident when we view the management process holistically, that is, as a system. This construct is propounded throughout the thesis, and it also happens to be the major strength of systems thinking. However, as this proposition is advanced, the thesis also addresses the key concern of systems theory, that is, the need to address specific problems in a profound manner; and quantitatively. Hence, quantitative techniques have been employed to enhance quantitative creative systems thinking, so that measurement can be made for control of risk; because control can only be achieved when there is some kind of measurement.

Five publications have been generated from this thesis. These have been submitted and published in peer reviewed journals and in conference proceedings. These include one article in International Systems Journal (ISJ) of the Institute of Electrical and Electronics Engineers (IEEE), one article in Electric Power Systems Research (EPSR), one paper published in the International Conference on Industrial and Commercial Use of Energy, one in the Southern

African Universities Power Engineering Conference; and the last one was submitted to the IEEE Transactions on Engineering Management.

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Furthermore, I am greatly indebted to the University of KwaZulu-Natal's High Voltage Direct Current Centre (HVDC); and to the Technology and Human Resources for Industry Programme (THRIP), through its Centre for Postgraduate Engineering Studies (CEPS) of South Africa for providing financial, technical and logistical support that enabled me to successfully conduct the research project. It is worth noting that Prof. Nelson Ijumba and Dr. Innocent Davidson played remarkable roles in channeling the CEPS support for my research work.

Additionally, I am indebted to Dr. Oscar Ngesa, a statistician, who validated the statistical results of my thesis. I am also very grateful to my brother Thomas Mthembu Mkandawire for providing the much needed logistical support that enabled me settle down to pursue the research project.

Besides, I would like to thank friends and colleagues in the Discipline of Electrical, Electronic and Computer Engineering in the University of KwaZulu-Natal for providing moral support during the process.

Finally, but not least, I am very grateful to my family, namely: my wife Sophia and children: Gracious, Elijah, Michael and Zaithwa, for enduring long periods of time without my companionship while conducting this research work. It is my sincere hope and prayer that the Lord God Almighty will bless you in your journeys in life, profession, carrier and business.

ABSTRACT

Current quantitative approaches to power asset management risk modelling have focused on financial aspects such as net present value. These approaches can neither determine nor trend the impact of technologies or renewal strategies on failure risk. As a result of this, combined with the fact that benefits of renewal strategies are hard to determine as renewal does not add additional capacity that is needed for revenue generation, the value of the strategies is not appreciated. In addition, it is currently difficult to measure the effectiveness of risk assessment activities in Reliability-centered maintenance (RCM) programs when the number of equipment is large and not adequate data is available. Thus, the main objective of this research was to develop a failure risk trend monitoring model and to improve performance measurement in the RCM activities. This could be useful for the management of power infrastructure assets such as transformers.

The risk trending model was developed by integrating systems thinking and system dynamics concepts with Markov processes, Weibull distribution and bathtub curve analysis to produce a quantitative measure of risk, called the risk factor. A set of 12 MVA substation transformer failure data was applied to compute the maximum likelihood estimates (MLE) of the Weibull parameters which were fitted into the risk factor, which was in turn trended with respect to changes in the number of components renewed during the asset life cycle.

The risk trending model quantitatively determined the impacts of the renewal strategies on the transformer failure risk profile which can be used to provide strategic direction to asset managers regarding the most appropriate timing of renewal strategies to maximize financial benefits. Besides, the Markov analysis was applied to trend the profile of mean-time-to-first-failure (MTTFF) and average annual repair costs which was used as a measure of the effectiveness of the RCM programs. It was shown that the MTTFF is inversely proportional to the annual repair costs. Furthermore, the systems approach revealed that: the best and sustainable metrics are those that indicate the loss margin and the run-to-failure strategy is a quick-fix, but very unsustainable in the long run.

The model developed can be used in risk assessment and in planning and development of asset management strategies in power utilities and in physical asset management firms in general.

TABLE OF CONTENTS

LIST OF FIGURES

Chapter Two

Chapter Three

Chapter Four

Chapter Five

Chapter Six

Appendix

LIST OF TABLES

Chapter Two

Chapter Three

Chapter Four

Chapter Five

Chapter Six

Appendix

LIST OF ABBREVIATIONS

AC	: Alternating current
AI	: Artificial intelligence
AM	: Asset management
ANNs	: Artificial neural networks
CA	: Condition assessment
CBM	: Condition based maintenance
CM	: Condition monitoring
CAPEX	: Capital expenditure
DC	: Direct Current
DME	: Department of Minerals and Energy
EHV	: Extra high voltage
ENS	: Energy not served (supplied)
EPRI	: Electric Power Research Institute
ETA	: Event tree analysis
FFT	: Fast Fourier Transformed
FL	: Fuzzy logic
FLPDE	: Fuzzy logic based transformer insulation paper deterioration estimation
GW	: Gigawatt
Hi-Pot	: High potential (voltage)
HV	: High voltage
IEEE	: Institute of Electrical and Electronics Engineers
IEC	: International Electrotechnical Commission
IPPs	: Independent Power Producers
IRR	: Internal rate of return
IT	: Information technology
LDA	: Loss distribution approach
LOEE	: Loss of energy expectation
LOLE	: Loss of load expected
MCBA	: Motor current balance analysis
MCrA	: Motor current analysis or MCE (Motor circuit evaluation)
MDP	: Markov Decision Process
MFA	: Motor flux analysis
MFPT	: Mean first passage time
MIMOSA	: Machinery Information Management Open Systems Alliance
MLP	: Multilayer perception

MPA	: Motor power or electric signature analysis
MTBF	: Mean time between failure
MTRM	: Medium Term Risk Mitigation Plan
MTTR	: Mean time to repair
MTTFF	: Mean-time-to-first-failure
MCDA	: Multi-criteria Decision Analysis
MV	: Medium voltage
MVA	: Mega volt ampere
MW	: Megawatt
NASA	: National Aeronautics and Space Administration
NPV	: Net present value
NN	: Neural nets
O & M	: Operations and maintenance
OPEX	: Operating expenditure
OSA-CBM	: Open System Architecture Condition Based Maintenance
PDM	: Partial discharge monitoring
PE	: Processing elements
PI	: Polarization index
RBD	: Reliability block diagrams
RBI	: Risk based inspection
RCM	: Reliability-centered maintenance
REDs	: Regional Electricity Distributors
RiBAM	: Risk-Based Asset Management
RTG	: Resistance to ground
SSA	: Steady state availability
SMDP	: semi-Markov Decision Process
TBM	: Time Based Maintenance
TDR	: Time domain refractometry
VAR	: Value at risk

NOMENCLATURE AND MATHEMATICAL NOTATIONS

CDF: Cumulative density function

LSM: Least squares method

MLE: Maximum likelihood estimation

MOM: Method of moments

PDF : Probability density function

β : Shape parameter

$\hat{\beta}$: Estimate of β

η : Scale parameter (characteristic life)

$\hat{\eta}$: Estimate of η

λ : Probability at which components are admitted into higher-load regime (overload)

λ_r : Probability at which components are relieved from overload

μ : Probability at which components are refurbished/renewed

λ_{F1} : Failure rate 1

λ_{F2} : Failure rate 2

μ_{R1} : Repair rate 1

μ_{R1} : Repair rate 2

Γ : The gamma function

ζ : Asset age group

CHAPTER ONE

GENERAL INTRODUCTION

1.1 Introduction

Power asset management (AM) is crucial in ensuring longevity of the power infrastructure assets. Management of risk to acceptable levels is the core feature of the best practice AM system [1]. The asset manager must trend the risk profile in order to prioritize asset treatment options such as maintenance and renewal. In a deregulated power utility, asset managers are often faced with the following challenges that underscore the importance of risk-based asset management process [2]:

1) Ensuring that asset strategies and processes match stakeholder expectations and objectives.
2) Achieving high reliability and at the same time minimize costs.
3) Improving asset performance in order to benefit from performance-based rates (tariffs).
4) Operating the utility while bearing in mind the penalties due to unmet level of service.

The Electric Power Research Institute (EPRI) also alludes to the fact that risk assessment and characterization is a contemporary issue that deserves great attention [3]. This is particularly important because financial constraints compel utilities to operate assets, which were designed for a 30-year cycle, on as long as a 60-year [4] or a 100-year cycle [3]. The ever increasing age of assets means that the risk is also on the rise, hence the need for more innovative ways of risk management.

1.2 Research problem and motivation

There are a number of risk assessment tools being employed in the power sector and in the physical asset management in general. Most quantitative risk assessment models in existence have focused on optimizing maintenance policies and inspection rates over a short time period [5] - [7]. They have not been able to trend the failure risk of components over their entire lifespan. There are also some commonly used tools that tend to evaluate the risk in terms of the time value of money, which include the net present value (NPV) and the internal rate of return (IRR) [8], [9]. These are good at selecting reinvestment strategies, but are not able to show the impact of strategies or technologies on business operations. Other types of risk evaluation tools have focused on the traditional risk matrix or the robot system (for example, see Appendix A), but they are not able to dynamically trend the component failure-risk [10] - [13]. These limit the presentation of the risk profile to a scale ranging from say, 1 to 9; or in very broad terms like: high, medium or low.

Risk is the unexpected or undesirable future event [4]. Hence, if a model can help to predict future risk profiles, it can as well enable asset managers to take preventive and proactive actions, or to determine the level of risk that is acceptable. The perception of risk in the electric power distribution asset management is different from that in the finance (accounting). In the financial realm, risk refers to loss incurred in monetary terms, whereas in the physical or power asset management it involves losses sustained due to component failure and the subsequent unexpected (undesirable) maintenance and reinvestment costs; and to the degradation in performance or reliability.

When a component fails, it increases the business risk. The risk of failure can be presented in terms of failure functions or cumulative density functions or as instantaneous failure rates [14]. These functions can be derived from component data (for example, the data in Appendix B). The methods for determining or expressing the failure function are widely used in the power sector (see, for example, the Perks' formula in [15], [16]), but they assume that the risk of failure does not vary as different asset management strategies, such as renewal or refurbishment are applied. Practically, the risk varies as the strategies are applied, hence the effect of the variation on the life distribution functions must be determined. However, there is no model that can trend the variation and determine its impact on sustainability of business operations over the entire technical life. Besides, renewal (refurbishment) is one of the most important end-of-life treatment options, but because it does not usually add new capacity to the system, its financial significance tends to be underrated or obscured. If renewal strategies can be viewed in the sense of reducing the risk of failure and the reduction can be quantified in monetary terms, it could help the asset managers to conduct sensitivity analysis to determine the best timing of refurbishment. This can encourage asset managers to prioritize renewal strategies in their business plans.

In addition, the risk evaluation tools that are based on the risk matrices tend to be too subjective to be reliable for the presentation of the risk profile. In general, these types of tools as well as those based on the time value of money falter in that they do not provide a dynamic risk trending model that is required to determine the variation of the risk with the application of asset management strategies. In some cases, the application of the tools to model the asset lifecycle requires lots of statistical data, which has been difficult to acquire [2], [4]. This research applies systems thinking (theory) which is augmented by stochastic as well as probabilistic techniques, to develop risk trend monitoring and assessment models that can prove useful in the planning and management of physical assets, such as transformers, in the power utilities.

1.3 Aim

The aim of this research is to develop models that can help power utility asset managers in planning and forecasting the acceptable level of risk associated with the strategies applied in the asset management processes. This will improve operations management and further maximize returns on power infrastructure assets.

1.4 Research question

The choice of research approach depends on the type of research questions that must be answered [17]-[20]. This research models the risk profile of power infrastructure assets through the application of systems thinking with the augmentation of stochastic and probabilistic inferences. It does so by answering the following research question:

How can the impact of the application of asset management strategies on component failure-risk be holistically modelled?

1.5 Research sub-questions

In order to answer the research question better, the following research sub-questions have been explored:

1. How do asset management processes (strategies) affect the physical asset risk?
2. Why and how do firms apply the different strategies?
3. How can the failure risk associated with the application of the strategies be modelled and trended?
4. What are the benefits of risk trending?
5. What are the existing, dominant asset management strategies or paradigms used in risk characterization or assessment?
6. How do the dominant paradigms affect sustainability of electric energy (power) supply?

1.6 Hypothesis

The research hypothesis is as follows: exploration of systemic (holistic) application of asset management philosophies (processes, strategies and technologies) in the industry can facilitate the identification of causes of business risk or unsustainable energy supply, and assist in the development of risk trend monitoring models that can be used for life cycle management of physical assets such as power transformers.

1.7 Objectives

The specific objectives of the study are as follows:

1. To explore, through a systems view, the impact of implementation of asset management processes on the risk profile.
2. To develop a formal dynamic failure-risk trending model for assessing the impact of asset management strategies on the risk profile.
3. To determine the financial benefits of the failure-risk trend monitoring.
4. To evaluate risk assessment and characterization models for critical power network assets.
5. To develop a model for evaluating the impact of dominant asset management paradigms on sustainable energy supply.

1.8 Scope and limitations

This research has tackled risk management and mitigation problems with respect to management of power utility assets, such as transformers. It uses data and case studies from power utilities in the sub-Saharan Africa region to illustrate the application of models that have been developed.

The risk trending models have been developed based on the number of components renewed, assuming that all the components have equal impact on the risk level, which may not always be the case in practice (as some components may have greater impacts than others). In addition, only failure data was applied in the computation of lifecycle modelling parameters, assuming that all the components in the population of transformers that were considered for the analysis had completely failed. It is also possible to include surviving components in the analysis, but this is beyond the scope of this thesis. Furthermore, for purposes of demonstrating how risk trending model can be applied to cost benefit analysis, simple cost models, utilizing only planned and unplanned maintenance costs, have been applied. These models are simpler than, say, Markov decision process (MDP) and Semi-Markov decision process (SMDP) models (that can utilize imperfect maintenance cost as well as the planned and unplanned maintenance costs). The MDP and SMDP models are normally applied in the optimization of maintenance strategies, policies and inspection rates. However, the application of the simple cost models suffices for the analysis in this thesis because the purpose of the risk trending is not to optimize maintenance strategies, but to show how the risk profile varies with time, so that appropriate risk mitigation measures can be timely forecasted and implemented. Suggestions on how to overcome these limitations in future research have been provided in Chapter seven.

1.9 Organization of the thesis and key themes of the chapters

This section describes how the rest of the chapters in the thesis have been organized. It also briefly discusses the key themes that each chapter presents.

Chapter two provides the literature review. The chapter addresses the first objective. It presents fundamentals of systems thinking, existing risk-based models and asset management (AM) practices. It uses the leverage provided by the literature to locate the position of the current research. The chapter accentuates the fact that the fundamental purpose of physical AM is to manage the whole lifecycle impact of costs, risk and performance. An overview of the role of AM processes, risk assessment models and mathematical models for data analysis in the risk evaluation process is presented.

Chapter three addresses the second objective, and it has partly been published in the International Systems Journal of the Institute of Electrical and Electronics Engineers (IEEE). It applies systems theory, augmented by stochastic and probabilistic inferences, to develop a dynamic and quantitative failure-risk trending model. It applies Markov inferences in system dynamics concepts, by employing a dynamic hypothesis (a theory on how problems are created or emerge), to demonstrate that in management systems, elements and decisions tend to amplify and attenuate each other. Mathematical models are incorporated in systems causal loop diagrams in a fashion similar to Markov state-space diagram manipulation. It shows how the model developed can be employed in risk management as well as in merit-compensation schemes, where workers who succeed in lowering the risk levels can be given incentives in the form of bonuses.

Chapter four builds on the constructs of chapter three to address the third objective. This is on the precept that chapter three left a gap that needed to be filled. That is, it developed a component (asset) risk trending model to show how the failure risk fluctuates as AM strategies are carried out, but it did not provide the cost-benefit analysis. Hence, chapter four evaluates the impacts of risk trending on costs so that the cost benefits of the risk trend monitoring can be quantified. Simple cost models are applied as illustrative cases (leaving the models such as SMDP and MDP as the scope of future work). Part of this chapter has been published by the Southern African Universities Power Engineering Conference, Durban, 2014; and another part is under review with IEEE Transactions on Engineering Management.

Chapter five takes the systems approach to another dimension, thereby fulfilling the fourth objective. Part of this chapter has been published by the EPSR Journal. It accentuates the reality that any systemic risk model cannot exist in isolation, but take cognizance of the dominant risk assessment and characterization models that exist. It examines the challenges faced during the implementation of the dominant risk assessment and characterization processes in the power sector and the physical AM processes in general. Through a critical review of literature, the chapter identifies Reliability-centered maintenance (RCM) as the dominant risk assessment and characterization philosophy. Next, it develops a model for conducting a Failure Mode Effect and Criticality Analysis (FMECA). The model addresses the shortfalls of the RCM, that is, the difficulty in measuring performance at initial stages of implementation when limited amount of data is available or when the asset population consists of numerous number of small components/units, as is the case in the distribution system; and lack of a failure probability distribution benchmarking model in the current approaches for conducting the RCM. It is envisaged that this approach will enable the RCM fulfil a substantial role of risk assessment in a holistic, integrated risk management model.

Chapter six evaluates AM paradigms and how they impact on sustainable energy supply. This chapter has been published in the proceedings of the International Conference on Industrial and Commercial use of Energy, Cape Town, 2014. This fulfils the fifth objective. Systems thinking is applied to highlight the importance of a holistic approach in reducing the business risk in AM processes. This is facilitated by a case study of assets from the generation, distribution and transmission business units; demonstrating how problems cascade from the generation all the way to the distribution business unit. The mathematical expectation and probability theories are applied to validate how paradigms can impact on costs without asset managers realizing. This has been referred to as revealing the hidden losses or risks. The chapter exposes the hidden losses due to the implementation of some performance measures (metrics), viewed as world class (the best) yet unsustainable. In order to illustrate the concept, three metrics are compared, namely: availability, loss of energy expectation (LOEE) and loss of load expected (LOLE). Furthermore, the negative impacts of the traditional application of the run-to-failure strategy on the so called ‘less capital intensive assets’ is exposed through the application of the systems approach. Conclusively, the chapter advances that a paradigm shift from a reductionist (mechanistic) approach to a systems (holistic) one is needed for sustainable energy supply.

Chapter seven briefly presents the conclusion and recommendations for future work. Only a brief overview is given because each of the preceding chapters in the thesis carries its stand-alone discussion and conclusions.

1.10 Contributions to knowledge

This section presents a summary of the contributions that this research makes to the body of knowledge. The list of publications generated from this thesis has been provided under declaration 2, whereas excerpts of comments from some the reviewers for journals and conferences where parts of this thesis were published can be viewed in Appendix C. The contributions are as follows:

- Firstly, Weibull parameters have been estimated, using the MLE and method of moments (MOM); and they have been integrated with systems thinking principles and Markov inferences to develop a quantitative risk trend monitoring model that: determines the impacts of renewal strategies on failure risk, models the reliability, and estimates the renewal and disposal timing. What is remarkable about the proposed model is that it trends the risk profile in time series and over the entire life-span of the physical asset. Existing risk evaluation techniques like those based on risk matrices and the 'distance-d-techniques' manage to evaluate the risk profile, but only over a short time-horizon of one to two years. This is not suitable for strategic planning purposes. Quantitative risk assessment techniques like net present value (NPV) analysis and internal rate of return (IRR) exist and are able to evaluate the suitability of asset re-investment strategies in time series (time value of money), but they are not able to determine the impact of the application of AM strategies on the failure risk; whereas the proposed model is able to do that. Moreover, the model incorporates modelling equations in the systems thinking approach, which has, traditionally, used qualitative models. The proposed model is primarily intended to be used in risk management, but it can also be applied in performance-based compensation schemes for workers (that is, where workers who have met risk reduction targets can be given bonuses or any other incentives to motivate them, thereby improving productivity).
- Secondly, a key performance indicator (KPI) for assessing the effectiveness of the RCM programs, obtained by trending the profile of the MTTFF (determined using Markov analysis) and the average annual repair costs, is applied. The study shows that the MTTFF is inversely proportional to the costs. Besides, the MOM is applied on statistical, historical data to generate a failure probability distribution comparative model; which lacks in the current practices for conducting the FMECA. Furthermore, the Markov analysis derives complements of the uptime-steady-state probability as input for the FMECA, using limited data; which is an improvement on the current approaches for applying the RCM. The overall approach developed offers a cost effective risk-priority-screening model, for components like

transformers, which can be applied prior to rigorous testing and inspection procedures on individual items during the RCM application.

- Finally, a quantitative, multi-criteria approach applies the MLE and MOM inferences to failure statistics for transmission and distribution transformers; mathematical expectation theories (namely: the LOLE and LOEE) and availability (a performance measure) in order to model the impacts of AM paradigms on sustainable energy supply. This approach demonstrates that the run-to-failure strategy leads to short-term cost savings, but it eventually results in unsustainable energy supply; and that the use of LOLE and LOEE can reveal loss margins that are not possible to detect using the availability. This could be useful in power utility AM planning and in developing strategies on industrial and commercial use of energy in the power utilities.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter provides a review of the literature. Firstly, it presents power utility AM structure, risk-based electric distribution AM models and the relevance of systems thinking to the modelling of risk in the current research. In physical AM, it is common practice to view risk in terms of the impact of failure on business operations [4], [21]. Secondly, it critically reviews previous AM approaches to highlight the motivations, viewpoints, limitations, advances, contributions and their relevance to the current study. Finally, it provides a summary of the key issues identified from the literature and how they provide leverage for the modelling of risk in the current research.

2.2 Structure of power utility AM system

Power infrastructure assets can be grouped into three hierarchies. Hierarchical level one (HL 1) is generation, hierarchical level two (HL 2) consists of the generation and transmission systems; and hierarchical level three (HL 3) comprises the generation, transmission and distribution systems [22]. Hierarchical level three represents the whole system which, in terms of evaluation of reliability and risk mitigation measures, is too big and impractical to handle or analyze as a single entity. Hence the normal practice is to deal with the distribution system on its own, as if the generation and distribution systems are separate entities or hierarchical levels. Figure 2-1 outlines these hierarchical levels.

Usually, problems and risks tend to cascade all the way from the generation through the transmission to the distribution system. Hence, when dealing with risk analysis and mitigation, it is important to take a holistic look at all the hierarchies and how they affect the sustainability of business operations. For this reason, this thesis has undertaken such a holistic approach.

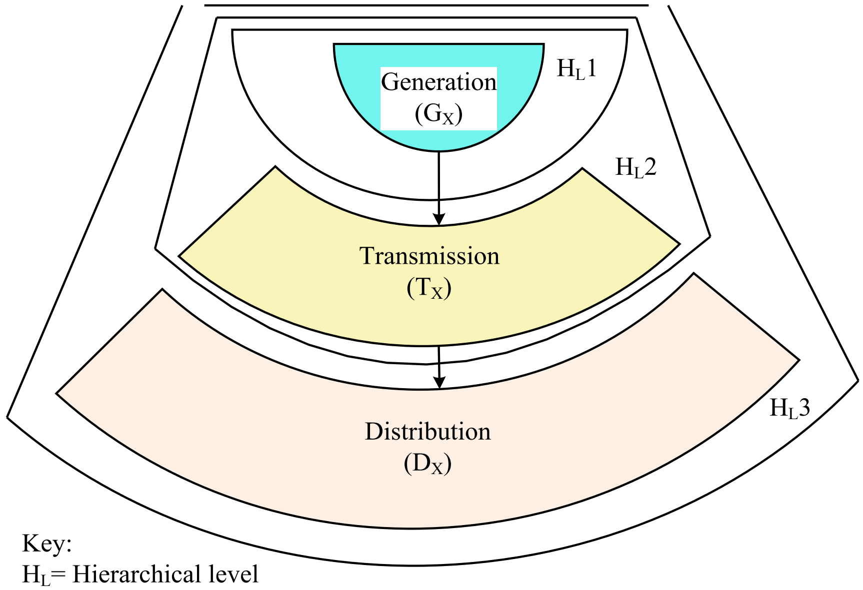


Figure 2-1: Power system functional (hierarchical) levels

Power utility asset managers tend to tailor the application of the strategies and technologies to these functional levels. The generation and transmission has few but capital intensive equipment whereas the distribution system has a vast number of installed equipment, but of relatively lower cost than in the generation and transmission when viewed individually. This background is the main justification for high investment in AM technologies in the generation and transmission [2]. Although the distribution system is largely composed of less capital intensive assets than its transmission and generation counterparts, it is equally important to the utilities' business performance because most of the system losses are encountered in it (due to low voltage levels). In addition, the distribution assets are worth the attention because they account for up to 40% of the investment in the power sector [23].

2.3 Scope of the AM

This section begins by giving the scope and context of AM. Then, it examines the application of AM technologies, strategies and models as well as their impact on the life cycle, risk and performance.

AM has been defined as a set of disciplines, methods, procedures and tools to optimize the whole-life business impact of costs, performance and risk exposure (associated with the availability, efficiency, quality, longevity and regulatory/safety/environmental compliance) of the company's physical assets [24]. The British Standard Publicly Available Standard 55 defines AM as systematic and coordinated activities and practices through which an organization optimally and sustainably manages its assets and asset systems, their associated performance, risks and expenditures over their life cycles for the purpose of achieving its organizational strategic plan [1]. The scope of AM is huge, but it can be summarized by the following key words in the two definitions above: optimization of impact of costs, risk and performance throughout the life cycle of physical assets.

In the process of decision making, AM encompasses the principles of Six Sigma from Total Quality Management (TQM), the Balanced Score Card (BSC), Reliability-centered maintenance (RCM), Reactive Maintenance, Preventive Maintenance (PM), Condition-based Maintenance (CBM), Proactive Maintenance and financial prioritization [25]. Analysis of NPV, IRR and Payback are the most common methods employed by the power utilities in determining financial risks associated with their investment strategies [5], [8]. The weakness of these methods is that they tend to ignore the effects of the AM strategies and their associated technologies on the assets [8].

Publicly Available Standard (PAS) provides a platform (model) for the implementation of best practice AM. It advances that legal and stakeholder requirements and customer expectations are the primary inputs to any best practice AM system [1]. This view is supported by the EPRI [10]. This means, physical assets, as well as their management systems, must be aligned to the organizational strategic plan and stakeholder expectations, but the alignment process presents the major challenge to asset managers in the deregulated electricity market [2]. This is the imperative for the development of models that link the application of AM strategies to the asset failure risk. Figure 2-2 demonstrates how the AM systems should be linked to the strategic plan and to legal and stakeholder expectations.

With respect to Figure 2-2, AM, strategies, technologies and techniques, maintenance, renewal, performance, and condition monitoring belong to the same group called processes (also see, for example, Figure 2-3). In addition, at the bottom of Figure 2-2, there are AM enablers and controls. These refer to decision support tools, techniques and philosophies that must be applied to assets or during the application of technologies. In most cases, it is very difficult to separate the enablers and controls from the AM technologies because these tend to complement each other. Strictly speaking, technologies refer to the equipment or machines that are utilized in condition monitoring, diagnostics and maintenance; whereas techniques generally refer to procedures and processes. However, some techniques can as well be regarded as technologies as is the case of chromatography, furans (2-furaldehyde) analysis of oil in power transformers.

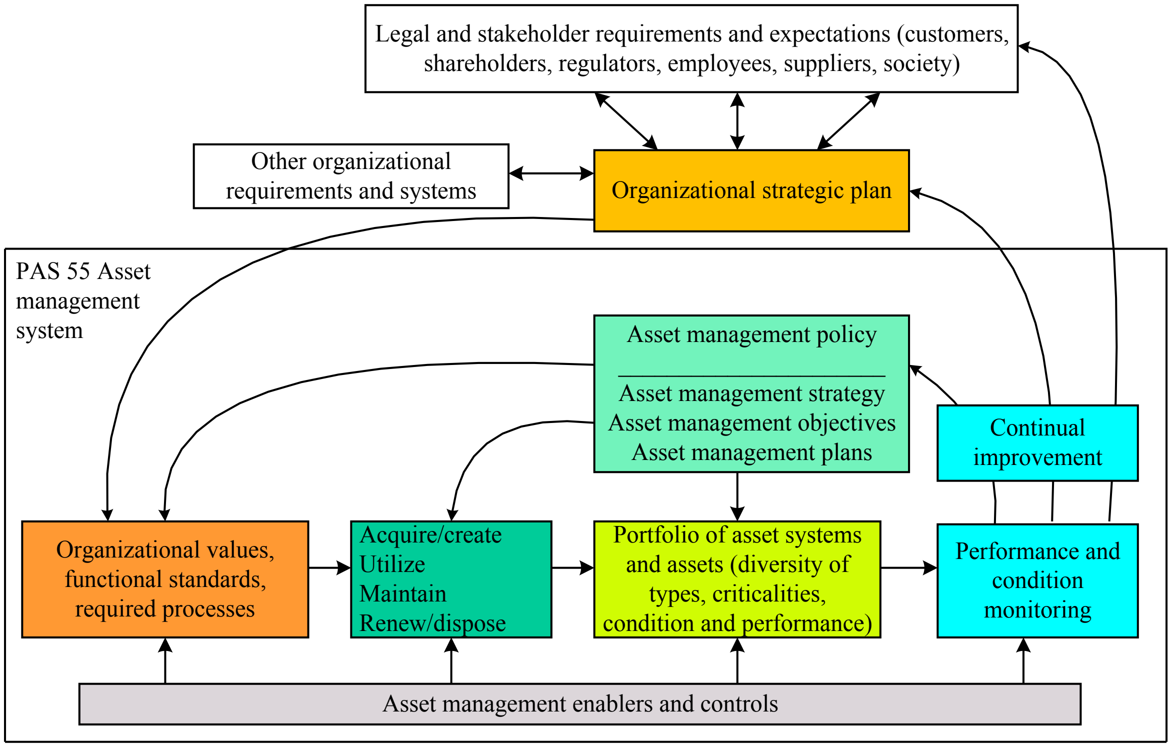


Figure 2-2: Overview of the AM system [1]

The PAS 55 model provides a solid basis for optimization of physical AM systems because it encompasses all the key elements affecting organizations whose survival depends on long term sustainability of the assets [1]. These are legal, regulatory, policy, strategy, objectives, AM plans, values, standards, processes, and the actual assets. The major weakness of the PAS 55 model is that it leaves continual improvement open-ended. Continual improvement is ineffective unless it is benchmarked [26]. The continuous improvement works if an organization is already a star performer; otherwise it is a dreadful and catastrophic idea, that is, if it is trailing behind the world standard by a wide margin [25]. Therefore, the continuous improvement process must be carried out relative to the best-of-the-best in the industry. Despite the weakness, the PAS 55 standard provides a systemic approach to AM, which is the core characteristic of an integrated or optimized AM system.

The best practice AM should be multi-dimensional (that is, it should incorporate AM tools, lifecycle models and risk-evaluation models); and it should employ an integrated approach [1]. The integrated approach to AM is characterized by six key principles and attributes, namely: holistic, systematic, systemic, risk-based, optimal, and sustainable [1], [26]. The following proposition suggests that authoritative bodies in the power utility AM have embraced the systems (holistic) approach when managing their assets [3]: a holistic, multi-dimensional AM approach aids in revealing synergies and overlaps between asset improvements in the same or different portfolios or levels, and is instrumental to ensuring that favorable, tangible benefits are obtained.

In the context of a power distribution utility, AM can be defined as a systematic process of cost-effectively operating, maintaining and upgrading of electrical assets by combining engineering practices and economic analysis with acceptable business practice [8]. AM technologies are technologies that are employed in the utilization, maintenance, renewal and any other action that promotes the integrity of the asset or asset system. Electric power assets fall into two categories, namely: primary and secondary equipment. Primary equipment includes overhead lines, power and instrument transformers, switchgear, lines and cables; whereas secondary plant consists of telecommunications, power system protection relays, metering and control infrastructure [8].

The structure of the AM system is hierarchical. Business or mission objectives form hierarchical level 1, strategy and processes constitute level 2, whereas reliability (service delivery) forms level 3 of the AM system [26]. Figure 2-3 outlines these AM hierarchies.

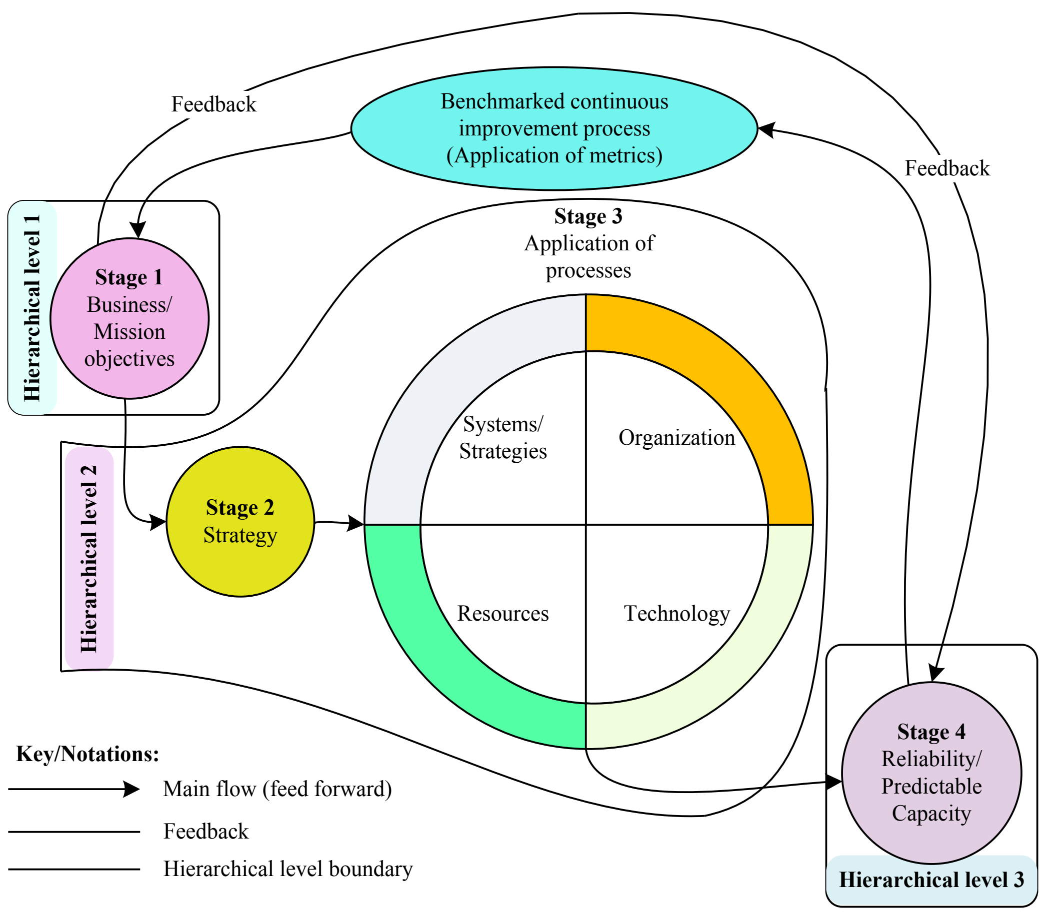


Figure 2-3: Hierarchical levels of AM systems

Viewed in terms of Figure 2-3, the risk models developed in the current work fall within level 2 and under stage 3.

The business or mission objectives must be set and stipulated in the firm's strategic objective to provide the direction for the firm. The strategy consists of strategic, tactical and operational plans that the organization must pursue in order to align the processes (systems, organization, technologies or strategies and resources) with its business objectives [2], [27].

Section 2.4 gives an overview of systems thinking, its relevance and application to the current work. It is worth mentioning that from this point onwards, systems thinking will be used interchangeably with systems theory or systems science.

2.4 Systems thinking theoretical and conceptual framework

The purpose of this section is to present a framework that describes and explains how systems thinking can be used to model the risk profile in AM systems. It provides the theoretical and conceptual tools that are central to systems theory, its applications and the source of data required for the modelling process.

2.4.1 Overview of systems theory

The theoretical framework of this research is founded around systems theory or systems thinking. Systems thinking is a conceptual framework, a body of knowledge and tools developed to solve problems in complex systems so that change can be effectively implemented [28]. Systems thinking is not new, but its application to engineering systems has emerged most recently. It employs principles from system dynamics to show how complex system characteristics vary with time [29]. Historically, the theory was first propounded by Professor Jay Forrester, who carried out extensive work on modelling of stock management systems [30]. Ever since, modern systems thinking theorists have emerged [28]-[30].

Systems theory incorporates ten central principles or dimensions, namely [29]:

1) Interdependence of objects and their attributes
2) Holism, whereby emergent properties not possible to detect by analysis should be possible to define by a holistic approach
3) Systemic interaction resulting in some goal
4) Transformation of inputs into outputs to obtain goals
5) System disorder (entropy)
6) Feedback for predictable system operation
7) Hierarchy (smaller subsystems making complex wholes)

8) Specialization
9) Convergence, which means alternative ways of attaining the same objectives
10) Divergence, which means attaining alternative objectives from the same inputs

Some of the above listed constructs (attributes) are easy to notice in a physical AM system, but others are not. For example, hierarchy and interdependence are easy to notice as they can be summarized by Figure 2-3, which portrays AM as comprising three hierarchies; and the application of AM processes (strategies and technologies) falls within hierarchical level 1. On the other hand, entropy is not so easy to see, but may be viewed in the context of reference [30] as amplification, that is, the way industrial flow systems, namely: information, orders, materials, money, personnel, and capital equipment engage to amplify one another and to cause change and fluctuation, which in turn forms the basis for anticipating the effects of decisions, policies, organizational forms, and investment choices. These hierarchies (see, for example, Figure 2-3) show the emergent nature of systems, that is, how small components develop to form a complete-whole; and systems thinking advances the imperative to look at this big picture before solving a particular (specific) problem [31].

Concepts derived from systems thinking give the ability to see a holistic picture, and at the same time to examine the details [32], [33]. Systems thinking utilizes model elements to consider the componential, relational, circumstantial and dynamic elements of interest [34].

2.4.2 Relevance of systems theory to the study

In this research, the failure risk of physical assets is modelled by evaluating the impact of implementation of AM strategies and technologies on the risk. Systems thinking theory is applied to provide a holistic view of AM in the power sector and to reveal cause and affect relationships before specific problems are solved to mitigate the risk.

It has been established that statistical tools may be able to show correlation, but not causation [35]. Henceforth, causation must be established by some other theory like systems thinking. The strength of systems thinking rests on the ability to show causality, to overcome the shortfalls of purely analytical concepts [26]. In recent years there has been a growing demand for a holistic, multi-faceted AM approach. This multi-dimensional approach can be facilitated by the following tools [1]: value engineering, life cycle costing, Reliability-centered maintenance (RCM), and Risk-based inspection (RBI). Furthermore, the multi-dimensional AM approach should be [1]:

1) Holistic: looking at the big picture by incorporating all elements of the assets, namely: physical, human, financial, information, and intangible (e.g., company image, reputation, etc.) aspects.

2) Systematic: adopting a methodological approach; encouraging consistent, replicable decisions (actions) and offering a clear and justifiable audit trail for the decisions.
3) Systemic: viewing the assets as a system and optimizing the system as opposed to the individual assets in seclusion.
4) Risk-based: directing resources and expenditure, and establishing priorities relevant to the recognized risk and the requisite costs or benefits.
5) Optimal: instituting the optimum mix between competing factors such as performance, cost and risk associated with the optimal utilization of assets over their lifespan.
6) Sustainable: accounting for the potential adverse impacts, to the organization, of short term decisions aimed at short term benefits (quick-wins).

In hierarchical systems like the AM, problems from one hierarchy may affect another hierarchy or system and that is where the merit of systems thinking comes in, because it helps to fix bottlenecks in other systems before dealing with pertinent issues. The notion of tracing and evaluating system interrelationships is called systems engineering. Systems engineering has led to related practices and standards that can be used in the lifecycle management of complex systems [36]. Most engineering systems, unlike in economics, are built on mechanistic (reductionistic) approaches from the knowledge of individual components, which tend to ignore some important links and causal typologies [31], [33]. Systems thinking bridges this gap by providing a holistic view of the environment in which the problem exists. It allows researchers to holistically construct models by working backwards from observed total system [28], [29], [33].

The antonym of systems thinking or holism is reductionism. Holism is a bottom-up system, it streamlines problems by considering the environment where the problem exists; whereas reductionism is a top-bottom system, it streamlines problems by breaking them down into smaller components [33].

2.4.3 Concerns about systems thinking and its application

The major criticism about system theories has been the lack of quantitative measurement [26], [29]. Furthermore, the claim that the theory is a component of the universal science has been disputed; some have argued that the theory is unrealistic and has no context because it encompasses everything [29]. However, a general understanding of phenomena may be required prior to exposition of the specific details. The following notion is advanced as the way to counteract the sceptics of the systems theory: as a science, systems theory gives the understanding of how things are aggregated and synchronized in integrated wholes, hence analysts need to comprehend the collective and emergent behavior rather than the behavior of individual components in the system [29].

Systems theory has been applied successfully, in developing practices and standards that can be used in the lifecycle management [36], and as a causality model in risk management of complex systems, in nuclear organizations [37] and in space administration [38]. Systems thinking was applied for root cause analysis (RCA) at National Aeronautics and Space Administration (NASA) to determine the cause of the Challenger spacecraft accident as well as that of the Colombia shuttle loss [38]. In addition, an approach to safety-driven design using a new hazard analysis method called System Theoretic Process Analysis (STPA) has been developed and applied in software controlled engineering systems, based on systems theory and Systems-Theoretic Accident Model and Process (STAMP) [39]. STAMP expands the potential causality model that was based on reliability theory and was generally applied for relatively simple electro-mechanical systems, in order to handle software failure in aerospace and automotive systems [39].

The growing popularity of holistic thinking has led to a great emerging wealth of different systems approaches. Generally, in systems theory, the focus has been on systems as a whole rather than on the individual parts [39]. However, analytical approaches have been applied to solve the specific problems identified by the systems approach [2], [26]. In power utility AM, systems theory has been applied to model relationships between engineering operations and investment or finance [2]. It has also been used to develop models for optimization of refurbishment in the power sector [26]. Besides, it has been applied in other fields, for example, for control of pests in the agricultural sector [40]. In summary, systems thinking has mostly been applied to encourage holistic rather than reductionist view of the problem environments, thereby promoting creativity through critical systems thinking [41].

2.4.4 Systems theory modelling framework

This section outlines symbols and conventions that are used in systems theory models. In practice, systems thinking has been applied in form of causal loop diagrams, to reveal cause and effect interrelationships between systems so as to help in directing efforts and/or resources to appropriate areas. The causal loop diagrams serve as statements of cause and effect. The causal loop models must be chosen so that they are able to predict the characteristic behavior or pattern of the system [28], [29], [36], [41].

Dynamic systems are often characterized by attributes such as compensating loops, reinforcing loops, balancing feedback (stability through self-correction), delays and archetypes [26], [28]. These attributes can best be explained in terms of dynamic system behavior as alluded to in [28].

First, a compensating feedback refers to strategies or interventions that result in system responses that counteract the intended benefits of the strategies [28]. For example, in a deregulated electricity market, the increase in power system reliability can result in increase in the number of satisfied customers, which in turn will exert pressure on system capacity and operating contingency [26], [2]. In this case, the capacity constraint tends to counteract the intended purpose of improvement of reliability.

Second, a reinforcing feedback system refers to a loop that describes how small inputs (actions) produce amplified results, as is the case when a few satisfied customers spread the news, with their word of mouth, which results in more customers getting (buying) the product [28].

Third, a balancing feedback stands for constraints imposed by reinforcing processes as they seek stability through self-correction [28]. An example of a reinforcing process is the component aging. This is typified when asset managers carry out asset renewal or maintenance processes to improve the asset condition, but the aging process tends to degrade the system [26].

Fourth, a delay can be imposed on the system either due to decision time-lags or when the effect of one variable on another is not immediately evident. In a study from the agricultural sector, a compelling example of a delay is shown when elimination of one pest, hoped to eradicate the crop damage problem, produces momentary pest control effects [40]. In this case, the pest controllers did not know that the pest that was eradicated provided a biological control of another, more dangerous type of pest. In the absence of a predator to keep the population of the deadlier pest under control, the later pest multiplied to uncontrollable proportions so that the crop damage caused by the later pest was greater than that caused by the former one. This was evident after a number of years had passed. Another example of delay often occurs when power utilities outsource refurbishment works, but the impact of the outsourcing action on the retention of maintenance skills only becomes evident after a long time. Another example of the delayed effect is when a firm retrenched its staff in order to reduce costs, but later on it turned out that the action resulted in irreversible loss of technical skills, thereby forcing the organization to hire consultants at a higher cost than before the retrenchment time [25].

Fifth, archetypes are generic system traits or patterns that tend to occur at different hierarchies (levels) of the system [28], [42]. Archetypes can be in form of very well-known constraints (limitations) to company growth or a phenomenon, which can be used to provide insights for improvement of systems. For example, asset managers can deal with the limitations to growth by eliminating them (the limitations), if possible [28]. For a phenomenon like sub-contracting of maintenance (technical) work, the revelation that unbalanced outsourcing can lead to loss of vital skills provides the managers with leverage (motivation) for instituting changes in the AM strategies [25].

Figure 2-4 illustrates how causal loop diagrams can be employed to represent causal typologies (relationships). The figure shows the cause and effect relationships existing in the process of outsourcing of maintenance works.

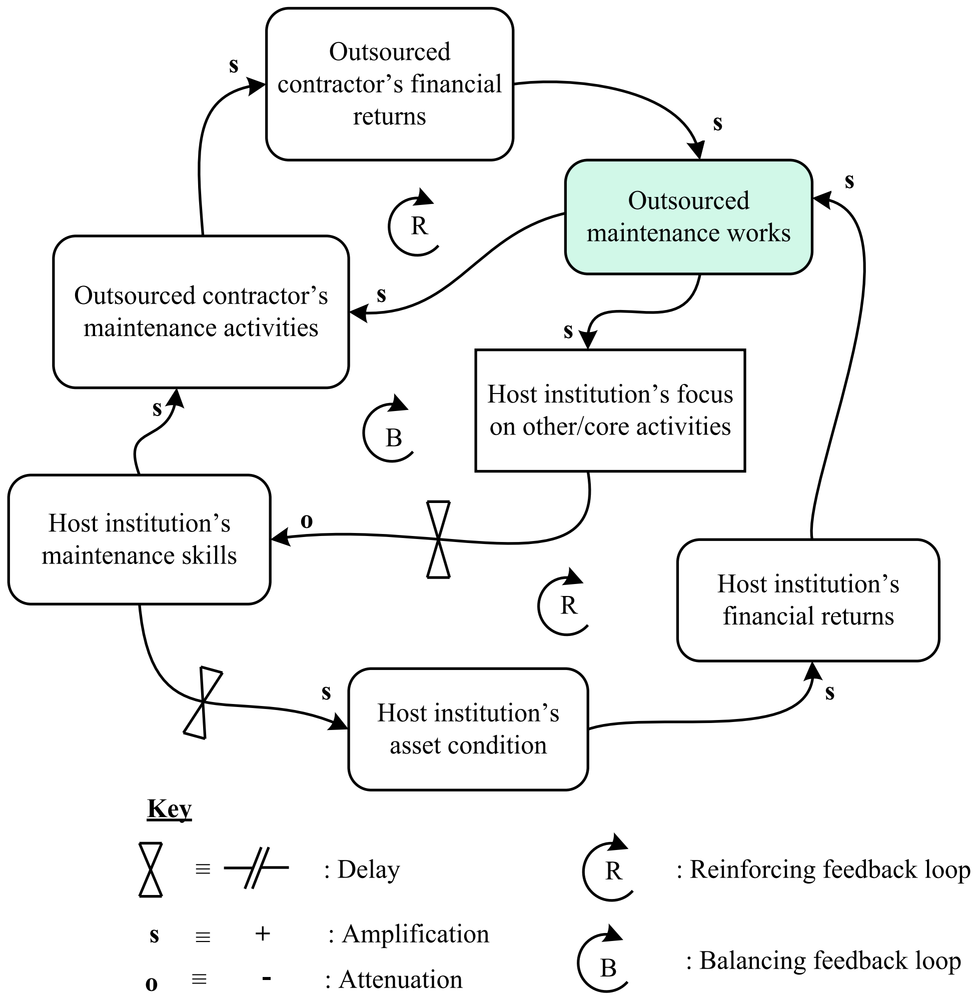


Figure 2-4: Symbols and conventions used in causal loop diagrams

The symbols and conventions that apply to causal loop diagrams (Figure 2-4) are described as follows:

1) A '+ or S' sign at an arrow head can be used to show that when an independent variable (at the beginning of the arrow) changes, the value of the dependent variable (where the arrow points) will be higher than the value it had before the input from the independent variable. Alternatively, these symbols represent the amplification effect.

2) A '– or O' sign at the arrow head indicates that when an independent variable changes, the value of the dependent variable will be less than what it was before the input from the independent variable. In other ways, these symbols stand for the attenuation effect.
3) A cross-hatch or valve symbol stands for a delay.
4) The R symbol with a curved arrow and the B symbol with a curved arrow represent a reinforcing and balanced (compensating) feedback loop, respectively.

Figure 2-4 indicates that outsourced maintenance works increase the host institution's focus on core activities, which in turn reduces the host institution's maintenance skills. As the host institution's maintenance skills increase, it improves the asset condition, financial returns and the amount of outsourced maintenance work-load. In addition, as the host institution's maintenance skills increase, the outsourced contractor's maintenance activities will reduce. On the other hand, as the activities increase, the contractor's financial returns will increase, thereby raising the potential for more outsourced maintenance works.

In systems theory, the validity of the chosen model is judged by the ability of causal relationships to determine dynamic rather than detail complexity [28], [42]. Once the causality has been established, systems modelers need to develop a dynamic hypothesis, that is, a theory describing how the problem propagated [41]. The dynamic hypothesis can be applied to develop modelling equations that can be used for simulation studies.

2.4.5 Source of research data for systems thinking

The preceding sections looked at systems thinking in broad terms and its framework for modelling the cause and effect relationships. The sections did not address the issue of data acquisition needed for use in solving the specific problems. This is addressed in this section. It has been shown that case studies can be used to obtain data for numerical analysis within systems thinking models [26], [28], [41]. Case studies may be used to explain causation and to relate phenomenon (case) with the environment in which problems exist even where the demarcation between the phenomenon and the context (external environment) is not very explicit [43]. Case studies emphasize a detailed contextual analysis of a limited number of events or conditions and their relationships [20], [44]; hence they are suitable for the application of systems theory. Thus, the case study research can be the primary means of collecting the research data or evidence, such as equipment data, needed for simulation studies.

The case study can also be used to determine causal typologies which can be expounded using causal loops from the systems theory. In order to ensure that the validity is retained, a multi-method approach can be used to capture longitudinal and snapshot time horizons; and both deductive and inductive inferences [26]. However, it is worth noting that case study critics often argue that case study research can neither be replicated nor generalized due to lack of clear units of analysis [20]. However, what makes research replicable in either case study or experimental research are not the cases (units of analysis), but whether the research is theory driven; and generalization can be based on a rival theory or on cases that are selected to represent the dimension of that theory [20], [45]. Furthermore, generalization can be made in terms of insights from a study [46]. Sometimes surveys can be embedded in the case studies in order to increase confidence in the generalizations, if necessary [20]. Even a single case could be acceptable as long as it establishes parameters and meets the intended objective [19], [20]. Case studies can be used to capture experiences of experts implementing AM strategies (as well as technologies) in industry. This is very important because empirical research relies on the experience of observations (data) made public [18]. Henceforth, at least one case should be chosen to reveal how decisions relating to AM practices cascade down from the generation through the transmission to the distribution system.

Section 2.5 examines the role of risk-based AM approaches on risk mitigation by considering merits and demerits of various risk evaluation or assessment techniques in the electric power distribution industry.

2.5 Review of risk-based AM approaches

2.5.1 Risk-based model framework

In recent years, there has been a growing realization of the importance of risk assessment in the electric power distribution AM [47]. Power utilities have applied risk management processes in various forms, but in most cases the salient features and concepts are similar. The most commonly used risk management standard is the International Electrotechnical Commission (IEC) 31010 [48]. At present, the imperative for the application of AM plans as a demonstration of good corporate governance in the power sector has led to the application of the PAS 55 [1]. The PAS 55 is not yet an international standard, but arrangements are underway to turn it into an international standard. In this section, a number of risk-based AM models are critically reviewed for purposes of determining the way risk has been modelled in the power distribution system AM.

A quantitative risk assessment model based on risk management standards of the IEC 31010, with some aspects from the British Standard Institution (BSI) Publicly Available Standard (PAS) 55 (that is, BSI PAS 55) was presented by [49]. The model highlights three main components of the IEC31010 standard, namely: risk management, risk assessment and technical standards. It incorporates the PAS 55 to provide risk assessment checklists and lists the following risk evaluation techniques: the Delphi method, failure mode analysis, failure mode and efficiency analysis, dangerous aspects analysis and key-point control, risk matrix, and butterfly pattern figure. The paper proposes a risk management organization based on Plan-DO-Check-Act (PDCA) cycle, similar to the structure of ISO 9000 and 14000 standards, covering the following management functions: network risk, asset risk, people risk, client risk and environmental risk. Besides, it identifies spare parts availability as one of the major sources of risk and encourages asset managers to pay particular attention to spare parts planning in their contingency plan. The paper is relevant to the current work as it lists the existing risk management standards, risk assessment checklists and techniques.

In another research paper [50], a 28-point requirements list contained in the PAS 55 has been adopted to carry out an asset risk gap analysis and to meet governance perspectives of AM, thereby maximizing or optimizing asset and organizational performance. Through a gap analysis, the paper applies the requirements of the PAS 55 in protection and control systems and identifies potential benefits of the implementation of the PAS 55 with respect to: risk AM, standardization of practices and repeatability of decisions. The paper uses a fault tree approach to identify critical risks and weighs the contribution of each asset to the total system failure, and then it translates the results into a risk matrix of the robot type (see, for example, Appendix A). The approach advanced seems to dictate the way risk management processes should be conducted in future; hence it is a point worth consideration in this thesis.

A risk-based framework for distribution system AM was presented in [27]. The paper shows that there is usually a considerable degree of subjective judgment in the risk decision making process. This compromises the validity of the outcome of the risk assessment process. Besides, it advances that the period of risk analysis is usually not long enough to cater for the long technical lives of power distribution assets. The relevance of the paper to this thesis is that it lists the following risk assessment methods currently in use in the power sector:

1) Event tree analysis
2) Failure mode and effect analysis
3) Markov analysis
4) Petrinet analysis
5) Truth table (structure function analysis)
6) Reliability block diagram (RBD) or analysis
7) Bow tie model
8) Bayesian Belief Networks (and Influence Diagrams)

According to the [27], for a long time, analysts have used risk matrices (based on the probability and consequence of risk) as a means of collating data and communicating the risk to stakeholders.

Section 2.5.2 critically reviews the risk-based techniques that incorporate risk matrices and demonstrates how these techniques have been used to provide strategic direction for the electric power utilities.

2.5.2 Risk-based approaches incorporating risk matrices

There is a general consensus in the power distribution AM systems that maintenance and reinvestment decisions are an important means of controlling risk, and that risk assessment provides the basis for reinforcing (invoking) the decisions [51]. A risk matrix (map) similar to the robot type (see, for example, Appendix A), is the most widely used method for modelling the risk profile. Table 2-1 gives an example of a risk matrix. In the table, risk impacts are broadly categorized as minor, moderate, major and catastrophic; whereas the risk likelihood is differentiated into improbable, remote, occasional, probable, and frequent.

Table 2-1: Risk matrix (profile) for MV/LV transformer [51] (*see the key beneath the table)

		Consequence				
		Insignificant	Minor	Moderate	Major	Catastrophic
Likelihood	Frequent					
	Probable					
	Occasional					
	Remote					
	Improbable					

*Key : = High-level risk; = Medium-level risk; = Low-level risk

The advantage of this type of risk analysis (Table 2-1) is that it is the traditional way of mapping or profiling the risk, hence the well understood by most analysts. However, it is often prone to a great deal of subjective opinion of experts (risk analysts) and it is not able to show the effects of low probability-high impact risks.

Despite these shortcomings, the risk matrix approach provides a valuable risk-based decision criterion for lifecycle management of physical assets as it gives a logical framework for capturing and portraying different layers of complex data in a single coherent format [4].

Different organizations may have different perceptions of risk, but they tend to agree on what constitutes the risk impact categories. These categories consist of issues pertaining to economy, safety, environment, reputation (image), quality of supply, and compliance to contractual obligations [47]. Moreover, the electric power distribution firms acknowledge that the main unaddressed challenge is on how to operationalize the risk management framework through the development of tools, methods and metrics to enable asset managers trend the risk profile. However, in most cases the risk trending process has been too subjective and so company-specific that it has been difficult to establish a universal way of trending the risk [47], [51]. Henceforth, this thesis focuses on the risk trending so that it addresses problems faced during the risk evaluation and analysis stage of the risk management framework.

A loss distribution approach (LDA) called value at risk (VAR) is a variation of the risk-matrix approach, traditionally used in financial and insurance institutions, that has been used to calculate operational risk of power system assets [52]. The method combines severity and probability of risk based on system reliability indices to produce risk indices that are utilized in sensitivity analysis with respect to two risk factors, namely: failure rate and maintenance expenditure. These factors are used as AM risk control units; the probability and severity of risk define the risk level, whereas the combination of probability and impact quantifies the risk in accordance to IEC 60300-3-9 standard. These are expressed as a single cohesive unit as the VAR. The main stages of this risk management process comprise risk identification, analysis, evaluation, and control; whereby the evaluation phase produces quantitative measures (metrics) needed for the risk decision making purposes.

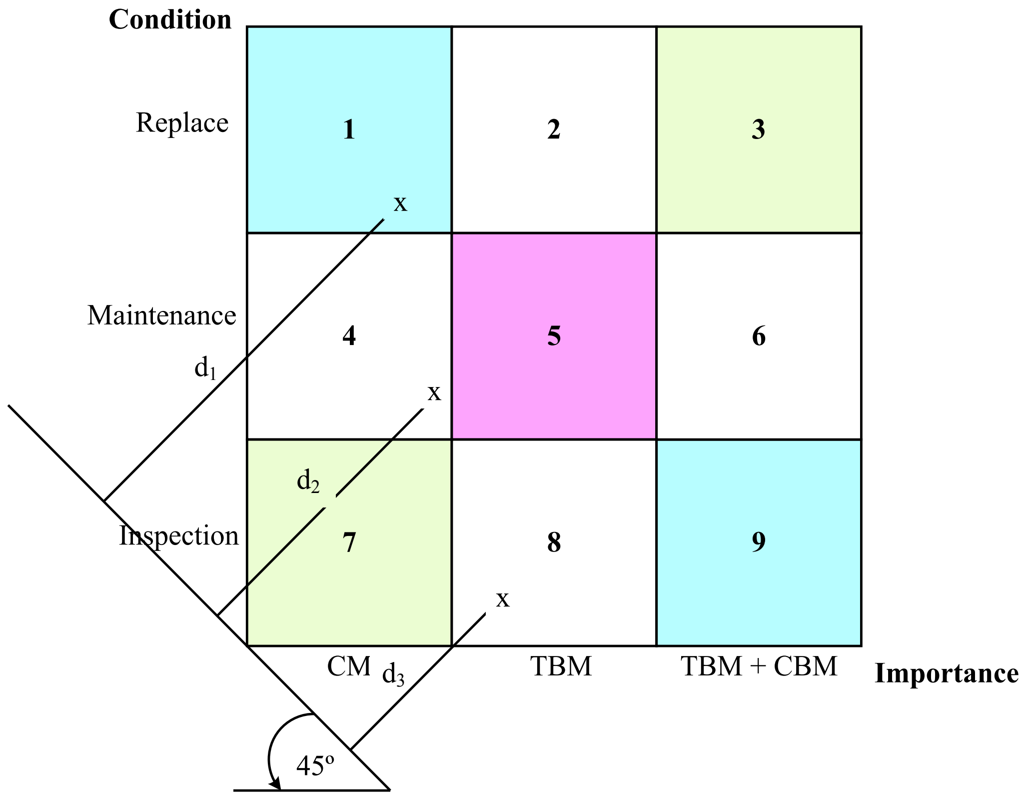
The major shortfall of the LDA-based sensitivity analysis is that it quantifies distributions of frequency and severity of risk (loss) over a one-year time horizon which tends to obscure the long-term perception or outlook of risk. Despite this weakness, the LDA-VAR approach is important to the current research as it outlines the following key assumptions for a risk-based AM approach:

1) Only major failures can be used to sufficiently analyze the physical asset risk.
2) FMECA can utilize results of simulation or sensitivity analysis in order to calculate the consequences of events.
3) Maintenance activities play a very important role in bringing the asset failure risk to acceptable levels, hence their costs should be considered in the analysis of the influence of the activities on the system risk.

It is advanced that the application of the VAR offers a better way of representing statistical uncertainties than the traditional point estimation approaches (risk matrices) and is simple, as it combines various risk indicators into a single coherent metric [52].

In the literature considered, the risk-based models have not considered the effect of spare parts on the component risk. A comprehensive model that incorporates spare part inventory strategies was presented in a study by [53]. The study presents an approach that systematically rates the asset condition using diagnostic tests to generate a health index, and the importance criteria through measures such as loading, probability and impact of failures; and impact on system reliability as well as on the environment. It breaks down the asset condition into three levels which can be addressed by the following treatment options: inspection, maintenance and replacement. The importance criteria helps in determining whether corrective maintenance (CM) or time based maintenance (TBM) should be employed during the risk treatment or not. A risk matrix, generated by the combination of condition and importance, provides the risk-based maintenance strategy for evaluating the risk of individual transformers. Spare parts re-ordering time and inventory levels are optimized using three Pareto inventory classes, that is, A, B and C, based on cost and usage. Class A consists of high capital (80%), low inventory (20%) items; which are ordered in terms of minimum stock levels by applying Normal and Poisson distribution statistical models. Class B items (20/30% of capital/inventory, respectively) are ordered based on economic batch quantities, whereas class C (20/80% of capital/inventory, respectively) are based on a simplified two-bin policy.

The study (that is, [53]) applies the Weibull distribution and advances that the application of the distribution helps to accurately analyze failure and forecast aging and reliability which are integral to the risk-based approach. It also highlights major challenges in dealing with the risk-matrix approach, such as the subjective nature of the asset scoring, weighting of condition and importance criteria (see Figure 2-5).



Key:
CM: Corrective maintenance; TBM: Time based maintenance; CBM: Condition Based Maintenance

Figure 2-5: Condition and importance risk-based matrix (adapted from [53])

The other challenge includes the difficulty in applying the concept to a large fleet of transformers or assets, as the process becomes too complex and tedious. Henceforth, the authors propose a decision support tool (database management) program to tackle the data handling (complexity) problem. The proposed methodology is viewed to be the best way of presenting and mitigating component risk to achieve a high level of system reliability, where the risk is expressed in terms of a distance-d-technique (d_1, d_2, d_3, etc.) with respect to a 45° reference line which specifies the equal weighting between condition and importance criteria as shown in Figure 2-5 [53].

The risk-based model (Figure 2-5) provides an excellent visual mapping of the asset risk. However, the method neither links the impact of AM strategies to the failure risk nor dynamically trends the failure risk. Furthermore, it is difficult to model asset aging with the distance-d-technique.

The main objective of power distribution risk analysis has been to establish a methodology that integrates risk and multi-criteria analysis for establishing the risk level [27]. As the multi-criteria analysis may become too complex to manipulate, software such as PRIME-decision can be used to construct value models [27]. The need to model risk preferences may introduce more complexities in the decision making process. A multi-attribute value function theory (MAVT) can be used to model the risk preferences by assembling a value function V (A_i) and comparing the outcomes against weights for each criterion, given as follows [54]:

$$V(A_i) = \sum_{k=1}^{n} w_k \, v_k \left(a_{ik}\right) \qquad (2.1)$$

where v_k (a_{ik}) are the scores and w_k are the weights.

The techniques and methods considered in Sections 2.5.1 and 2.5.2 have mainly specified the risk management standards or guidelines and used risk matrices to evaluate the risk level. Section 2.5.3 gives an overview of NPV-based approaches.

2.5.3 Risk-based approaches with NPV

The NPV-based approaches can be used to conduct a business case evaluation by comparing reductions in total cost of ownership to the total investment costs in order to maximize the NPV of the investment [13]. The NPV can be expressed as follows:

$$NPV = -I + \sum_{n=1}^{n} \frac{E_i - E_x}{\left(1+r\right)^n} \qquad (2.2)$$

where I = initial investment or nominal project cost, the term (E_i - E_x) = net cash flow, E_i = cash inflow or income, E_x = cash out flow or operating expenditure (OPEX), r = net discount rate, and n = time-period (years) considered in the analysis.

The NPV analysis can be combined with a qualitative score of asset condition based on their impacts on customers and probabilities, expressed as a cumulative hazard function (CHF) [13]:

$$CHF = \frac{PDF}{1 - CDF} \qquad (2.3)$$

where PDF and CDF are probability density function and cumulative density function, respectively.

As discussed earlier on, one of the key challenges in electric power utility AM involves selection of appropriate lifecycle-treatment options such as maintenance, overhaul and renewal which are crucial in risk management. A computer program called Risk-Based AM (RiBAM) was developed and applied in selecting re-investment strategies for equipment such as breakers, disconnectors and transformers [55]. The RiBAM (Figure 2-6) can assist power utility asset managers in dealing with a challenge of multiple decision options (e.g., do nothing, continue with current maintenance practice, overhaul, replace, monitor) regarding the best course of action required to maximize reliability at minimum cost [55].

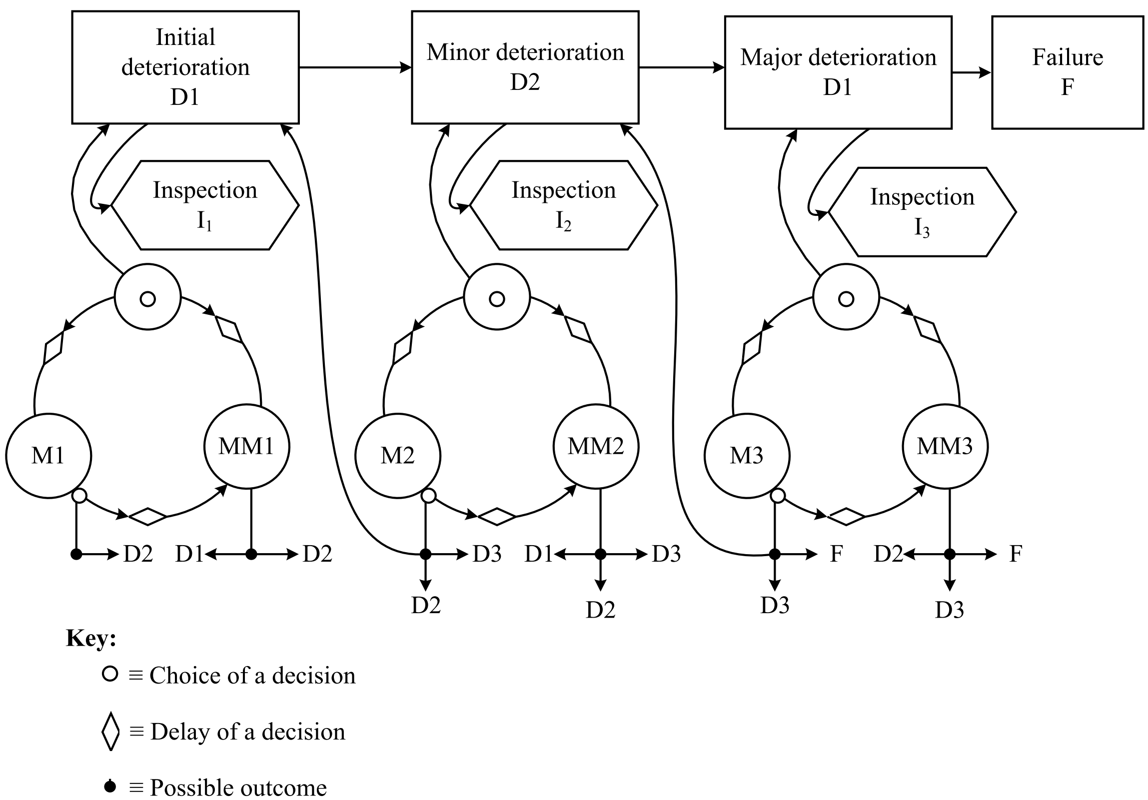


Figure 2-6: Risk-based AM decision algorithm [55]

Furthermore, the RiBAM optimizes the NPV decision criterion by converting engineering analysis into financial consequences such as cost of failure associated with various decision options. Thereafter, it employs probabilistic modelling and Markov process to generate life curves based on deterioration states provided by the user (modeler). In addition, it models the component lifecycle using three deterioration states, namely: initial (D1), minor (D2) and major (D3). Failure (F) may follow if there is no operator intervention after D3.

The RiBAM case study is very relevant to the current research as it underscores the importance of the following aspects in risk modelling:

1) Use of Markov processes to formulate a probabilistic modelling methodology that is required to augment decision support tools.

2) Inclusion of equipment degradation phases and decision-delays in asset simulation models.
3) Application of failure probabilities to compute the expected life cycle costs.

The NPV analysis can also be considered as a means for implementing a risk-based AM when applied to evaluate and compare the impact of electric power asset technologies on operating costs. For example, it was applied to conduct a cost benefit analysis between 400 kV Sulphur-hexafluoride (SF_6) and air-blast circuit breakers that helped to select the most sustainable technology for a power substation [9]. The NPV analysis of OPEX showed that the NPV for the SF_6 switchgears was lower than that for the air blast switchgears. This showed that the SF_6 breakers presented lower financial risks than the air-blast ones; hence the SF_6 breaker technology was evaluated as a better one than that of its air-blast counterpart. The SF_6 breakers also provided better personnel safety features than the air-blast breakers. The major drawback, however, is that the NPV analysis only shows the financial benefits in terms of the time value of money. It fails to show the effects of the application of maintenance strategies and technologies on the asset failure risk.

Section 2.5 presented a critical review of the literature on risk-based power distribution AM techniques. Although the section mentioned about the application of the health index, which utilizes some AM processes and technologies, it did not fully elaborate the role of AM processes on risk mitigation. These processes include strategies for inspection, maintenance, renewal and condition monitoring techniques. Section 2.6 critically evaluates these processes to determine their role in the risk management process.

2.6 The role of AM processes on risk mitigation

This section examines the role of AM processes on risk management and mitigation process. It evaluates how the past and present AM practices and models have tackled the risk management aspect.

AM can be viewed as the process of guiding the acquisition, use and disposal of assets to make the most of their future economic benefit and manage the related risks and costs over their entire life cycle [56]. For the short term AM, the number of customer interruptions and customer minutes lost per connected customer are common measurements of the reliability and risk. The basic rationale of the implementation of the AM process is to help firms optimally and sustainably manage their assets and asset systems, their associated risks, cost (expenditure) and performance [1], [24]. This research focuses on the risk modelling aspect of the AM, which is one of the central pillars of the AM process. It is worth noting that the risks, cost and performance are so interdependent that they tend to influence each other. Thus, optimizing the risk will also optimize the cost and performance.

A critical evaluation of processes (i.e., tools, techniques and strategies) is necessary before an AM model can be fully formulated as it gives insights into their strengths and weaknesses as well as the best practices that can be employed in the model [26], [57]. The tools can be used in planning of maintenance and refurbishment; and in contextualizing, exploring, assessing, treating and monitoring of risks. Besides, AM strategies and management paradigms have certain types of technology applications associated with them; hence the evaluation of the strategies and paradigms also reveals the underlying technologies and how they influence the risk profile of assets.

Models play a vital role in reducing system complexity. Conceptually, the investigation of complex systems using models can be divided into the following steps [58]:

1) Definitions of a problem to be solved or a question to be answered and of a system, that is, a part of reality that pertains to this problem or question.
2) Analysis of systems, that is, identifying parts of the system relevant for the problem or question.
3) Development of a model of the system based on the results of the systems analysis step.
4) Simulation or applying the model to the problem or question; and deriving a strategy to solve the problem or answer the question.
5) Validating the strategy that was derived in the simulation step to check if it solves the problem or answers the question for the real system.

Deregulation of the power system market has been the major drive for change in the type of models applied in the electric power utility AM systems [2], [8], [59], [60]. Mathematical models linking AM or maintenance strategies to failure rate have been developed, in [5]-[7], [50]. However, these have not tackled component failure risk trending. Most models in use, typically in the RCM and in transformer condition quality indication (see, for example, Appendix E), are discrete thus are not able to dynamically model the risk profile.

Increasing competition and deregulation in electricity markets compel energy suppliers to optimize utilization of their equipment by focusing on technical and cost effective aspects using methods from systems dynamics, risk assessment, lifecycle costing, and life assessment techniques [2]. Causal loops, derived from system dynamics models, can be used to visualize relationships and interdependencies between system elements, and simulation can be used to model aging and related life management strategies. The increasing need for holistic modelling has led to the adoption of systems thinking as a vital tool for modelling maintenance strategies and life assessment techniques and to predict long term monetary consequences of maintenance and renewal strategies in electric power grids [2].

The AM process refers to systems, strategies, organization, resources and technologies. The AM process involves risk prioritization at both design and operation phases as follows [25]:

1) At the design stage, it begins by critical risk prioritization using strategies like the RCM and FMECA.
2) During the operation phase, it continues with prioritized RCM involving root cause failure analysis (RCFA) and maintenance effectiveness assessment.

The application of AM processes embraces several methodologies and models aimed at reducing the risk of failure of the physical assets for sustainable energy (power) supply. In terms of the electric power infrastructure AM, the assets must be utilized for purposes of sustainable energy supply. Sustainable energy supply refers to resource endowment, existing energy infrastructure, development needs, favorable environmental quality and energy efficiency [61]. The aspects of sustainable development that this research addresses are the resource endowment and the existing energy infrastructure, that is, the physical assets.

Sustainable energy systems are instrumental to the attainment of sustainable development. The United Nations (UN) described sustainable development as the development that satisfies the current need without compromising the ability of future generations to satisfy their own needs [62]. It comprises two key elements, namely: meeting the needs of the world's poor, eliminating restrictions imposed by technology and social structures on the ability of the environment to meet both the present and future needs. Sustainable systems must therefore be pivotal to environmental, economic and social sustainability. Energy is amongst five thematic areas instrumental to achieving sustainable development [63].

AM processes play a crucial role in enhancing sustainable development by: encouraging resource endowment, promoting integrity of existing energy infrastructure, providing a catalyst for development through energy savings, and preventing environmental degradation. The sub-sections that follow (Sections 2.6.1 to 2.6.4), therefore, critically reviews the AM technologies, strategies and models to determine the extent to which they address the physical asset risk mitigation process. Henceforth, the gaps that are identified can be exploited to improve reliability assessment and risk mitigation approaches in the power distribution AM.

2.6.1 AM technologies and techniques

There are many ways of perceiving that risks exist within power utility AM systems. This can be in terms of: occurrence of unscheduled events, removal of components from service for corrective action, failure, type of strategy used and operation of an aging power infrastructure system. The current approaches to risk assessment have been driven by the imperative to keep power infrastructure assets for as long as possible, even as long as double their design lives. For example, it has been shown that almost one half of transformers currently in the power grid have exceeded their 30-year design life, but economic constraints are likely to compel the power utilities to keep them in service for up to 60 years [4]. In fact, it has also been reported that the asset replacement cycle can reach up to 100 years [64]. The tendency to utilize an aging infrastructure implies that the risk profile will be on the rising trend, hence the rising demand for new models for assessing the risk profile and for mitigating the risk.

However, current models for reliability and risk mitigation have traditionally been based on repairable failures without incorporating aged, non-repairable failures. A new method to incorporate aging failures in power system reliability evaluation was presented in [21]. The inclusion of aging failures in reliability evaluation can avoid underestimation of system risk and of the most definite misleading conclusion in system planning that can result from the underestimation [21]. Therefore, aging assets such as transformers should be prioritized during the risk modelling process. The traditional way of prioritizing a large number of aging transformers is by screening them using a simple ranking by age, but a more comprehensive method can be achieved by a risk assessment method which also incorporates contingency plans for ensuring that the spare parts are available [4]. In addition, the optimal number of spares should be determined. There was no probabilistic model for estimating the optimal number of transformer spares for a long time. A probabilistic model for determining the optimal number of transformer spares, based on the Poisson probability, was recently developed in [65]. The determination of the optimal number of spares and usage of transformer spares are important in ensuring that the system withstands occasional, catastrophic failures so that an acceptable level of system reliability is sustained [65].

AM technologies in electric power can be divided into hardware based and software based technologies. Hardware based technologies involve use of physical equipment for fault diagnosis, or condition monitoring or repair. Software based technologies comprise information technology (IT) that normally comes in the form of decision support tools. The electric power sector has seen a leap in progression of technological advancements over the last two decades. The most common conventional technologies employed in condition monitoring include [25]: resistance to ground (RTG) testing, surge comparison (surge) testing, high voltage (Hi-Pot) testing, motor current balance analysis (MCBA), and partial discharge monitoring (PDM), whereas newer technologies consist of motor circuit analysis (MCrA), motor current signature analysis (MCSA), motor power or electrical signature analysis (MPA), motor flux analysis (MFA), motor normalized temperature analysis, and time domain reflectometry (TDR). Decision support based technologies include: artificial intelligence, rule-based systems and inference engines, fuzzy logic, model-based approaches, neural networks, and data mining or automated rule-extraction. A detailed discussion of the above technologies and techniques can be viewed in Appendix D.

Since good experts are rare, even if a condition monitoring program is in operation, failures still occur, defeating the very purpose for which the investment in CBM was made. This has led to the application of artificial intelligence techniques (AIT) like expert systems, artificial neural networks, fuzzy logic; and later on, to distributed artificial intelligence which subsequently evolved into agent technology or multi-agent system (MAS) [66]. For example, the latest trends in AM demand that each power transformer be fitted with a special diagnostic apparatus, hence fuzzy logic presents a good option of ensuring non-intrusive diagnostic approach on the transformers. This is on the precept that a transformer's life is mainly dependent on the life of solid insulation and the life-limit is determined by thermal degradation of the paper winding resulting in reduced Degree of Polymerization (DP); and generation of carbon monoxide (CO), carbon dioxide (CO_2), and furans compounds. These are typical by-products of the degradation which fuzzy logic detects [67], [68]. An example of transformer condition monitoring health indicator is provided in Appendix E.

A fuzzy logic based transformer insulation paper deterioration estimation (FLDPE) is an example of advanced, novel fuzzy-based approach that uses inference rules to estimate insulation paper conditions, even where standard ANSI or IEEE methods could not, through three phases of insulation paper diagnosis, namely: tentative selection of CO_2, CO; mechanical-fit process; and estimation and optimization of insulation paper status [67]. Expert systems are needed to interpret Dissolved Gas Analysis (DGA) results because the conventional DGA techniques face a difficulty in diagnosing slow developing and slight faults [69].

Within the power utilities, quantities of interest with respect to condition monitoring are so many that in a large power plant, the number of parameters measured may be too many to handle and artificial neural nets (ANNs) have the capability to effectively handle such data sizes. ANNs can be used in both estimation and classification mode to give an on-line indication of the power transformer condition with respect to the physical integrity of the windings [70]. The results from the ANNs analysis can thus be used in the fault root cause analysis and in the mitigation of failure risk [4].

Open System Architecture Condition-Based Maintenance (OSA-CBM) and (Machinery Information Management Open Systems Alliance (MIMOSA) initiated the development of Information and Computer Technology (ICT) protocols in condition monitoring and maintenance [66]. The IEEE contributed to these ICT protocols, especially in the development of condition monitoring transducers and in fault root cause analysis [4], [25]. However, synergy of the latest and proposed technologies to the existing ICT platforms is lacking [66].

It is generally believed that IT based technologies like Supervisory Control and Data Acquisition (SCADA) and Geographic Information System (GIS) are crucial for real-time monitoring, tracking asset condition and restoration of the faults that result in supply interruption due to the radial topology of the distribution systems, and they form an integral part of Automatic Control System (ACS) and Feeder Automation System (FAS) [56]. Although many numerical or mathematical models have been developed to prioritize power distribution asset maintenance activities, there is a need for mathematical models which represent the effect of maintenance on reliability, to find the optimal strategy for the RCM where IT applications can play a central role in the data repository and acquisition.

Web and agent technologies are the latest developments in the AIT. Table 2-2 demonstrates their applications in the electric power industries.

There are three major challenges associated with the application of ICTs in the electric power infrastructure AM [66]:

1) First, the major setback to the advancement of ICT application to condition monitoring and maintenance has been the unsystematic application, as firms fail to adopt the already existing research efforts like OSA-CBM and MIMOSA.
2) Second, despite different architectures, methodologies and tools being proposed by researchers for the development of agent systems, the use of mobile devices (agents) is still low.
3) Third, AITs are still at infancy stage and their application has been sporadic, limited and inconsistent; where some progress has been made, the technologies have either been at proposal or experimental stage, or have been applied to an isolated practical case (a particular type of machine).

Table 2-2: Application of ICT in the power sector [66]

Baseline technology	Application
Multi-agent system	Monitoring of gas turbine start up sequence
	Gas insulated sub-station (GIS) monitoring
	Condition monitoring of a gas turbine during start-up
	Off-line monitoring of power transformers using UHFoPD (ultra-high frequency of partial discharge)
	Diagnostic and condition monitoring applications
	Post-fault disturbance diagnosis in power systems
	Condition tele-monitoring and diagnosis in a power system
	On-line condition monitoring of transformers
	Integration of software systems
	Monitoring and diagnosis in supervisory systems
	Transmission and distribution systems
	Integration of maintenance systems
Multi-agent system, Web technology	Maintenance management
Mobile agents, Web technology	Circuit breaker maintenance
Web technology	Monitoring and diagnostic of a remote power system
Multi-agent systems, Mobile agents, Web technologies	On-site monitoring of distributed transformers in a power grid
	Remote analysis and reporting functions for data stored in sub-station databases
	Remote control of distributed systems

Issues of ICT and decision support have a great bearing in power utility risk-based AM [70]. Improved decision support is very useful in tackling challenging decisions that utility asset managers face [64]. However, the electric power sector experiences significant changes in business environment that, in turn, make management decisions increasingly challenging. The challenges are as follows [64]:

1) An aging infrastructure that is wearing out on a 30-year cycle and being replaced on a 100-year cycle;

2) An electricity demand growth rate that, with the current cost models, threatens shareholder value;
3) Dramatically shorter planning horizons accompanied by increasingly constraining planning considerations such as environmental factors;
4) Expectations from the financial community, utility asset managers and financial managers for improved risk characterization and management; and
5) Increasing pressure from customers and regulators to maintain or even enhance service reliability and to control or reduce costs.

Transformer AM is generally considered to be one of the most important parts of power system equipment AM because they take most of the investment and are a major factor that affects reliability of the power system [68]. In addition, they are an integral part of power systems, and their reliability directly affects the reliability of the whole network because their outages can only be in one of the two forms: either forced by operation of automatic switching of protection systems due to external or internal causes or scheduled [71]. The management of transformers consist of three major activities, namely: the application of condition monitoring techniques in the operation, performing maintenance plans whilst investigating the less costly methods, and assessing the health and end of life of the transformer [68].

AM strategies in the power distribution sector can be described based on short term (operational), mid-term (asset maintenance) and long-term (strategic planning); whereas the main maintenance categories include CM, TBM, CBM and RCM [2], [56]. The CBM leads to high availability with moderate maintenance costs and is mainly applied in Extra High Voltage (EHV) and in High Voltage (HV) grids but the strategy is slowly being employed in Medium Voltage (MV) level as well. Furthermore, traditionally, statistical analyses are suitable for determining the remaining technical life in networks that have a large number of components like in the distribution systems [2].

Reasons for transformer outages are geographical dependent since environmental conditions, loading levels, and qualification of maintenance crews are geographical dependent factors [71]. This implies that physical asset risk profiles are also geographical dependent, hence when analyzing the risk profiles, it is worth noting that assets from different operating regions should be evaluated separately.

The condition monitoring techniques discussed so far are a means of determining probabilities of failures during fault and event tree analysis. However, the best way of determining the failure probability is by the application of statistical models to life data [4]. Hence, Section 2.6.2 examines how the life data can be applied in the power distribution risk AM.

2.6.2 Life data analysis

This section gives an overview of life data analysis, because the application of analytical life data handling concepts is common in most power utility AM models. Life data analyses are applicable to almost all types of studies, whether involving humans, plants or machines. These are usually tailor made to specific type of study or population. In this thesis, some of these concepts have been applied in the development of the models proposed. The grid is essentially a process involving a number of aging assets that are being inspected, maintained and refurbished or renewed, thus asset simulation models should be able to describe the asset aging process and the actions needed to prevent a decline in reliability; however data unavailability often subjects the process to certain approximations which imply a certain degree of risk [2]. Although the data is hard to get, it still forms the main input into most statistical AM models.

2.6.2.1 General approach for life data analysis

Owing to the long life expectancy of power equipment, the application of statistical techniques only commenced a few decades ago [72]. In equipment management, the focus of data analysis or statistical techniques is based on the imperative to minimize probability of failure in order to improve reliability, thereby mitigating the risk. If $F(t)$ is unreliability or probability of failure relative to time (number of cycles) and $R(t)$ is reliability or probability of survival, then by definition, for a total population:

$$F(t)+R(t)=1 \tag{2.4}$$

$$F(t)=\int_0^t f(t).dt \tag{2.5}$$

and

$$f(t)=\frac{dF(t)}{dt} \tag{2.6}$$

Failure rate is the most important quantity in maintenance and reliability theory [59]. The instant (instantaneous) failure rate, $\lambda\ (t)$ or hazard function $h\ (t)$ can be obtained from conditional probability as follows:

$$\lambda(t)=\frac{Number\ of\ failures\ per\ unit\ time\ at\ any\ given\ time\ of\ life}{\begin{array}{l}Number\ of\ items\ \exp osed\ to\ failure\ at\ the\ same\ space\\ of\ time\ (i.e. number\ still\ surviving)\end{array}} \tag{2.7}$$

Thus,

$$\lambda(t) = \int_{t}^{t+1} f(t).dt / R(t) \tag{2.8}$$

$$\lambda(t) = \frac{f(t)}{R(t)} = \frac{f(t)}{1-F(t)} \tag{2.9}$$

where $f(t)$ is the probability density (distribution) function.

Also,

$$\lambda(t) = \frac{dF(t)}{dt} \cdot \frac{1}{R(t)} \tag{2.10}$$

Integrating equation (2.8) from 0 to t gives:

$$\int_0^t \lambda(t).dt = \int_0^t \frac{dF(t)}{R(t)} \tag{2.11}$$

Alternatively,

$$\int_0^t \lambda(t).dt = \int_0^t \frac{d[1-R(t)]}{R(t)} = -\int_0^t \frac{dR(t)}{R(t)} = -\log_e R(t)$$

$$\therefore R(t) = \exp\left[-\int_0^t \lambda(t).dt\right] \tag{2.11}$$

In analyzing life data for electrical equipment like transformers and reactors, the most commonly used distribution functions for fitting the data are as follows [73]:

1) Normal distribution
2) Lognormal distribution
3) Extreme value distribution
4) Weibull distribution

The normal distribution may be applicable when the sample size is large, but it is occasionally used for life data analysis because it always gives an increasing hazard rate. Thus, it is particularly suitable for the life of products with wear-out types of failure [73]. The normal PDF is given by:

$$f(x) = (1/\sigma)(2\pi)^{-\frac{1}{2}} \exp\left[-(x-\mu)^2 / (2\sigma^2)\right], \; -\infty < x < \infty \tag{2.12}$$

where x is the random variable and σ is the standard deviation.

The lognormal distribution empirically fits many types of data adequately, especially if the range of the data is several powers of 10 as is the case of some life data involving metal fatigue and electrical insulation [73]. The lognormal PDF is expressed as follows:

$$f(x) = \frac{0.4343}{(2\pi)^{1/2} x\sigma} \exp\left\{-[\log(x) - \mu]^2 / (2\sigma^2)\right\}, \ x > 0 \tag{2.13}$$

where σ is the log standard deviation.

The Weibull distribution can be used to fit many kinds of data as well as many types of distributions based on the variation of the shape parameter. It does so by establishing an expression for $\lambda(t)$ which can permit variability so as to fit a range of probable failures (thereby transforming equation 2.8) as follows [74]:

$$\lambda(t) = a t^b \tag{2.14}$$

Then, equation (2.14) becomes:

$$R(t) = \exp\left[-\frac{a.t^{b+1}}{b+1}\right] = \exp\left[-\left(\frac{t}{A}\right)^{b+1}\right] \tag{2.15}$$

where

$$A = \left[\frac{b+1}{a}\right]^{\left[\frac{1}{b+1}\right]}$$

Thus,

$$R(t) = \exp\left|-\left(\frac{t-\gamma}{\eta}\right)^{\beta}\right| \tag{2.16}$$

where t is time to failure, γ is location parameter, that is time at which *F (t)* = 0, i.e. when R(t) = 1 = datum parameter (= the failure free life); η is characteristic life or scale parameter; and β is shape parameter.

Therefore, the substitution of equation (2.16) in (2.4) gives the following:

$$F(t) = 1 - \exp\left|-\left(\frac{t-\gamma}{\eta}\right)^{\beta}\right| \tag{2.17}$$

$$f(t) = \frac{dF(t)}{dt} = \frac{\beta.(t-\gamma)^{\beta-1}}{\eta^{\beta}}.\exp\left|-\left(\frac{t-\gamma}{\eta}\right)^{\beta}\right| \tag{2.18}$$

$$\lambda(t) = \frac{f(t)}{R(t)} = \beta.\frac{(t-\gamma)^{\beta-1}}{\eta^{\beta}} \tag{2.19}$$

If:

$$\eta = (t-\gamma), R(t) = \exp(-1) = e^{-1} = 0.368 \tag{2.20}$$

then,

$$f(t)=1-R(t)=63.2\%$$

Thus the scale parameter η represents the time from $\gamma=0$ (the starting point of equipment operation) to when 63.2% of the population can be expected to have failed; η is independent of β, which is the shape of the Weibull distribution curve. Figure 2-7 illustrates how the Weibull distribution can be used to model different types of distribution by changing the values of β. It shows three Weibull PDFs at three values of β.

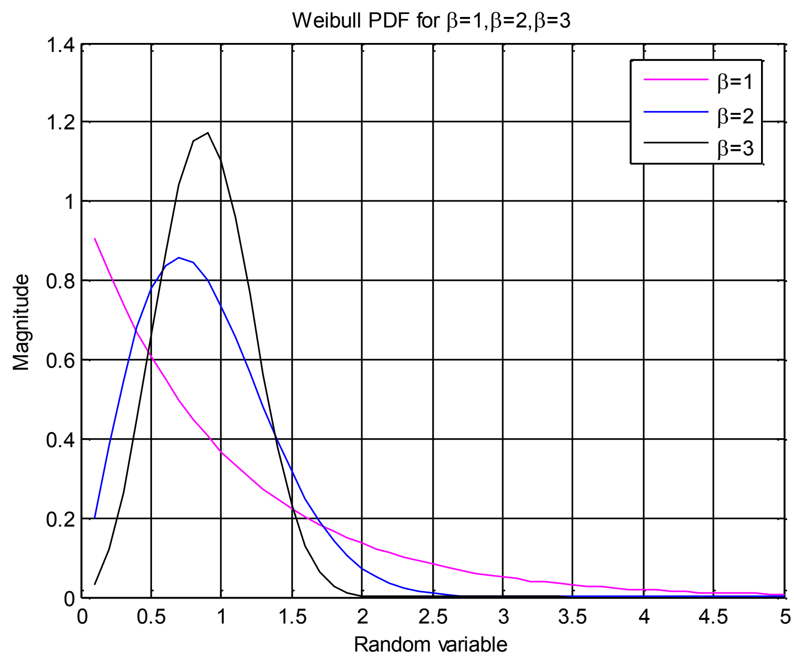


Figure 2-7: Fitting various distributions using Weibull shape parameter β

Section 2.6.2.2 presents special cases on how the life data can be applied in electrical equipment, whereas Section 2.6.2.3 discusses data analysis techniques.

2.6.2.2 Special cases applicable to electrical equipment

Electric power and aerospace engines are among products with complicated layouts. They usually have high infantile mortality rate, and the hazard rate increases more rapidly with age due to the aging process under heavy duty [75]. In recent years, some power utilities have adopted Perks' formula to incorporate transformer life data, which gives the hazard rate, *h (t)* as follows [16]:

$$h(t)=\frac{A+\alpha\exp(\beta t)}{1+\mu\exp(\beta t)} \tag{2.21}$$

where A is a constant representing risk of failure by random events such as lighting and collisions; α and β are constants that control the shape of the hazard increase with passage of time; and μ is a constant to slow down the rate of hazard increase at older ages.

The Makeham's formula is another fitting model that has been used by transformer insurance companies in the USA, for a number of years, to represent the instantaneous risk function. It is a simplification of the Perks' formula, given as follows [76]:

$$h(t) = A + \alpha \exp(\beta t) \tag{2.22}$$

Another fitting technique employed in the life data analysis is the Iowa Survivor Curve. Utilities apply it to analyze transformer reliability [15]. Figure 2-8 is an example of the Iowa Survivor Curves. This fitting technique contains 18 basic Iowa curves, each with a unique two-character name. The first characters consist of R, L or S to indicate whether the curve has a right, left or symmetrical mode, respectively. The second character comprises digits ranging from 0 to 6 to show the steepness of the modal peak.

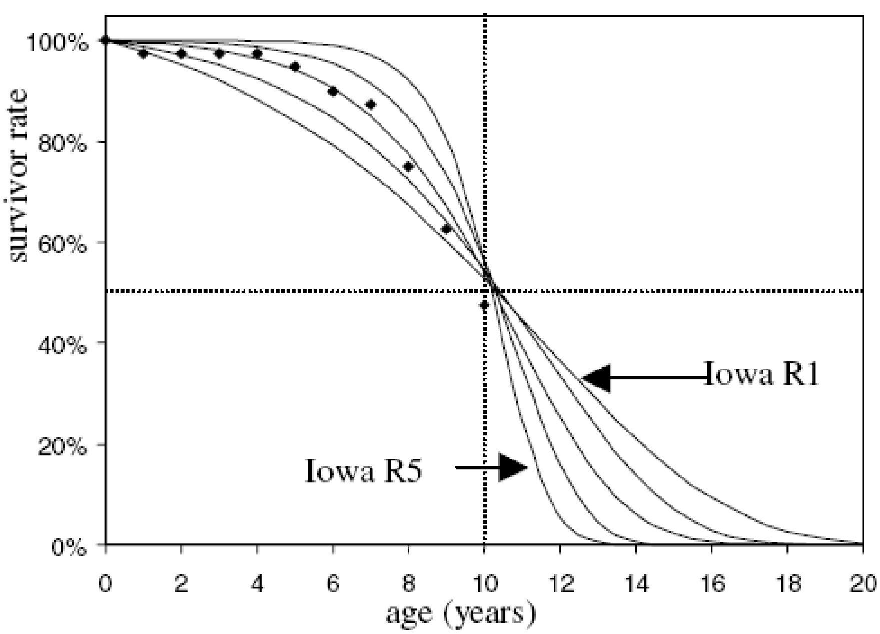


Figure 2-8: Simplified IOWA type R1-R5 Survivor curves (single vintage) [15]

The major flaw of the use of the Iowa Survivor Curves is that the decision on the best fitted curve is subjective. In addition, it is very difficult to identify the best fitted curve if the life data is too short in comparison to the full extent of the Iowa Survivor Curves, resulting in data misfit [72]. In general, analysis of power system equipment suffers from many set-backs which, among others, include:

1) Different equipment vintages (i.e. varying in-service times).
2) Similar equipment in different zones may be subjected to different loading conditions.
3) Equipment installed in different regions or zones may be subjected to different fault levels and failure rates; hence combining data from different zones may not represent statistical inferences accurately.

The above listed challenges have resulted in a tendency to derive mean lives and to use them for the statistical analysis [77], [78]. However, the fitted results depend largely on the type of distribution used [72]. Generally, the Weibull and Lognormal distributions have better statistical data fitting capabilities for electrical equipment [73], [79]. The Weibull distribution tends to be used most because it is flexible enough to represent all types of distributions. The Gamma distribution can also be used to model random lifetimes of items (products) as it can also assume a number of shapes, but it is less flexible than the Weibull distribution because its PDF is always right modal regardless of the type of data used [80]. In general, when modelling equipment life data using parametric family of distributions, the accuracy of the parameter estimates depends on the type of method used [35], [81]. For example, the LSM is suitable for large sample sizes, the MLE is the most appropriate for handling both censored and non-censored data (as well as extremely small sample sizes), whereas the MOM may be used to validate the results of the MLE. When applied to large sample sizes, the MLE simply reduces to the LSM [82].

The statistical data analysis in the power sector is not common because of data unavailability due to poor record keeping, as utility asset managers tend to lose the track record of failure as the time progresses. In the same regard, in large power utility grids, it is viewed that statistical inference for components like transformers can only be considered valid if the number of components exceeds 200 [72]. However, this proposition can be questioned, because in a small grid, where only a small number of equipment are installed, it is possible to get accurate times to failure that can be used to get accurate statistical data analysis. In addition, special techniques for handling extremely small data sizes exist. For example, [77] carried out a statistical data analysis with as few as four reactors. Therefore, the credibility of statistical data analysis does not always lie on the quantity of the data alone, but also on the method used for computing the parameter estimates.

There are three main data analysis approaches in engineering and science, namely: Classical Analysis (CA), Exploratory Data Analysis (EDA) and Bayesian Analysis (BA) [83], [84]. Sequence of data analyses for the three techniques is as outlined in Table 2-3.

Table 2-3: Sequence of data analysis techniques [83]

Technique	Sequence				
CA	Problem	Data	Model	Analysis	Conclusions
EDA	Problem	Data	Analysis	Model	Conclusions
BA	Problem	Data	Model	Prior distribution	Conclusions

These approaches are classified according to the way they deal with the underlying data. For the CA, the data collection is followed by the imposition of a model such as normality, linearity, etc. The analysis, estimation, and testing that follows are focused on the parameters of that model. For the EDA, the data collection is immediately followed by analysis with an objective of inferring which model would be appropriate. On the other hand, for the BA, the analyst attempts to incorporate either scientific or engineering knowledge or expertise into the analysis by imposing a data-independent distribution on the parameters of the selected model. Thus the BA analysis consists of formally combining both the prior distribution on the parameters and the collected data to jointly make inferences and/or test assumptions about the model parameters [84].

Practically, most data analysts would combine all the three approaches. The current research predominantly uses the CA and some aspects of the EDA. The merit of combining the EDA and the CA techniques is that the EDA can provide a broad spectrum of data analysis to gain insight into the engineering process behind the data (that is the data structure), to provide a good fitting and to estimate the parameters; whereas the CA approach can be used to measure strength of associations and to identify patterns that can help in the drawing of conclusions [83], [84].

2.6.3 Typical life-data application examples

This section highlights some examples of the application of life data analysis techniques in AM models. These consist of age dependent models, stochastic models, and stochastic models with some probabilistic inferences.

2.6.3.1 Age dependent models

A common approach to age dependent modelling is the application of single stress models [35]. Single stress models, such as the Inverse-Power law and the Arrhenius model, as well as the Weibull function (distribution) can be applied to historical failure statistics to model failure of in-service electrical components in the following form provided appropriate model parameters are chosen [60]:

$$L = L_o\left(E/\ E_o\right)^{-(n-bT)}.\left(M/M_o\right)^{-m}.e^{-BT}\ ;\ T = 1/\vartheta_o - 1/\vartheta \qquad (2.23)$$

where E, M, T and L are, respectively: electrical stress, mechanical stress, thermal stress and lifetime; E_o and M_o are, respectively: scale parameter for the lower limit of electrical stress and scale parameter for the lower limit of mechanical stress; L_o is the lifetime corresponding to E_o and M_o; n, m, B, b, ϑ, ϑ_o are, respectively, as follows: voltage endurance coefficient, mechanical stress endurance coefficient, activation coefficient taking the reaction of materials under combined stress into account, absolute temperature and reference temperature.

The Weibull distribution can be used to treat failure time obtained from aging tests to determine a statistical model for the likelihood of failure *P* at given stresses as follows [60]:

$$P(L) = 1 - \exp\left[-\left(\frac{L}{L_{63\%}} \right)^{\alpha} \right] \tag{2.24}$$

$$P(L) = 1 - \exp\left[-\left(\frac{E}{E_o} \right)^{\alpha(n-bT)} \cdot \left(\frac{M}{M_o} \right)^{m\alpha} \cdot \left(\frac{L}{L_o} \right)^{\alpha} \cdot e^{\alpha BT} \right] \tag{2.25}$$

where α = Shape parameter, $L_{63\%}$ = failure time for the failure probability of 63% as a function of the lifetime L, at which a fraction (1- e^{-1}) = 63% of the electrical components will have failed.

Equations (2.23 to 2.25) form the foundation of the renewal-theory-based cost models. The failure probability of aging electrical equipment can be expressed in terms of the lifetime *L*, as a random variable *t*, which has a CDF $F(t) \equiv \Pr\{L \le t\}$ with right continuous and a PDF $f(t) = dF(t)/dt$ given as [59]

$$F(t) \equiv \Pr\{L \le t\} = 1 - \exp\left[-\left(\frac{E}{E_o} \right)^{\alpha\left[n - b\left(\left(1/\vartheta_o\right) - \left(1/\vartheta\right)\right)\right]} \cdot \left(\frac{M}{M_o} \right)^{m\alpha} \cdot \left(\frac{t}{L_o} \right)^{\alpha} \cdot e^{\alpha B\left(\left(1/\vartheta_o\right) - \left(1/\vartheta\right)\right)} \right] \tag{2. 26}$$

where the notations in (2.24 and 2.25) also apply to (2.26).

The application of the age dependent models, that is, equations (2.24 to 2.26), can help to model costs of maintenance strategies. In addition, failure rate data can provide a valuable input into the mathematical models. The major challenge faced when applying the models is that the data used to estimate the model parameters must be collected from a long time-span [59], [60]. Other research studies have shown that the data must not only be collected over a long time-period, but also be of a high quality and should be from the equipment from the same manufacturer and of the same age for the models to produce accurate results [4]. This premise provides the direction for future research, whereby models that can utilize limited data, from short time-periods should be employed rather than relying on data collected over a long time-period which is usually too difficult to acquire. An example of a step in that direction has been provided in [77].

Section 2.5.3.2 examines stochastic AM models. These are the most recent developments in power utility AM. The motivation for reviewing these models rests on the fact that they have the capability to optimize the maintenance strategies that can be applied in the risk trending model. It is worth noting that the risk trending model does not optimize the maintenance strategies, but is able to forecast how the risk profile would change with the application of strategies or technologies. Hence, in future, the stochastic models can be combined with the models being developed in this study for a more effective risk management approach.

2.6.3.2 Stochastic AM models

This section critically reviews key models that have been developed to evaluate the effects of maintenance parameters on reliability. These models represent the recent developments in the evaluation of risk associated with the AM decisions. These have been grouped as follows:

1) Markov models for maintenance and reliability.
2) Semi-Markov Decision Process for inspection policy.
3) Markov decision process for maintenance policy.

2.6.3.2.1 Markov models for maintenance and reliability

A probabilistic model on the effect of transformer maintenance parameters on reliability and cost was presented in a study by [5]. The overall view of the study is that there is not much literature on the quantification of the effect of maintenance on reliability in power systems. MTTFF, maintenance and failure costs, and inspection costs are the model parameters for determining the effects of maintenance on reliability and cost [5].

The study is confined to the representation of deterioration process of transformers by three discrete stages determined by the results from four oil conditions as per monitoring (inspection) procedure according to IEEE standard C57.100-1986 and C57.104-199. The study is not able to dynamically trend the risk associated with the application of strategies and technologies. However, its major contribution is that it reveals that simulation of first passage time and steady state probabilities suggest that the cost effective maintenance occurs at small inspection rate of minor deterioration stage (D1) and high inspection rates of moderate (D2) and adverse (D3) deterioration stages. These deterioration stages are similar to what is presented in Figure 2-7. This represents some kind of risk assessment stages that can be employed during the risk-based power distribution (or utility) AM processes.

The paper is relevant to the current work as it indicates that the MTTFF and steady state availabilities (SSA) are very important in modelling the impacts of maintenance on reliability and on risk mitigation. In addition, it shows that, the increase in the MTTFF reduces cost, whereas the

SSA indicates the proportion of costs that are associated with the various probabilities. Therefore, it is advanced that transitional probability matrices, generated by the Markov analysis, and the resulting steady state probabilities form the central pillar of the probabilistic model for determining the effects of the maintenance parameters on reliability, costs and risk [5].

In summary, it has been shown that the evaluation of the transitional probability matrices can ultimately lead to parameters such as the MTTFF, needed to model the failure costs. Furthermore, oil conditions can be assigned probabilities according to the level of deterioration. This approach could be useful in power infrastructure asset modelling.

2.6.3.2.2 Semi-Markov decision process for inspection

Physical asset risk profile can be viewed in terms of policies that a firm employs. There is a very strong link between the inspection rate and the policies that are applied in the management of power utility assets, as discussed in a study by [6]. The study is about a semi-Markov decision process (SMDP), employing transitional probabilities and Laplace transforms for the maintenance policy optimization of condition-based preventive maintenance problems. The study presents the approach for joint optimization of inspection rate and threshold maintenance policy. Threshold maintenance means carrying out maintenance action based on three maintenance thresholds, namely: for smaller than minimal, between minimal and major, or larger than major maintenance threshold. The SMDP model can be expressed as follows [6]:

$$C(i,a) = \begin{cases} c_d \int_0^{\infty} (1 - F_d(t))\, dt \\ c_d \int_{-\infty}^{\infty} (1 - F_d(t))\, dt \\ C_d \int_0^{\infty} (1 - F_d(t))\, dt + C_m(1 - F_d(t))dt + \acute{C}_m \\ C_d \int_0^{\infty} (1 - F_d(t))\, dt + C_M(1 - F_d(t))dt + \acute{C}_M \\ C_R \int_0^{\infty} (1 - F_R(t))dt + \acute{C}_R\, dt \end{cases} \tag{2.27}$$

where ‘i’ and ‘a’ stand for inspection and availability, respectively.

C_M = cost per unit time of maintenance downtime

C_d = cost per unit time of inspection downtime

C_R= cost for each unit time due to repair

$\acute{C}_m$= cost for each minimal maintenance

$\acute{C}_M$= cost for each major maintenance

$\acute{C}_R$= cost for each repair

F_d= distribution of the time to carry out inspection

F_m= preventive minimal maintenance duration distribution

F_M= preventive major maintenance duration distribution

F_R= failure repair time distribution

The general view advanced by the study is that actions taken during condition-based preventive maintenance comprise no action, or minimal maintenance (to recover the system to the previous stage of degradation), or major maintenance to bring the system to as good as a new state. Minimal maintenance restores the system to the previous deterioration stage, whereby deterioration failures are modelled as several stages of exponential distributions [6]. The study does not trend the failure risk and is limited to the determination of overall system availability through maintenance policy, whilst jointly optimizing system parameters (which were the focus of the past research efforts). The paper, however, makes a significant contribution by using the SMDP model for a CBM problem, to capture or represent the system in order to model both deterioration and Poisson failures; and to optimize both the inspection rate and maintenance system policy. This is in contrast to the previous research that focused on inspection policy only. The paper is relevant to the current work by revealing the shift of paradigm from using the inspection rate as a modelling parameter to the application of the maintenance policy. It is advanced that the MDP algorithm can be applied in searching for the optimal maintenance policy for the CBM, and for joint optimization of inspection rate and its corresponding maintenance policy. The paper shows that when the optimization objective is SSA and the deterioration rate at each failure state is the same, the optimal policy is a threshold-type maintenance policy. In summary, although the paper does not trend the failure risk, the SMDP algorithm employs Markov transitional probabilities and Laplace transforms to optimize both maintenance policy and inspection rate when the goal is SSA at constant failure rate. The optimization is found to be a threshold-type of maintenance policy. This could be useful in a multi-method, risk-based power distribution AM approach for critical assets like transformers.

2.6.3.2.3 Markov decision process for maintenance policy

In AM, risk presents itself in a number of ways, which includes the maintenance policy pursued by the physical AM firm. In another case study [7], a Markov Decision Process (MDP) iteration algorithm for finding the optimum maintenance policy has been applied. The viewpoint of the study is that in a growing competitive power delivery environment, electric utilities are compelled to apply more proactive AM methods in capital budgeting as well as in operations and maintenance (O & M), but the later offers more saving potentials. It is envisaged that a probabilistic maintenance policy is the best way of ensuring that an effective maintenance strategy is implemented and that it can deliver a safe, reliable and economic electric power to customers [7].

Apart from reflecting the random nature of the equipment operating times in a better way, a stochastic maintenance policy could lead to substantial savings in maintenance costs. Three policy actions are outlined, namely: repair, overhaul and do nothing, which can be formulated as the MDP with the objective of finding an optimal maintenance policy which maximizes the expected benefits [7]. The study is limited to modelling maintenance with deterioration and full repair after a random failure, where maintenance is assumed to be a Poisson process parameterized as mean-time-to-preventive-maintenance (λ_m). It is not able to dynamically monitor the trend of risk associated with the application of AM strategies or technologies, but it determines the optimum maintenance policy. It first calculates probabilities and then the optimal value of the λ_m by taking the derivative of the availability, A (λ_m) with respect to the λ_m.

What is remarkable about the case study is that it determines the optimal stationary policy of the model by setting up the problem as a MDP. Generally, a MDP is a 4 — tuple (S, K, R, T) where S is a set of finite system states, K is a set of available actions, R is a set of state - and action dependent immediate rewards or costs; and T is a set of state-and action-dependent transitional probabilities. The study’s relevance to the current work is that it shows that optimum policy through the MDP is one of the ways of ensuring that optimum maintenance strategies are applied so that costs are reduced, thereby reducing the asset risk and ensuring sustainability during the execution of AM processes.

The study advances that the reduction of the mean time of repairing a deterioration failure is one of the best ways of reducing the mean time to minimal maintenance, thereby minimizing the risk. That is, the deterioration failures must dominate the failures mix in order to have an effective preventive maintenance, because the Poisson failure cannot be prevented through the preventive maintenance.

In summary, the Markov processes, in form of the MDP, can be used to calculate the state probabilities so that the optimal value of the mean-time-to-preventive-maintenance is determined. This can be implemented by the policy iteration algorithm on the state probabilities, whereby single component availability is maximized with respect to mean-time-to-minimal-preventive-maintenance. This is a risk assessment approach with very promising future applications (results). Furthermore, the question of optimum maintenance selection can be best addressed by a suitable decision-support tool with stochastic capabilities so that it accounts for reliability at optimum costs.

However, the level of skill needed for the stochastic modelling may be beyond an average line manager's competence.

2.6.4 Paradigmatic-systems view of risk

Electric power and aerospace assets are one of the most complex network assets, and optimization of AM in such systems is difficult because of the complexity of causes and effects of problems in the systems [39]. In a case study conducted in South Africa and Malawi, some guidelines on how to solve systemic problems pertinent to the current research were presented [26]. The study applies systems thinking methodology for optimization of maintenance and refurbishment within AM systems based on case studies from the electric power sector and on experiences from other industries to provide comparative perspectives. It outlines the evolution of equipment management practices and their implications on types of technologies applied in each evolutionally stage. The view point expressed in the study is that in order to optimize AM, systems thinking should be used to determine causation and then analytical tools, such as linear programming and probabilistic techniques, should be applied to solve specific problems; whereas metrics should be employed to monitor asset performance.

Equipment management practices have evolved from reactive phase (generation) through preventive and condition-based to proactive generation, whereby each generation represents an AM paradigm that can be distinguished by its unique characteristics, strategies and motivations [26]. The study is limited to critical evaluation of AM techniques, strategies and metrics; to linear programming for optimization; and to the application of systems thinking methodology to determine causes of sub-optimal refurbishment of electric power system assets. However, the study makes a significant contribution to the current research by providing a critical review of tools, strategies and techniques as well as examples of the application of systems thinking methodology, namely: clarifying causal typologies and providing the hypotheses needed for developing risk trending models. The paper is relevant to the current study in that it spells out that there are motivations for the application of AM strategies and technologies; and it demonstrates that AM decision structures can be modelled both in abstract and mathematical terms which can be applied in modelling of power utility (distribution) AM risk profiles.

The study advances that the application of systems thinking can determine the root cause of sub-optimal renewal strategies and then analytical methods can be incorporated for collation of data needed to solve specific problems. In summary, the evolutions of equipment management practices have evolved together with their underlying technologies and the associated inherent risks. This means that AM paradigms in an organization are good indicators of the level of AM technology application and the anticipated risks. This fact can be applied in the evaluation of paradigms in the current research. Furthermore, it has been shown that these paradigms have been driven by different motivations or goals; from cost containment, through cost reduction, to equipment management and opportunity driven business models that reduce risk and optimize returns on the assets being managed by a firm.

2.7 Leveraging policy initiatives

This section gives an overview on how policies have impacted on the operations of the power sector, and articulates how best practice AM strategies can leverage policy direction in the sector. In the early 2000, deregulation of electric power utilities brought a rethink in the operation of the utilities in the world, which saw almost all of them moving from vertical integration to decentralized, profit centered institutions [2], [13]. Under the deregulated electricity market, the power utilities are faced with strict regulatory compliance requirements with regard to the quality of supply and risk mitigation (reduction of customer damage functions), failure of which could result in severe legal and economic consequences [2]. However, the state of affairs has been rather different in Africa. Policies governing the energy sector in most African countries are very similar and are predominantly dictated by the historical background.

Historically, African electric utilities were state owned, and operated as vertically integrated companies, performing the role of generation, transmission and distribution [8], [85]. Policy formulation, administration and regulation were often carried out by one government ministry, with uniform national tariffs applied to consumers with the same load profiles. This is still the case with most African power utilities; and it is also particularly true for South Africa (the second largest economy in Africa and one of the emerging world economies) which, historically, has had electricity supply centralized with the bulk of power generated, transmitted and distributed by Eskom (the wholly state owned and largest utility in South Africa) [85]. Cross-border interconnections and power exchange in Africa began in the early 1950s when some North African countries first linked their electricity networks to exchange power in emergency cases which was followed by linking Congo DRC to Zambia [8]. Later on, South Africa was interconnected with Zimbabwe and Mozambique. Energy policy for South Africa hinges on the 1998 White Paper on Energy which focuses on the security of supply through diversity, increasing access to affordable energy, managing the energy-related environmental impacts, and improving energy governance [61].

The 1998 policy White paper, proposed to rationalize distribution through creation of six Regional Electricity Distributors (REDs) to serve the whole country. Municipalities were to group their distribution assets and obtain shares in each RED proportional to those assets while Eskom was to hand over its distribution assets, a move that later Eskom objected, arguing it should also have shares in the REDs [85]. Later on, Electricity Distribution Industry Blueprint report recommended that the South African Government should have power to restrict changes in ownership for five years following the establishment of the REDs. In 2004, the Government of South Africa set up the Electricity Distribution Industry (EDI) Holding Company to implement the plan for the six REDs; and in July 2005, set up the first RED in the Western Cape, which was short lived [86]. According to stakeholders, key issues hindering the setting up of the REDs were lack of planning and specificity in setting up the REDs, including lack of clarity on unresolved issues such as shareholding, asset transfer and levies. Eskom and twelve largest municipalities account for more than 90% of the electricity distribution industry and these municipalities also influence the adoption of policies, practices and technologies in the power sector [86].

Globally, there are three approaches to policy issues, namely: political, economic and technical [87]. The political orientation views problem solving in terms of value conflicts, organizational change and modifications in power relations. The economic approach treats energy as a commodity concerned with the use of various sanctions and incentives such as price and investment. The technical approach involves bringing scientific and engineering expertise to help solve energy problems [87, pp.85-92]. The economic approach also dictates the way utilities rethink their strategies regarding supply of electric power in Africa, which in turn affects the risk that firms are ready to take as well as access of electric power to the poor people. For example, in South Africa, one of the greatest setbacks to the creation of the REDs and Independent Power Producers (IPPs) has rested on profitability. The policy direction for South Africa is to supply cheap and affordable electricity which means heavy government subsidies [61], [85]. Potential IPPs fail to get into production or distribution of electricity because the tariffs are too low to make profits, which is perceived as a risk. This scenario is very different from the general global trend where the market is deregulated and policies pursued by the power utilities are driven by profitability, coupled by penalties (set by regulatory bodies) for failure to meet the relevant levels of service [2].

The question that follows the above background concerns recoupment of the investment in the view of the low electricity tariffs. The high and medium income population as well as industries located in the city distribution networks normally bear the cost of that cheap electricity in South Africa [85]. The subsidizing of the rates by the city distribution utilities usually creates some rivalry between Eskom and the municipalities for rights of distribution to the users. Overall, Eskom accounts for 40% of customers but 60% of the value of sales. Furthermore, Eskom, in its New-build policy, embarked on construction of new power generating plants and bringing back mothballed generating stations into service and mounted an active demand side management (DSM) [85]. Despite Eskom's new capacity and more active demand management for South Africa, a Medium Term Risk Mitigation Plan (MTRM) assumes high demand hence anticipates short supplies of electric power through to 2016. In view of the foregoing challenges, it is envisaged that reliability analysis and risk mitigation approaches will play a vital role in providing a strategic direction in physical AM policy initiatives in future, as inferred from [6].

Policies for sustainable energy supply have not emphasized on the advancement of technical approaches that bring scientific and engineering expertise to bear on energy problems through asset risk profile trending. Much focus has been placed on DSM [61], which is a form of the non-asset type of strategy aimed at delaying investments in new power plants. Generally, there is neither imperative nor incentive for organizations to take a uniform stand on the implementation of sustainable, risk-based management strategies. This thesis attempts to demonstrate that in order to lobby support from policy makers (or energy stakeholders in general) on the technical innovations, such as component risk trending, there must be evidence of the tangible benefits that can be realized from the innovations. These benefits can be in the form of cost or energy savings. This can provide the imperative for change, as demonstrated by a Turkish study in [88].

The Turkish study was conducted by the National Energy Conservation Centre (NECC) in Turkey. It showed that what drives the imperative for energy efficient systems and technologies is the quantification of the great energy saving potentials that can reduce resource consumption and save money. The NECC study was carried out within the Directorate of Electrical power Resources Survey Administration (called EIE in Turkey). It concluded that the Turkish industrial sector had an annual energy saving potential of approximately 30%, which brought the imperative for establishing a regulation on industrial energy efficiency in 1995.

It is believed that the electricity distribution industry has energy saving potential that would significantly defer new investment in power generators thereby reducing the operating (business) risk. Losses due to the inefficiencies, either because of poor maintenance or wrong choice of technology (or strategy), can lead to increased resource or fuel consumption. This project (research) endeavors to explore the energy saving potential, through the risk mitigation measures, for economic advancement of the power distribution companies. Indirectly, this project works towards increasing access to electricity that will benefit consumers (as they will have to pay less for the kWh), and will reduce the detrimental effects on the environment. For example, in Africa, deforestation occurs due to over-dependence on biomass sources of energy and is a major cause of environmental degradation. For instance, in Malawi, deforestation occurs as people process the firewood into charcoal to supply it to 89% of the population of 15 million people; the processing of the charcoal mostly uses traditional earth kilns, a technology known for wastefulness and inefficiency [89]. The charcoal industry is worth R231.2 million [≈US$ 23.12 million] per year. It is estimated that 6.08 million standard bags (50 kg bags) of charcoal are used in four largest urban areas in Malawi requiring 1.4 million cubic meters of wood representing 15, 000 hectares of forestland cut per year; of which 60% is from forest reserves and national parks, 40% from customary land and 2% enters Malawi from Mozambique [89]. If half of the population that depends on charcoal gets access to affordable electricity, about R115 million can be saved per year, translating to about R 1.2 billion per decade (in Malawi alone), a saving that can create tangible investment and create more jobs.

If the benefits of component risk trending (advanced in this thesis) can be computed in a similar fashion to the Turkish case study or the Malawian charcoal case study, it would provide leverage for lobbying regulatory institutions to press for reforms in the way electric power distribution firms manage their infrastructure asset risks.

2.8 Chapter summary

This chapter reviewed the literature on key concepts regarding systems thinking, the field of AM, the risk-based power distribution AM concepts, the role of AM processes and/or technologies in mitigating physical asset risk, how various statistical distributions can be incorporated in the risk modelling process; and how the quantification of tangible benefits from innovations or strategies can influence policy directions.

The chapter demonstrated that systems theory can be applied as a causality model, to show how system components interact and synergize, and that it (systems theory) provides a better foundation for risk modelling than reliability theory alone. However, the application of systems theory for modelling purposes demands that the analysts possess a very good knowledge of the system and must be able to establish a dynamic hypothesis, that is, a model that defines how problems evolve and propagate.

The literature review showed that the majority of quantitative risk-based AM approaches currently is use apply either risk matrices or the NPV analysis. Those utilizing risk matrices involve a great deal of subjective judgment, which tend to compromise the validity of outcome of the risk assessment and evaluation process. Furthermore, they fail to give a long term (whole-life) perspective of the risk profile for the components. The techniques that apply the NPV analysis are excellent at presenting the risk profile in terms of the time value of money and can help in the selection of the most suitable technologies (or investments), but they are unable to related the NPV to the type of technology or strategy applied during the equipment lifecycle.

The chapter further showed that AM technologies can be broadly grouped into hardware; and information and computer technology or software-based. Despite the different categories of the technologies, their basic rationale is to provide a platform for equipment condition rating and for the subsequent interventions needed to mitigate risks associated with the assets.

Expert systems are inevitable in managing complex and critical modern power utility assets like transformers as they help in detecting problems even where uncertainties with conventional DGA standards exist and is a very important AM technology. Fuzzy logic is a new paradigm of AM technologies that can be linked to standard DGA methods for remote, online condition monitoring of power assets to diagnose incipient failure condition in oil-filled electrical equipment such as transformers, thereby facilitating appropriate replacement and planned maintenance activities. Expert systems and fuzzy logic belongs to the ANNs or AIT systems. Their main shortfall is that their success depends on the quality of the data used for the analysis. Despite the shortfall, the application of ANNs is a good non-intrusive way of improving power asset condition and performance monitoring; especially if they are combined with intelligent systems, and can greatly minimize the risk of failure. Web and agent technology is the latest development in artificial intelligence systems and have been successfully applied in condition monitoring and maintenance of electric power assets, but the speed of their acceptance (penetration) and the maturity of the proposed technologies for condition monitoring and maintenance has been hampered by failure to integrate them with the existing standard ICT protocols (platforms) such as OSA-CBM and MIMOSA. ICT systems can help to speed up fault location and restoration in a risk-based AM approach.

Most AM technologies in the reviewed literature suggest that power transformers have been identified as the most critical part of the power infrastructure assets; hence they deserve greater attention than other types of assets. It is advanced that a holistic transformer AM must play a pivotal role in the management of power utilities. Furthermore, it should be able to assign appropriate maintenance strategies and condition monitoring and assessment techniques to tackle both transitive and intransitive aging processes. In general, the choice of AM strategy depends on the intended level of minimization of asset degradation, which also determines the type of AM technology to apply. For example, CBM is most suitable in critical, EHV and HV assets, whereas statistical methods are most suitable where a large population of assets exists, typically in such regimes as the LV and MV networks.

The electric power distribution system has a great influence on the quality and cost of power supply, but the vast number of assets (installed equipment) in the system makes individual asset condition monitoring too expensive. Historical data can be fitted into the appropriate models to determine the expected hazard rates and lifetimes which are vital for the risk modelling process. However, data storage and archival problems in power utilities make it hard to get adequate data for credible statistical inference. Hence, analysts need to employ techniques that can give valid analytical results even with only a few sets of data or small sample sizes. It is envisaged that the analysis of failure data can highlight areas that need technological, design and maintenance improvements, hence it should form part of a comprehensive risk-based AM strategy of a power utility. The data can also be applied in models for optimizing maintenance and inspection rates within AM systems.

The Weibull and Normal distributions are used for fitting statistical data of electrical machines more than any other statistical distribution models as they fit the data more accurately than other distributions. However, the Normal distribution has a tendency to always show an increasing hazard rate regardless of the type of data being applied. On the other hand, the Weibull distribution is flexible, as it can fit different types of distributions as well as hazard rates. For this reason, the Weibull distribution is the most commonly used type of distribution for both electrical equipment and other types of machines in industry.

The literature also showed that policy and regulatory initiates have a great impact on the way the power sector develops (creates), operates and manages its infrastructure assets, but the sector lacks the incentives required to accomplish these functions. However, policy makers and regulatory stakeholders can be influenced to adopt models developed by the industry if these models provide proven tangible socio-economic benefits.

The literature has provided great insights on the role of AM technologies, techniques and models in the improvement and optimization of the total lifecycle impact of risk on business operations. However, the literature is silent on how to dynamically trend the component risk over its expected technical life. The risk trending (profiling) could be a useful tool for modelling the long term impacts of AM strategies on the assets. It could also help in determining the best possible timing of renewal strategies. In addition, the data unavailability problem and its impact on risk assessment and characterization has not been adequately addressed in the literature. These challenges provide avenues for future research work, and the current research attempts to tackle some of them.

Chapters three to six present models that have been developed to address the research hypothesis, aims and objectives; and some of the gaps identified in the literature review.

CHAPTER THREE

COMPONENT RISK TRENDING USING SYSTEMS THINKING INCORPORATING MARKOV AND WEIBULL INFERENCES

3.1 Introduction

Electric power utility asset management (AM) is a complex hierarchical system consisting of generation, transmission and distribution systems. This chapter applies systems thinking philosophy to the AM system. Systems thinking helps to show system synergies in complex systems so that a holistic problem-solving approach can be applied to the systems.

The main challenge facing physical asset managers when optimizing their assets is how to trade-off reliability (performance), costs and risks [2]. Physical AM involves optimal management of a firm's assets and asset systems, their associated performance, risks and expenditures over their lifecycles, for the purpose of achieving its organizational strategic plan [1]. This chapter tackles the risk aspect of the physical AM in order to mitigate the risks.

This study was initiated when a survey of ninety power utility firms in South Africa and Malawi showed that there was no model to trend the risk of failure of components in the sector. It integrates some spatial transitions from Markov processes and the MLE of Weibull parameters to develop a risk trend monitoring model for critical physical assets. In operations and maintenance, critical assets are those for which the economic and service level impacts of component failure justify pre-emptive actions to restore them to their functional state [9]. The risk trending is conducted on a set of AM systems. The setting of AM system boundaries to define a set of AM systems is the responsibility of the asset manager [1]. An example of a set of AM systems is transformers at a substation.

It is worth noting that Markov and MLE inferences are not new, however, their integration with systems thinking is a significant development towards the advancement of quantitative capabilities of systems thinking. The major criticism of the systems thinking theory has been its claim to be part of the universal science; viewed by some as the theory of everything, hence it has no real context and might as well be superficial [29]. Its major strength is that it has been able to show the emergent nature of management systems, that is, how small things make complete wholes [26], [41]. The electric power industry tends to use qualitative and semi-quantitative risk management tools more than fully quantitative ones [3]. The fully quantitative tools have mainly focused on financial aspects such as the net present value (NPV) and internal rate of return (IRR) [8], [9], [25]. This chapter centers on component failure risk in substation transmission transformers.

Although the primary purpose of the model developed is to trend the component risk, it can be used for setting up performance-based (merit) compensation schemes for workers. The two are related, because reduction in risk levels may be attributed to outstanding AM practices by work teams. Workers who have managed to reduce levels of risk in the power network can thus be identified for merit compensation in the form of bonuses or other incentives.

3.2 Problem and approach

The Reliability-centered maintenance (RCM) is one of the most recent strategies for risk assessment (management) in the power sector [68]. It has been used successfully in establishing the maintenance requirements of physical assets based on failure modes [59]. However, the approach is heuristic, and its successful implementation depends on the judgment and experience of the implementers [90]. The transformer failure risk model is presented in [15] and [16]. It is based on Perks' formula. The model does not show how the risk profile varies with respect to the application of AM strategies. Most risk assessment tools in the power utility AM employ financial techniques such as the NPV and the IRR [8]. These are unable to show how the risk profile is modified by the application of AM strategies and/or technologies [8], [9]. Most of the other risk evaluation tools (described in Section 2.5.2) use risk matrices. These can only model the risk profile for a short time-horizon. That is, they cannot predict the variation of the risk profile over the entire life cycle of the asset.

In this chapter, systems thinking is used to express parts of an AM system as a system in state-space transitions. Thereafter, Markov transitional inferences are employed to demonstrate how these inferences can be adapted in systems thinking. Systems thinking uses principles from system dynamics to integrate the inferences into a risk trending model. Furthermore, concepts from the Weibull analysis are assimilated in the model to represent a failure function that can be modified by the application of AM activities, specifically by renewal strategies. Finally, the risk is trended as different AM renewal strategies are carried out on assets.

Systems thinking is an approach that holistically establishes synergies and cause and effects in dynamically complex structures, thereby clarifying system links for componential analysis [26]. Systems thinking provides the ability to see the big picture, yet still retain the ability to read the details [34]. It has been used successfully as a risk management tool for space programs at National Aeronautics and Space Administration (NASA) [38] and in risk management in general [33], [39].

System dynamics is a concept that systems thinking employs to model changes of complex system behavior over time.

Most simulation models in the power sector depend on reliability and/or statistical data. They may be used to predict the long-term monetary consequences of maintenance and renewal strategies, but data unavailability is often the major problem [2]. The use of the Weibull distribution allows analysts to draw relatively good inferences with a small number of data points [91] based only on failure mechanisms [60], [91]. For this reason, the Weibull distribution has been applied in this chapter.

In this study, only failure data is used to estimate the Weibull parameters. Methods which are able to employ failure data alone to compute the parameters have been demonstrated by [35], [81]. These parameters are unique to a given component population, and can be fitted into appropriate equations to model component life cycle and reliability [35].

3.3 Generalized Markov Process

If a repairable system or component can exist in either a failed or a non-failed state, probabilities associated with these states can be defined on a discrete or continuous basis using state-space analysis or spatial transitional techniques from Markov processes [92]. The Markov analysis uses discrete tree diagrams and matrix methods (differential equations) to produce stochastic transitional probabilities. Statistically, if t represents points in time or space and $X(t)$ the state of a system, a stochastic process $\{X(t)|t \in T\}$ is a family of random variables such that, for each t contained in the index set *T*, $X(t)$ is a random variable. For a discrete time stochastic process, *T* will be integers, whereas for a continuous time stochastic process *T* will be a line. The stochastic process $X(t)$ is stationary if $X(t_1), X(t_2), ..., X(t_n)$ has the same distribution for any value of *n*. A discrete parameter stochastic process, $\{X(t)|t = 0,1,2,...,n\}$ or a continuous parameter stochastic process, $\{X(t)|t \geq 0\}$ is said to be a Markov process, if, for any set of '*n*' time points $t_1 < t_2 < ... < t_n$ in the index set of the process, and any states $j_1, ..., j_n$, the joint distribution of $[X(t_1), X(t_2), ..., X(t_n), X(t_{n+1})]$ is such that:

$$P\left[X(t_{n+1}) = j_{n+1} \middle| X(t_1) = j_1, X(t_2) = j_2, ..., X(t_n) = j_n\right] \tag{3.1}$$

$$= P\left[X(t_{n+1}) = j_{n+1} \middle| X(t_n) = j_n\right] \tag{3.2}$$

If $X(t)$ takes the value *x*, transition from *j* through an intermediate step *m* to *r* can be expressed as follows:

$$p_{j,r}(x) = \sum_{m} p_{j,m} p_{m,r} \tag{3.3}$$

and

$$\sum_{r} p_{j,r}(x) \le 1 \text{, for all j and r} \tag{3.4}$$

State probability after *n* time intervals is given as follows:

$$P^{(n)} = P(0)P^{n} \tag{3.5}$$

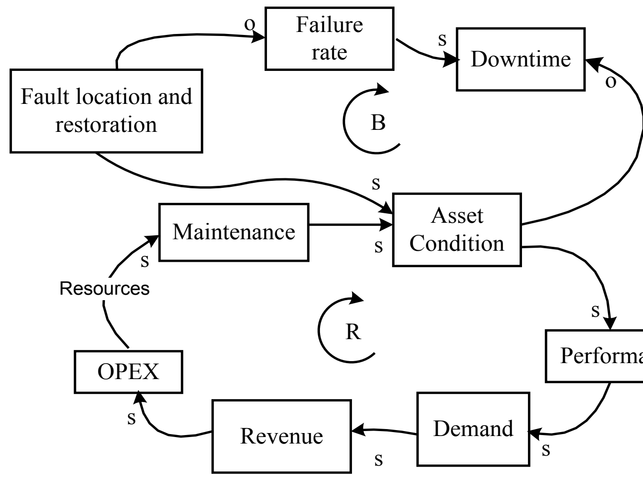
where *P(0)* is the initial state vector.

In system dynamics, probabilistic approaches applied to the Markov analysis are modified in order to accommodate interactions and amplifications of industrial systems using techniques in [93]. The next section shows how transitional probabilities are incorporated in a power utility AM system and how the modifications to the generalized Markov process are made.

3.4 Systemic Model Development

3.4.1 Systems approach

In recent years, methods applied to system dynamics have been applied to management of assets in the electric power sector [2], [26] and the space industry [8] in order to determine cause and effect relationships. Modern systems thinkers, for example [28], [29], [31] and [93], have mostly used qualitative models that employ causal loops. Systems thinking concepts can best be presented using causal loop diagrams [2], [26], [28], [31], [38], [93]. In this chapter, a power utility AM system has been presented as comprising components that are operating, being maintained and renewed using causal loop diagrams demonstrated in Figure 3-1. The key to the notations and symbols that apply to the diagrams is given in the notes below Figure 3-1.



Key to causal loop symbols and notations:

R ≡ Reinforcing feedback ≡ Delay effect

B ≡ Balancing feedback

s denotes that when the independent variable changes, the value of the dependent variable will be above what it was before the input from the independent variable, whereas o denotes that the value will be below what it was before the input from the independent variable

Figure 3-1: Performance and operations subsystem

Figure 3-1 represents a performance and operations or maintenance subsystem. It shows that, as asset condition improves, it increases performance. Performance increases demand, revenue, operating expenditure (OPEX), resources for maintenance and the asset condition. Furthermore, improved asset condition reduces downtime. In addition, fault location and restoration reduces failure rate while increasing the asset condition. Finally, failure rate increases downtime.

Figure 3-2 represents investment (enclosed in dotted lines) and renewal subsystems. It can be noticed that, as expected in a real system or subsystem, there is some degree of overlap in the subsystems.

The investment subsystem shows that increase in demand raises revenue for capital expenditure (CAPEX), CAPEX increases resources for investment and network strengthening. Furthermore, the application of AM technologies improves the operating condition and relieves items from a high operating load regime. The operating condition has a delayed effect on aging. Finally, PESTEL (Political, Economic, Social, Technological, Environmental and Legal) factors exogenously impact on investment decisions [1].

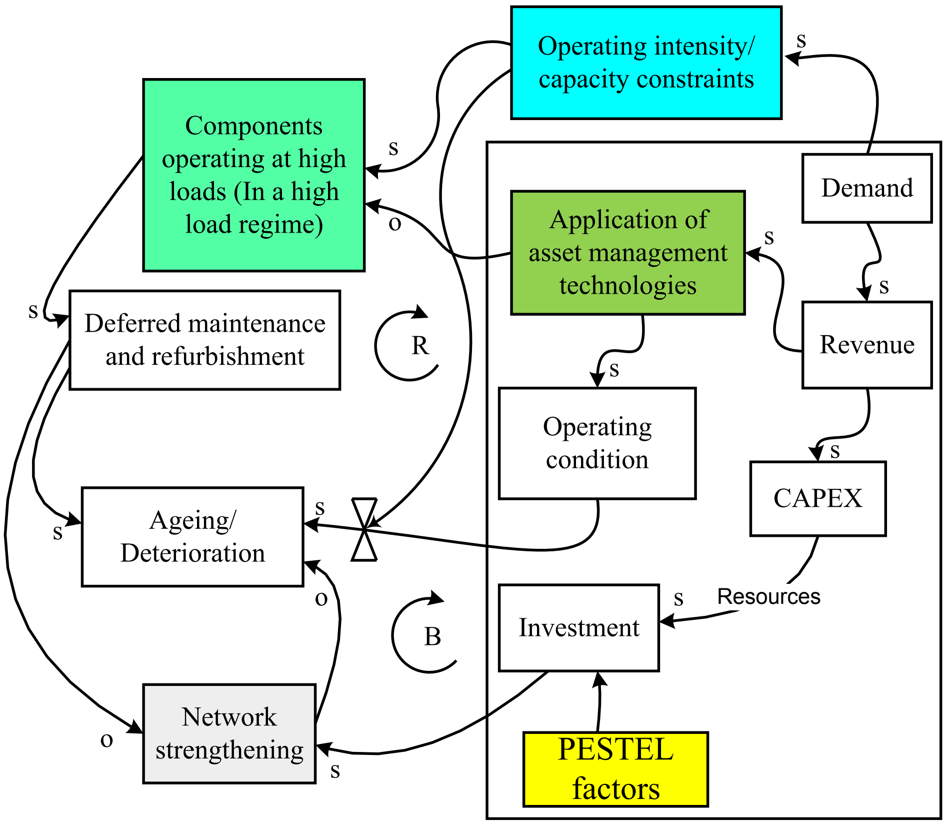


Figure 3-2: Investment (dotted) and renewal subsystem

The renewal subsystem shows that demand increases operating intensity (capacity constraints) which, in turn, increases the number of components operating at high loads (in a high-load-regime). These components lead to deferred maintenance and refurbishment, thereby increasing deterioration and reducing network strengthening efforts. In addition, the operating intensity increases asset deterioration but its effect is delayed. Finally, network strengthening reduces aging.

Figure 3-3 combines the subsystems (Figures 3-1 and 3-2) to show the holistic picture (systems view) of the power grid AM. The system can be viewed as comprising several state-space transitions so that the Markov transitional inferences can be applied to the entire system, or to selected parts of the system, if probabilities of state transition are known.

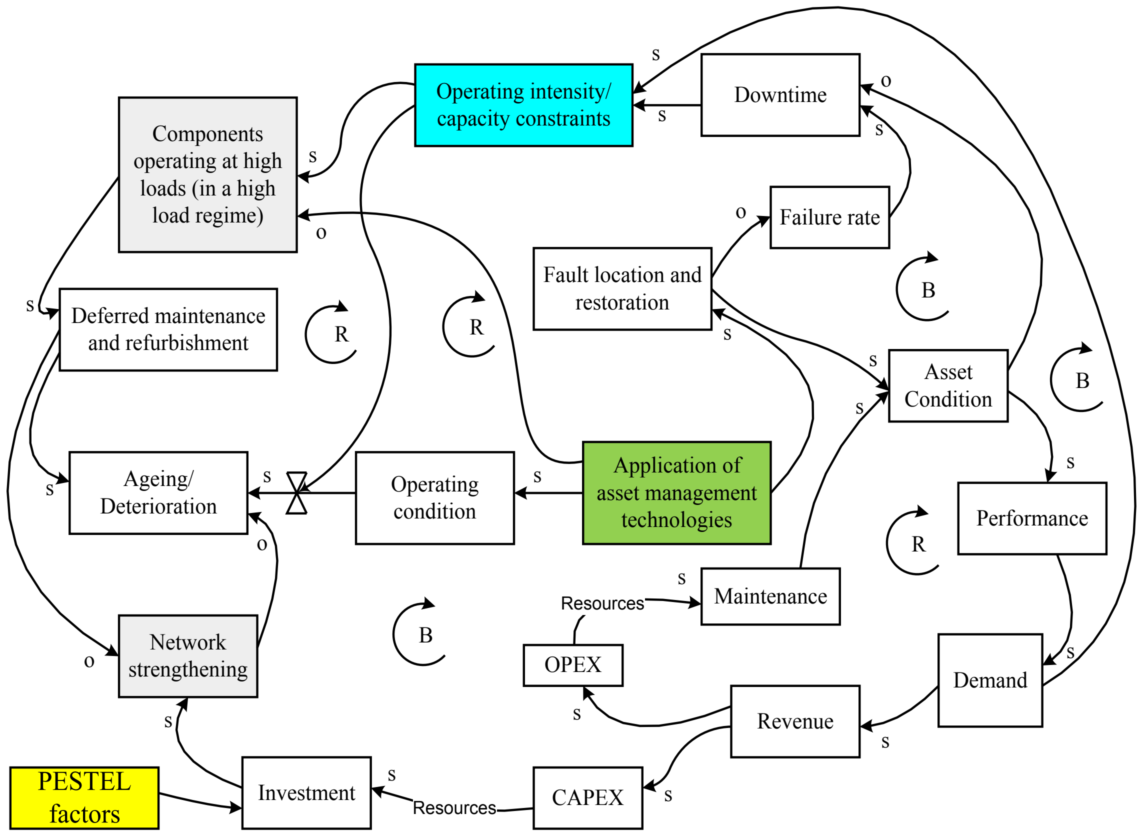


Figure 3-3: Systems view of power utility AM

In practice, some of the transitions are in equilibrium while others are not. The ones not in equilibrium can be described as reinforcing vicious cycles [28], as ill-structured messes [33], and as oscillations [93].

The next section shows how the spatial transitional inferences are adapted in the model formulation process. The subsystem with components operating in the high-load-regime was chosen for further analysis and for the application of the Markov concepts.

3.4.2 Markov inferences and risk modelling

3.4.2.1 Spatial transitions

In this section, spatial transitional inferences from the Markov processes are incorporated in the model. The subsystem with components operating in a high-load regime (at high loads) was selected for the application of Markov inferences. It was selected because its transitional probabilities can easily be obtained from refurbishment, repair and failure rates. In practice, the probabilities can be computed from historical records of the rates at which items fail, are refurbished, repaired and overloaded. Moreover, technologies like SCADA, if installed in the network, can be used to provide the data needed to calculate some of the probabilities [2].

The subsystem can be viewed as consisting of spatial transitional probabilities λ, λ_r and μ as outlined in Figure 3-4. The probability λ stands for the probability that components operate in a high-load regime or overloaded state (State 1). The probabilities λ_r and μ designate the probability that overloaded components are relieved from the high-load regime (from State 1 to 2) and renewed or repaired (from State 1 to 3), respectively. When components are renewed, they also relieve those that are overloaded. Therefore, the probability λ_r is also used to denote a transition from State 3 to 2. Components that are relieved from overload may also be renewed or repaired at a probability μ (State 2 to 3). For power transformers, overloaded components can be detected by hot spot temperature (HST) through thermal analysis [68].

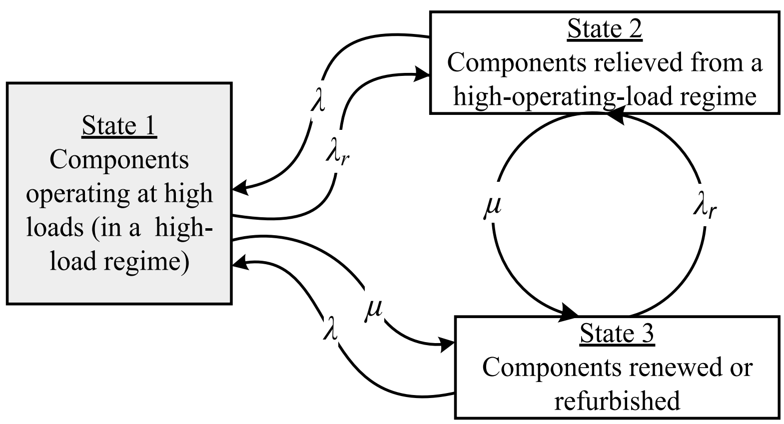


Figure 3-4: State-space transition in the context of a generalized Markov process

A state space matrix can be derived based on the transitional probabilities [92]. A stochastic transitional probability matrix, P, arising from the three states of Figure 3-4 can be expressed as follows:

$$P = \begin{bmatrix} 1-\lambda_r-\mu & \lambda_r & \mu \\ \lambda & 1-\mu-\lambda & \mu \\ \lambda & \lambda_r & 1-\lambda_r-\lambda \end{bmatrix} \tag{3.6}$$

Applying equation (3.6) according to equation (3.5), assuming that $P(0)=\begin{bmatrix}1 & 0 & 0\end{bmatrix}$, λ = 0.032, λ_r = 0.022, and μ = 0.03, transient probabilities after n = 45 time-steps are as shown in Figure 3-5.

Probabilities of not being in State 1, 2 and 3 are shown as 1-State 1, 1-State 2 and 1-State 3, respectively.

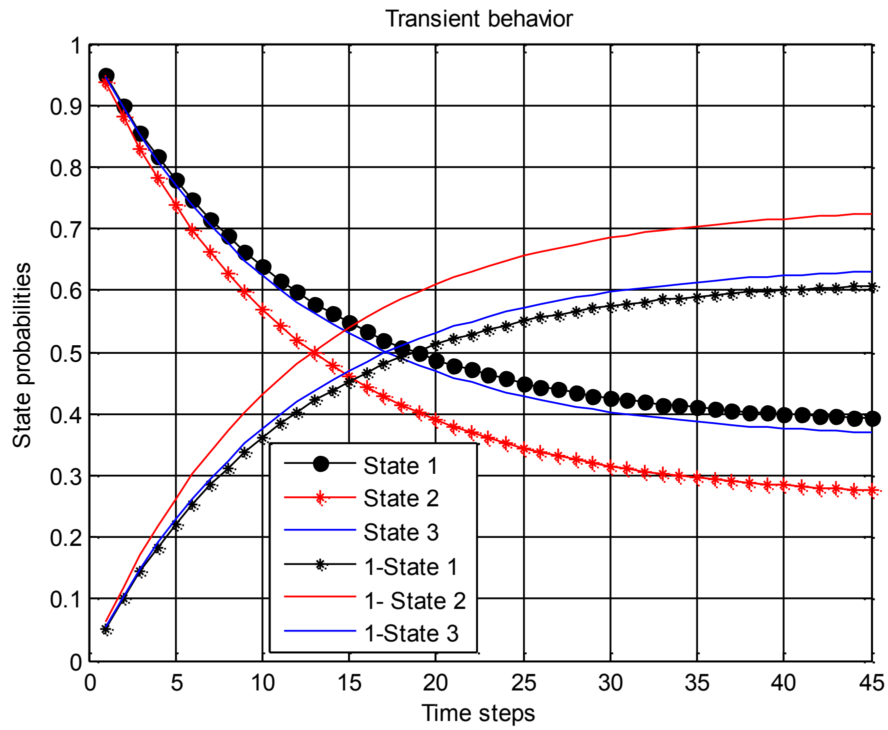


Figure 3-5: Transient behavior in the context of a generalized Markov process

However, Figure 3-5 only shows the transient behavior leading to limiting states. It does not show how components and aging effects interact in a dynamic system; hence modifications are made to the generalized Markov process by employing system dynamics principles, so that the system shows the effects of management decisions or strategies. In a dynamic system, the nature of decisions and actions may be oscillatory due to interaction of industrial system elements [26], [93]. The modifications made are shown from Sections 3.4.2.2 to 3.4.2.4. In Section 3.4.2.2, components that generally describe a set of power utility AM systems are added in order to model their effects on the system. For simplification of the modelling process, the components are assumed to have the same or equal effect on the system risk profile.

3.4.2.2 Incorporating components

Application of AM strategies plays a significant role in modifying the behavior of components in the system. The power network can be viewed as containing components that are operating, aging, failing, and being repaired [2], [26]. Operating capacity constraints cause some components to operate at higher loads than others. Repair of the components tends to reduce the capacity constraints and the number of overloaded items [26]. The network also has components that are renewed or refurbished. Furthermore, the network consists of critical and non-critical components. In terms of a power network, a critical component is that for which functional loss leads to a high severity of impact on the system output. An example is the active part of a transformer that has no redundant capacity. In that case, its failure can result in loss of load or in severe safety and/or environmental consequences.

Table 3-1 lists notations that have been used to describe types of components in the development of the risk trending model. The components described in the table are applied from Sections 3.4.2.3 to 3.4.2.5. In Section 3.4.2.3, life phases are added to the model in order to take the aging process into account. In Section 3.4.2.4, Markov concepts are integrated with systems thinking. Finally, in Section 3.4.2.5, a risk trending model is developed by assimilating ideas from the preceding sections and by adapting system dynamics concepts.

Table 3-1: Description of types of components used in the model

Notation	Description
ϕ	number of critical components in the system
γ	total number of components in the system
σ	number of components operating in the high-load regime at time *t*
ρ	number of components admitted to the high-load regime after time *t* (in a time interval between *t* and *y*)
τ	number of components relieved from the high-load regime after time *t* (in a time interval between *t* and *y*)
ω	number of components that are renewed/refurbished after time *t* (in a time interval between *t* and *y*)

3.4.2.3 Incorporating life cycle phases

In this section, concepts from the bathtub curve analysis are adopted in the model in order to show how the aging process affects the risk profile. The bathtub curve breaks down the aging process of maintainable engineering systems into three phases based on the Weibull shape parameter β. This is shown in Figure 3-6. In the figure, the hazard rate is the probability that a component that has survived up to a given time will fail after that time [35]. In this chapter, it is assumed that lifespan or technical life *t* can be broken down into groups of five years instead of the three bathtub phases. This is in alignment with the strategic planning horizon of five years, that is, the time in which major AM decisions and actions are carried out [3], [64], [94]. Each age group is designated by ζ (zeta), i.e., $\zeta = \frac{t}{n}\Big|n = 5$. For example, the average lifetime of power system assets ranges from 30 to 60 years [2], [60]. That lifetime represents 6 to 12 times ζ.

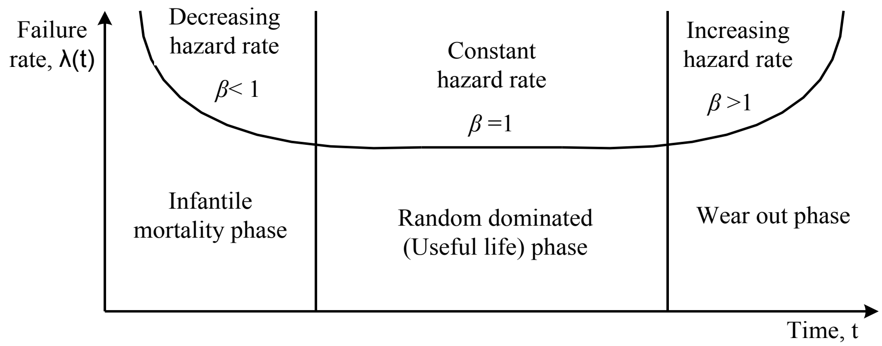


Figure 3-6: Bathtub curve (Life phases of maintainable engineering systems)

If a component is added to a high-operating-load regime later in the life cycle phases (i.e., at higher values of ζ), the impact on operating intensity or on system overload will be higher than in earlier phases, due to the effects of the aging process on the component. Similarly, if a component is removed from the high-operating-load regime later in the lifespan, its impact on relieving the stress from the system will be greater than in earlier life cycle stages. Network strengthening and refurbishment or renewal have an impact similar to that of reducing the number of components that are operating in the high-load-regime because they tend to increase the operating contingency.

The next section demonstrates how systems thinking employs Markov inference models to incorporate the age groups in the model. That is achieved by incorporating the age groups defined in this section and the number of components from Section 3.4.2.2 into the state-space diagram of Figure 3-4, so that the result portrays how system elements interact to amplify or attenuate each other.

3.4.2.4 Application of Markov concepts in systems thinking

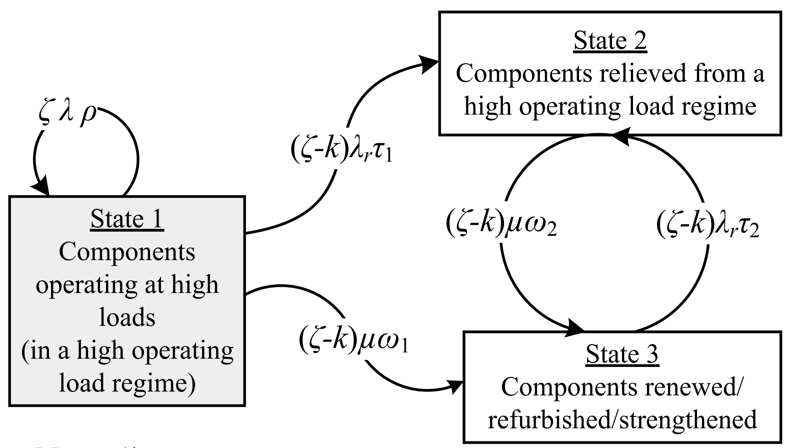
In this section, Markov processes are applied in systems thinking. The Markov processes are modified by integrating transitional probabilities from Section 3.4.2.1, some components from Section 3.4.2.2 (Table 3-1) and ζ from Section 3.4.2.3, in order to define risk amplification and attenuation factors. The modifications change Figure 3-4 to the form shown in Figure 3-7. This is implemented in the following three steps:

a) Components operating in a high-load regime

Components operating in a high-load regime are assumed to pose a greater risk to the system than those at normal load. An aging term ζ, which also serves the purpose of risk amplification, as in system dynamics [93], is incorporated. The term is multiplied by the probability that components are admitted to the high-load regime λ and the number of components ρ to make $\zeta\,\lambda\,\rho$ (see Figure 3-7, State 1).

b) Components relieved from a high-load regime

Components relieved from a high operating load regime, through application of technologies or strategies, are envisaged to reduce the risk of failure of the system. The probability of removal from the high-operating-load regime λ_r is multiplied by ζ to yield $\zeta\,\lambda_r$. A term, k, is incorporated to slow down the rate of deterioration as the denominator does in Perks' formula in [15]. Hence, $(\zeta - k)\lambda_r$ is used to modify τ to make $(\zeta - k)\lambda_r\tau$, where k is an integer. In Figure 3-7, it is assumed that this term is the sum of the probabilities of transition from States 1 to 2 and 3 to 2, where $\tau = \tau_1 + \tau_2$. If $k = 1$, the value of ζ in the first age group (phase) will be zero. It is assumed that there is only one-way communication between States 1 and 2 and 1 and 3.



Note: 1) $\tau = \tau_1 + \tau_2$, $\omega = \omega_1 + \omega_2$
2) ρ, τ and ω are as described in Table 3-1

Figure 3-7: State-space transition in the context of system dynamics

c) Effects of renewal or refurbishment strategies

In practice, the power grid is a process involving a number of assets that are being inspected, maintained and refurbished or renewed [2]. Incorporation of renewal or maintenance helps to model their effects. Components being strengthened or refurbished ω at a probability μ will bring new life to the network, thereby reducing the risk of failure. The effect of refurbishment is assumed to be the same as that of relieving components from the high operating load regime. This equals $(\zeta - k)\mu$

which modifies ω to make $(\zeta - k)\mu\omega$. It is assumed that this term is the sum of the probabilities of transition from States 1 to 3 and 2 to 3, where $\omega = \omega_1 + \omega_2$.

In summary, the terms $\zeta\lambda\rho$, $(\zeta - k)\lambda_r\tau$ and $(\zeta - k)\mu\omega$ denote the risk amplifications and attenuations due to the interaction of system elements. A state-space matrix (3.7) is derived from Figure 3-7. The system behavior is presented in Figure 3-8.

$$P = \begin{bmatrix} \zeta\lambda\rho - [(\zeta - k)\lambda_r\tau_1 + (\zeta - k)\mu\omega_1] & (\zeta - k)\lambda_r\tau_1 & (\zeta - k)\mu\omega_1 \\ 0 & 1 - (\zeta - k)\mu\omega_2 & (\zeta - k)\mu\omega_2 \\ 0 & (\zeta - k)\lambda_r\tau_2 & 1 - (\zeta - k)\lambda_r\tau_2 \end{bmatrix} \tag{3.7}$$

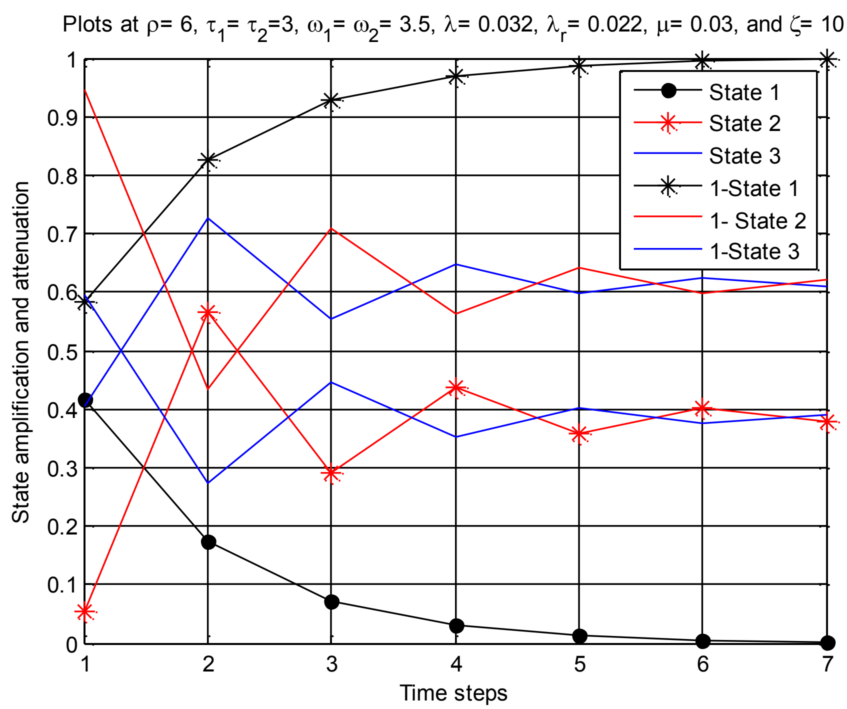


Figure 3-8: System behavior derived from the application of system dynamics

Figure 3-8 shows dynamic system oscillations similar to what is postulated by [30], [93]. State 1 is reduced to zero in six time-steps. In contrast, the generalized Markov approach (Figure 3-5) shows neither oscillations nor attenuations that arise from the interaction of system elements.

Section 3.4.2.5 applies system dynamics principles to derive a linear algebraic form of risk model that is easier to manipulate than the matrix approach presented in Section 3.4.2.4.

3.4.2.5 System dynamics in risk trending model

This section adapts system dynamics principles in order to develop a risk trending model. In system dynamics, the concern is about evaluating amplification of actions [26] and the emergent nature of those actions [28], [29], [31], [33], [93]. Therefore, this section integrates the number of components from Section 3.4.2.2 (Table 3-1), the age groups from Section 3.4.2.3 and the terms derived in Section 3.4.2.4 to account for the system amplifications and attenuations. The number of components in a set of AM systems can be represented by equation (19) in [26] as follows:

$$CHL_y = CHL_t + \left(CAHL_{ty} - CRHL_{ty}\right)\Delta t \qquad (3.8)$$

where CHL_y is the number of components at time y, CHL_t is the number of components that are operating in the high-load regime at time t, $CAHL_{ty}$ is the number of components admitted to the high-operating-load regime in a time interval between t and y, and $CRHL_{ty}$ is the number of components being relieved from the high-operating-load regime during the time interval.

Equation (3.8) is used as a dynamic hypothesis for this study. In system dynamics, a dynamic hypothesis is a working theory of how the problem arose or arises [93]. If the number of components renewed/refurbished in the time interval are denoted as CRN_{ty} and are added, equation (3.8) becomes: $CHL_y = CHL_t + \left(CAHL_{ty} - CRHL_{ty} - CRN_{ty}\right)\Delta t$ (3.9)

For simplification and using notations from Table 3-1, let $CHL_y = F$, $CHL_t = \sigma$, $CAHL_{ty} = \rho$, $CRHL_{ty} = \tau$, and $CRN_{ty} = \omega$. Hence, expressing equation (3.9) with Δt implicit results in the following:

$$F = \sigma + \rho - \tau - \omega \qquad (3.10)$$

At this point of model development, the components are normalized using a method applied in construction project risk in [95]. The total number of components normalized to the number of critical components is ϕ/γ. This will be added to equation (3.10). It represents the non-age-related inherent risk similar to a constant of 0.005 for random failures in Makeham's formula in [16]. Normalizing σ, ρ, τ, and ω to the number of critical components leads to the following: σ/ϕ, ρ/ϕ, τ/ϕ, and ω/ϕ, respectively. Therefore, equation (3.10) can be expressed in a new form as follows:

$$F = \frac{\phi}{\gamma} + \frac{1}{\phi}\left(\sigma + \rho - \tau - \omega\right) \qquad (3.11)$$

In Section 3.4.2.4, the terms ρ, τ, and ω were modified to $\zeta\lambda\rho$, $(\zeta - k)\lambda_r\tau$ and $(\zeta - k)\mu\omega$, respectively. Therefore, equation (3.11) can also be expressed as follows:

$$F = \frac{\phi}{\gamma} + \frac{1}{\phi}\{\sigma + [\zeta\,\lambda\,\rho] - [(\zeta - k)\lambda_r\,\tau] - [(\zeta - k)\,\mu\,\omega]\} \tag{3.12}$$

It has been shown that a failure probability function can be used to stand for the risk of failure [35], [81]. Therefore, a failure probability function *F (t)* is introduced to represent the risk of failure at this point. The equation resulting from the inclusion of *F (t)* is referred to as a risk factor (*RF*). The *RF* is defined as the ratio of number of critical components to total number of components in the system, plus the product of failure probability and the algebraic sum of factors representing risk amplifications and attenuations during the life cycle. It is given as

$$RF = \frac{\phi}{\gamma} + \frac{F(t)}{\phi}\{\sigma + [\zeta\,\lambda\,\rho] - [(\zeta - k)\lambda_r\tau] - [(\zeta - k)\mu\,\omega]\}\,|1 < \zeta < t/n, \phi > 0 \tag{3.13}$$

By letting *F (t)* = *F (ζ)* and assuming that *k* = 1, equation (3.13) can be expressed as follows:

$$RF = \frac{\phi}{\gamma} + \frac{F(\zeta)}{\phi}\{\sigma + [\zeta\,\lambda\,\rho] - [(\zeta - 1)\lambda_r\,\tau] - [(\zeta - 1)\mu\omega]\}\,|1 < \zeta < t/n, \phi > 0 \tag{3.14}$$

From equation (3.14), sensitivity of the *RF* with respect to variations in the number of components renewed at different life cycle stages can be trended.

In reliability analysis (see, for example, Section 2.6.2), the following relationships apply:

$$f(t) = \frac{dF(t)}{dt} = \frac{d[1 - R(t)]}{dt} \tag{3.15}$$

$$\lambda_F(t) = \frac{f(t)}{R(t)} \tag{3.16}$$

$$R(t) + F(t) = 1 \tag{3.17}$$

where $f(t)$ is probability density function (PDF), $\lambda_F(t)$ is failure rate, $R(t)$ is survival probability or reliability function, and $F(t)$ is failure probability or cumulative density function (CDF).

The form of *F (t)* that utilizes the Weibull parameters can be obtained by integrating equation (3.16), rearranging the result to make *R (t)* the subject of the formula and substituting for the *R (t)* in equation (3.17) according to [35] as follows:

$$F(t) = 1 - \exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right] \tag{3.18}$$

where β and η are shape and scale parameters, respectively, of the Weibull distribution.

Advantages of the Weibull distribution are: flexibility (capability to model various types of distributions), ease with which the parameters can be interpreted and linked to failure rates (or hazard rates) and the bathtub curve [35], [81]. The Weibull hazard rate, for example, Figure 3-6, is given as follows [35]:

$$h(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \tag{3.19}$$

Section 3.4.3 focuses on the Weibull parameter estimation process and shows how times to failure are utilized in the model. In Section 3.5, equations (3.15) to (3.19) are applied in analyzing and plotting reliability functions. In addition, equation (3.18) is expressed as a function of ζ and inserted in the risk trending model, that is, equation (3.14).

3.4.3 Parameter estimation

This section shows how likelihood functions are applied to estimate the Weibull parameters. The likelihood functions are expressed as functions of times to failure and are processed according to the procedure outlined in this section.

The Weibull PDF for a continuous random variable *X* is given according to [84] as follows:

$$f(t) = \begin{cases} \alpha\beta t^{\beta-1} e^{-\alpha t^{\beta}}, & t > 0 \\ 0, & elsewhere \end{cases} \tag{3.20}$$

where $\alpha > 0$, $\beta > 0$, $\alpha = 1/\eta^{\beta}$, and t is time to failure.

Equation (3.20) is a two-parameter Weibull model. It is chosen instead of a three-parameter model, because, in most cases, it sufficiently describes the failure data [35].

Least squares method (LSM) and the maximum likelihood estimation (MLE) are the main methods for estimating the Weibull parameters. The LSM provides accurate results for a large number of failures and when data is non-censored (i.e., non-truncated or obtained from items that reached the end of their lifespan) [81]. The MLE can be used to overcome the weaknesses of the LSM in dealing with censored data and small sample sizes [35], [81]. The MLE has been applied in this chapter because the number of failures encountered is small.

The likelihood function L of a PDF can be expressed as follows [84]:

$$L(t_1, t_2, ..., t_n, \theta) = f(t_1, \theta) \cdot ... \cdot f(t_n, \theta) \tag{3.21}$$

For the Weibull PDF, the likelihood function becomes

$$L(t_1, t_2, ..., t_n, \theta) = \prod_{i=1}^{n} \frac{\beta}{\eta}\left(\frac{t_i}{\eta}\right)^{\beta-1} \exp\left[-\left(\frac{t_i}{\eta}\right)^{\beta}\right] \tag{3.22}$$

where $\theta = \beta, \eta$.

Taking the natural logarithm of equation (3.22), partially differentiating it with respect to η and β and then equating it to zero results in:

$$\frac{\partial \ln L}{\partial \eta} = -\frac{n}{\eta} + \frac{1}{\eta^2}\sum_{i=1}^{n}(t_i)^{\beta} = 0 \tag{3.23}$$

$$\frac{\partial \ln L}{\partial \beta} = \frac{n}{\beta} + \sum_{i=1}^{n}\ln t_i - \frac{1}{\eta}\sum_{i=1}^{n} t_i^{\beta} \ln t_i = 0 \tag{3.24}$$

From (3.23) and (3.24), estimates of η (i.e.,$\hat{\eta}$) and β (i.e.,$\hat{\beta}$) are derived as follows:

$$\hat{\eta} = \left[\frac{1}{n}\sum t_i^{\beta}\right] \tag{3.25}$$

$$\hat{\beta} = \left[\frac{\sum_{i=1}^{n}(t_i)^{\beta}\ln t_i}{\sum_{i=1}^{n}(t_i)^{\beta}} - \frac{1}{n}\sum_{i=1}^{n}\ln t_i\right]^{-1} \tag{3.26}$$

Then the Newton-Raphson iteration in the following form is applied to equation (3.26) to determine the parameter estimate for β:

$$\beta_{i+1} = \beta_i - \frac{f(\beta_i)}{f'(\beta_i)} \tag{3.27}$$

The estimate of β is then substituted in equation (3.25) to obtain η. Table 3-2 outlines times to failure (t), used to compute the MLE, and the corresponding DP (at the time of retirement or decommissioning) for substation transmission transformers. The DP is an indication of the mechanical integrity of cellulose insulation, where a DP ≤ 200 signals the end of insulation life [68]. The data in Table 3-2 is for a small electric grid (from Appendix B), for same transformer vintage which is singly censored (i.e., containing complete failures).

Table 3-2: Times to failure and the corresponding DP

t ($x10^5$) [hours]	1.892	1.971	1.971	2.182	2.31	2.418
DP	150	200	200	180	200	180
t ($x10^5$) [hours]	2.365	3.715	3.925	4.03	4.188	4.366
DP	150	150	180	200	200	200

Section 3.5 presents the results of computed parameters, plots of reliability functions and simulated risk trends. It also discusses the results.

3.5 Results and discussion

This section presents, analyzes and discusses results from the application of the model developed from Sections 3.1 to 3.4. Thereafter, the conclusions are presented in Section 3.6.

3.5.1 Computed parameters and reliability functions

Failure statistics from Table 3-2 were applied to compute the Weibull parameter estimates using the MLE as described in Section 3.4.3. Table 3-3 presents the parameter estimates together with their 2.5% and 97.5% confidence intervals (ci).

Table 3-3: Computed Weibull parameters and their confidence intervals

Parameter	β	η (x10^5) [hours]
Estimated value	3.43	3.29
2.5% ci	2.19	2.76
97.5% ci	5.39	3.92

The parameters from Table 3-3 have been used to plot some reliability functions and risk trends, which are presented, analyzed and discussed in this section.

It should be noted that the estimated parameters have been used to generate two types of plots. In the first type, the abscissa represents the technical life, whereas in the second type it stands for the age groups. The purpose of the first category (Figures 3-9 and 3-10) is to project the whole asset life for analysis of reliability, whereas that of the second type (Figures 3-11 to 3-15) is to align the risk trending model with the age groups that were introduced in Section 3.4.2.3. This section presents the first type of plots. Section 3.5.2 presents the second category.

Figure 3-9 outlines plots of survival and failure probabilities as well as the hazard rate of the transformers at the estimated Weibull parameters. The hazard rate increases with time, indicating age-dependent failure pattern. The figure shows that the number of surviving and failing components is the same at 33.7 years. This suggests that the best time for refurbishment could be the 33rd year, just before the number of failing items exceeds that of the surviving ones, so that costs of failure are minimized.

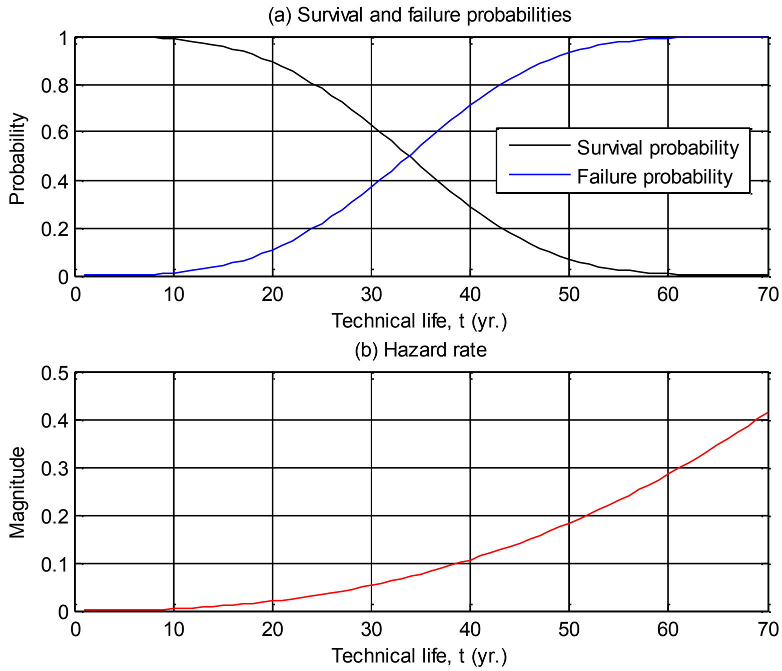


Figure 3-9: (a) Survival and failure likelihood, and (b) hazard rate

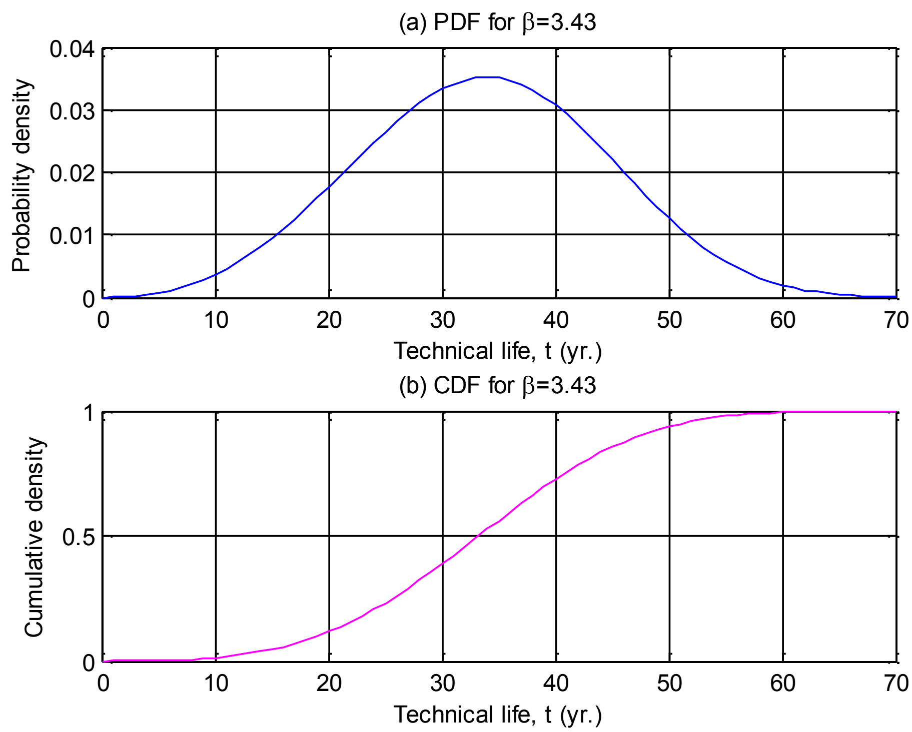


Figure 3-10: (a) PDF and (b) CDF based on the technical life

Figure 3-10 shows plots of PDF and CDF. In system reliability analysis, a PDF indicates the chance of a unit failing at age t, whereas a CDF shows the probability of having a lifespan of at most t [14]. In the figure, at $t = 0$ the PDF is zero; it rises and returns to zero at $t = 67$ years. At $t = 0$ the CDF is zero and it gets to one at $t = 67$ years. That implies that, at $\beta = 3.43$ and $\eta = 3.29 \times 10^5$ hours, the transformers reach the end of life with probability 1 at 67 years of age. This means the analysis of the PDF and CDF projects a lifespan of 67 years for the transformers at the estimated parameters. The life of power assets varies greatly according to maintenance strategies and operating conditions to which they are subjected. In general, the life ranges from 40 to 100 years [59], [60]. This is corroborated by [96], who advances that resource constraints compel electric utilities to manage an aging infrastructure that is wearing out on a 30-year cycle and is being replaced on a 100-year cycle.

3.5.2 Simulated risk trending

In this section, simulation results are presented to show how the risk trending model can be applied. The sensitivity of the risk factor to changes in the number of components renewed and the number admitted to or relieved from a high-operating-load regime during the lifecycle was carried out. The age groups presented in Section 3.4.2.3 are used to represent the abscissa. For example, the PDF and CDF for the 70-year period of Figure 3-10 are represented by 14 age groups as shown in Figure 3-11. These age groups are in accordance to the risk trending model proposed.

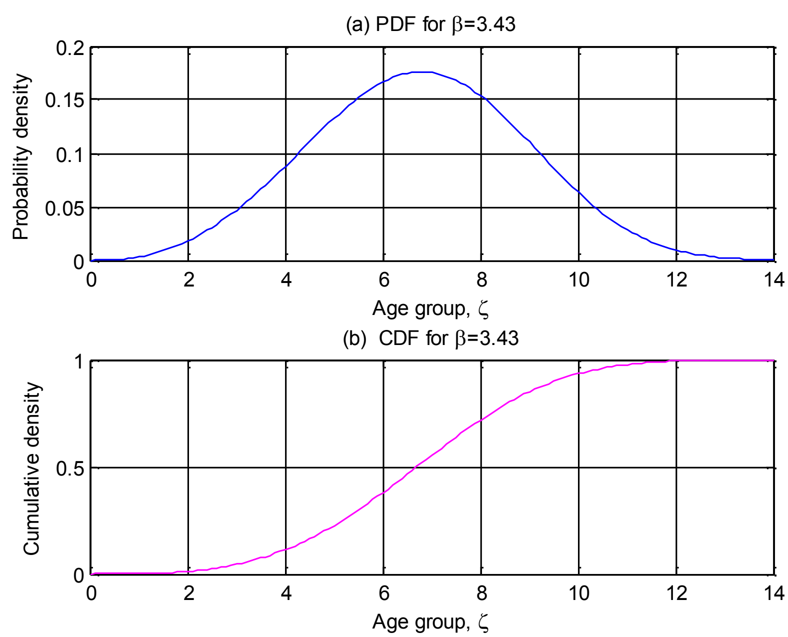


Figure 3-11. (a) PDF and (b) CDF based on the age groups

Equation (3.14) is applied to model risk trends. The following are fitted into the model: the estimates of β and η (see Table 3-3), $\phi = 3$, $\gamma = 20$, $\sigma = 6$, $\lambda = \lambda_r = 0.02$, and $\mu = 0.03$. Thereafter, sensitivities of the risk factor with respect to changes in ρ, τ and ω at various values of ζ are analyzed.

Results for the trend of risk for business as usual (unmodified risk) are plotted and compared with the trends of risk when major mid-life and major end-life renewals or refurbishments are carried out as demonstrated in Figure 3-12. Plots in Figures 3-12 to 3-15 indicate how the model can be used to modify the failure risk as AM strategies, such as renewal, are executed.

Figure 3-12 outlines trends of risk for business as usual (unmodified risk), with major mid-life renewal and with major end-life renewal strategies. The horizontal line inserted at the top is a cut-off point that asset managers could set to measure the acceptable level of risk.

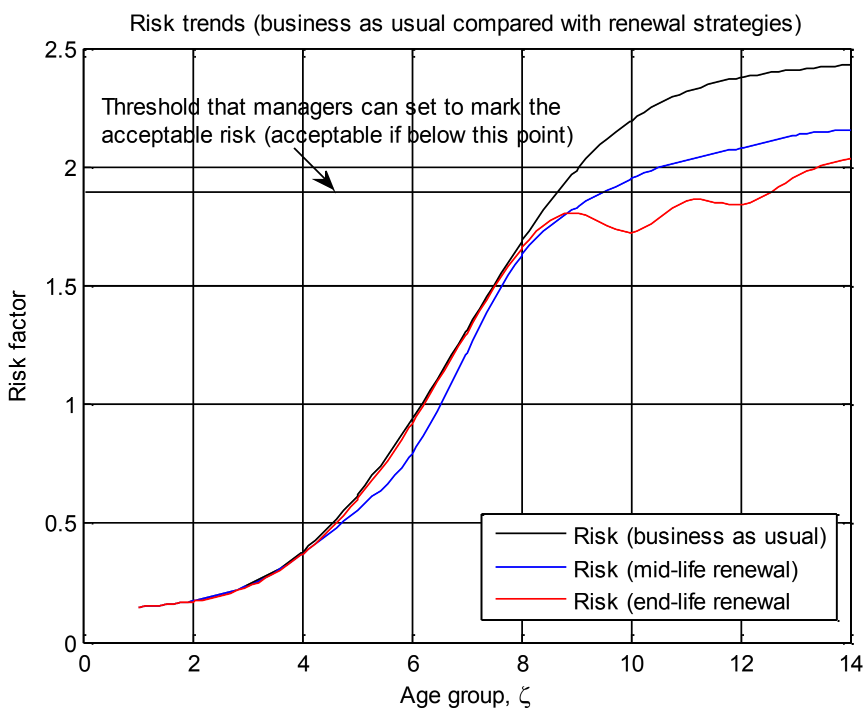


Figure 3-12: Risk trends for various strategies

Figures 3-13 and 3-14 present the trends of risks from Figure 3-12, but with magnitudes of risk reduction due to major mid-life and major end-life refurbishments, respectively, plotted beneath them. The horizontal lines across the risk reduction curves (see annotations) show the threshold that may be set for performance-based compensation to workers who exceed performance objectives.

Figures 3-13 and 3-14 portray a similar scenario, but where more renewal effort is applied towards the end and at the middle of component life, respectively. Plots of the magnitude of risk reductions are added beneath Figures 3-13 and 3-14. The horizontal lines that are inserted could be used by asset managers to determine the level of risk reduction that may justify the award of performance-based (merit) compensation to work teams. This could take the form of bonuses to employees for exceeding expectations (for reducing the risk).

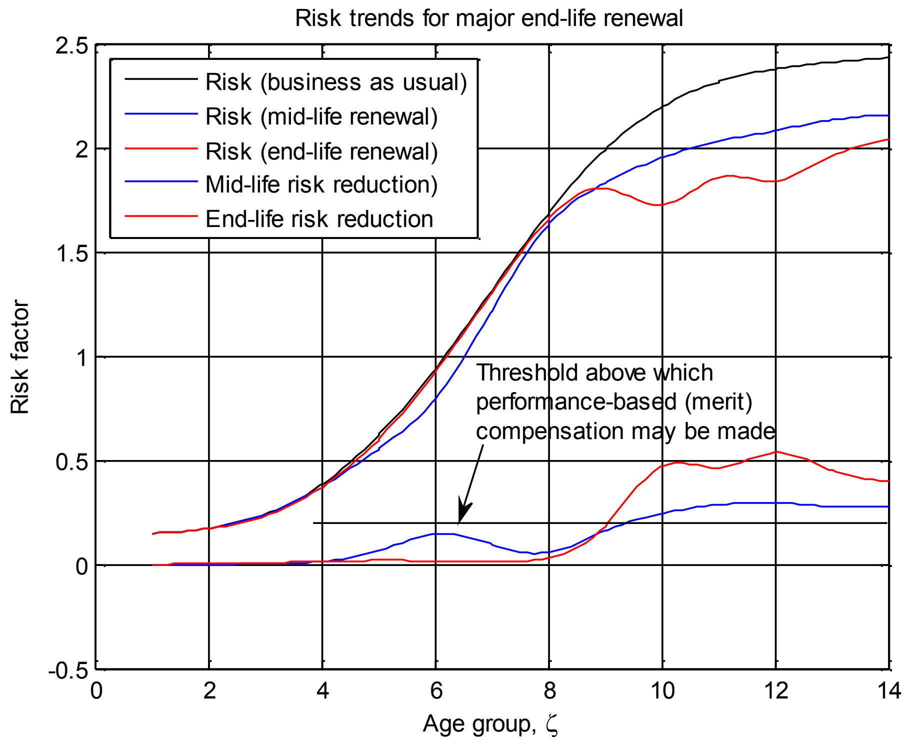


Figure 3-13: Risk trends with reduction levels (major end-life renewal)

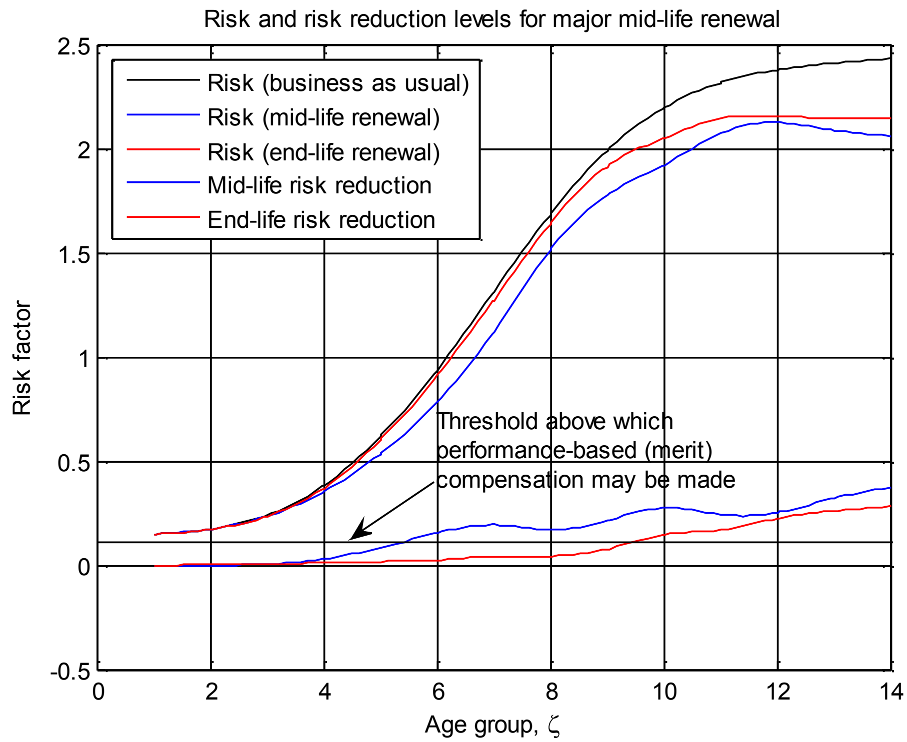


Figure 3-14: Risk trends with reduction levels (major mid-life renewal)

Figure 3-15 presents cumulative risk reductions (benefits) derived from Figures 3-13 and 3-14. Basically, these are the benefits which would show the asset manager whether the strategies do mitigate risks or not. They may be translated to cost benefits by superimposing empirical cost models on the risk model.

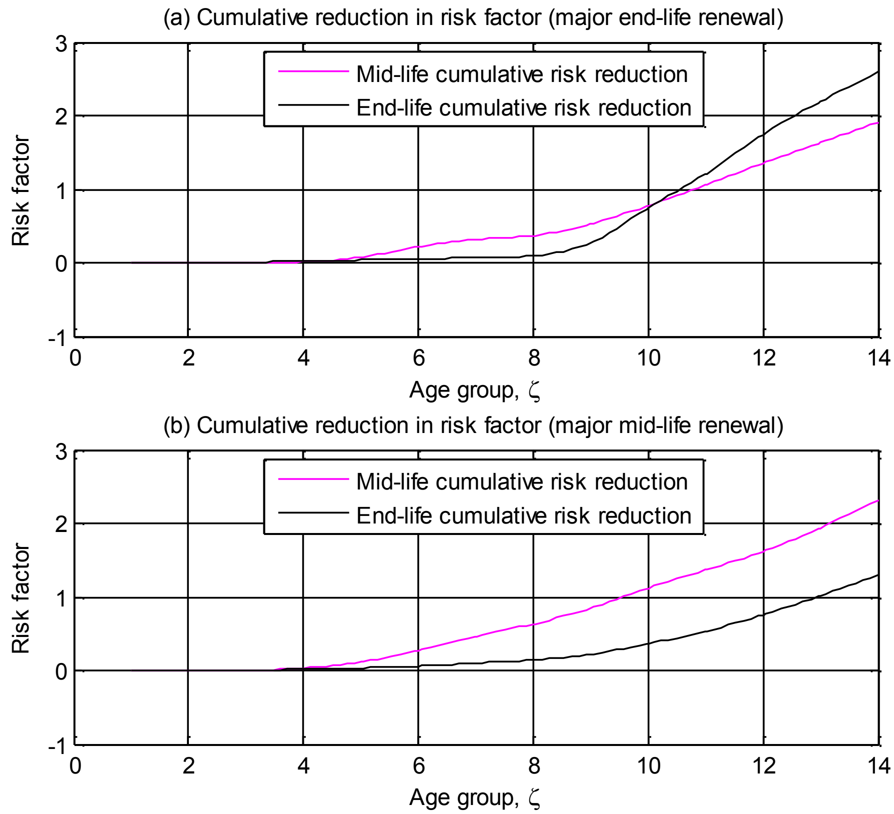


Figure 3-15: Cumulative benefits: (a) end-life and (b) mid-life

3.5.3 Comparison of PDF and CDF for reactors

This section presents data that has been extrapolated from a population of 20 reactors. It is worth noting that this serves only to further demonstrate how the model can be applied because the renewal regimes that are applicable to power transformers are different from the reactors. The plots given below have been computed using four life parameters (i.e., mean, standard deviation, shape parameter and scale parameter) from 20 retired (failed) reactors based on a study by [77]. Tables outlining the parametric and failure data for the reactors are presented in Appendix F.

Figure 3-16 outlines the Normal and Weibull probability density functions for the reactors, whereas Figure 3-17 presents the cumulative density functions for the two types of distributions.

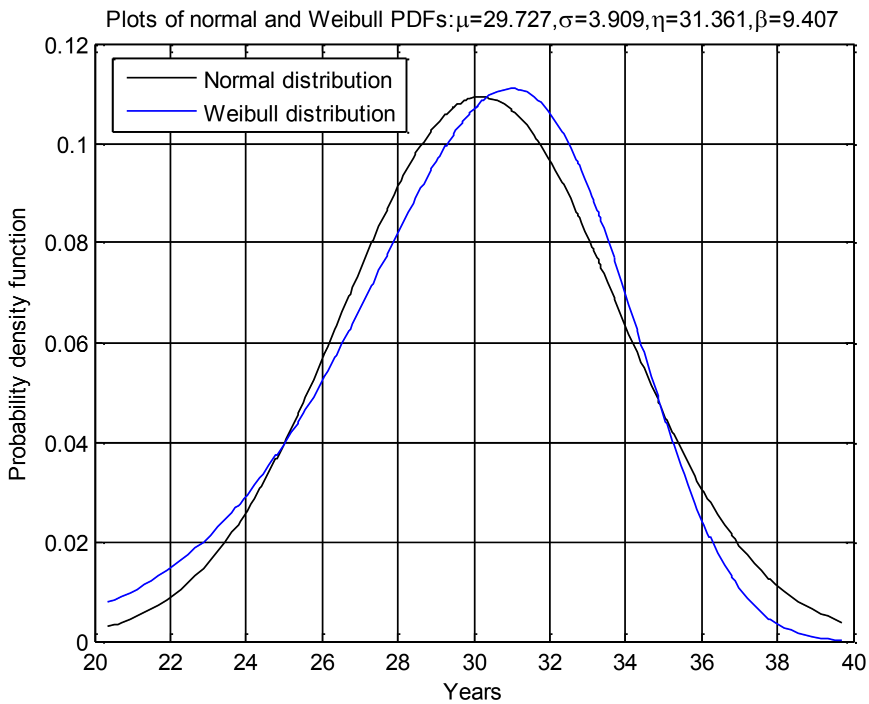


Figure 3-16: Comparison of Normal and Weibull PDFs for 500kV reactors

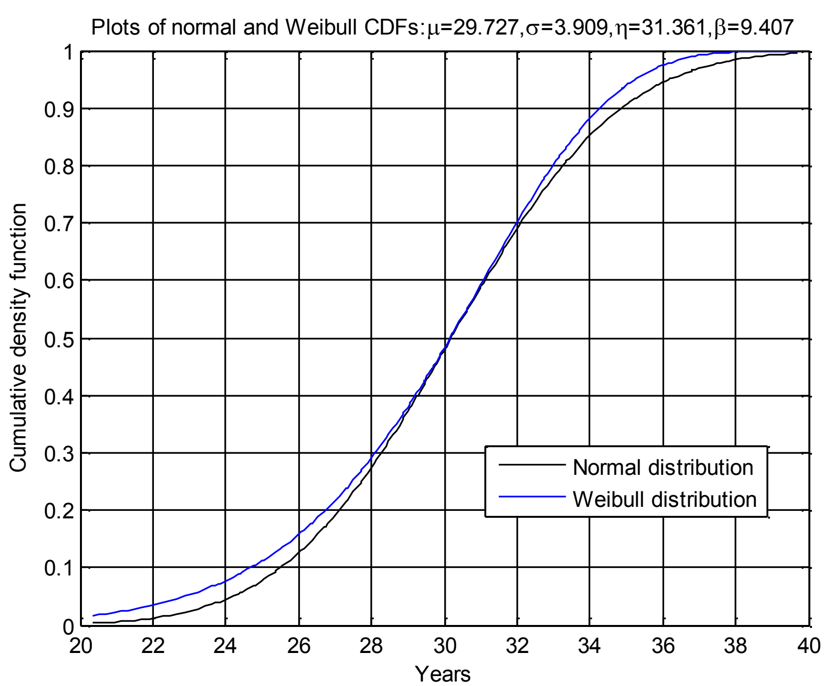


Figure 3-17: Comparison of Normal and Weibull CDFs for 500kV reactors

Figures 3-18 and 3-19 show how the risk trending applies to the data for the reactors. The figures show that for the reactors, the risk in the first twenty years is very low. This is due to the high reliability of reactors, in general.

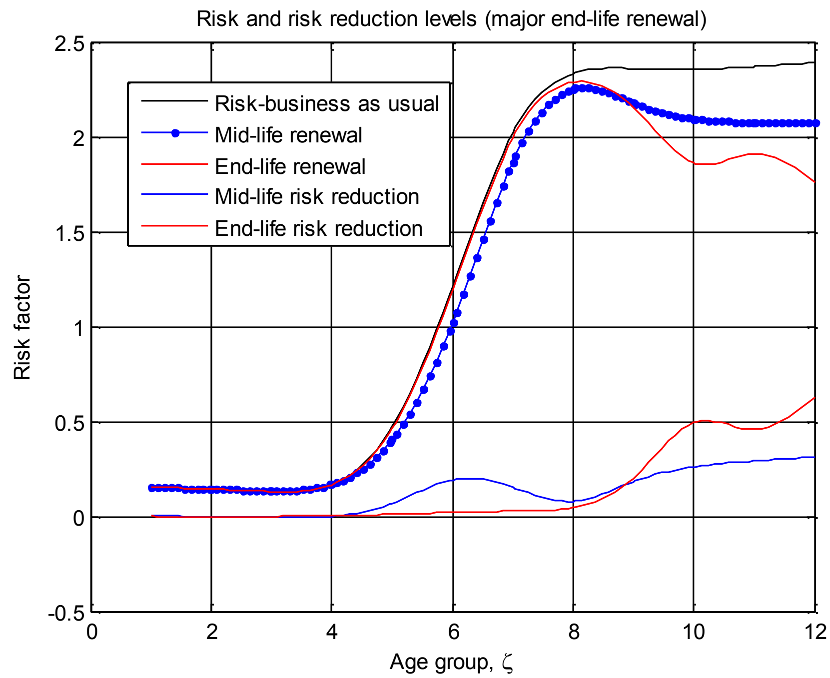


Figure 3-18: Application of the risk trending model to reactors (end-life renewal)

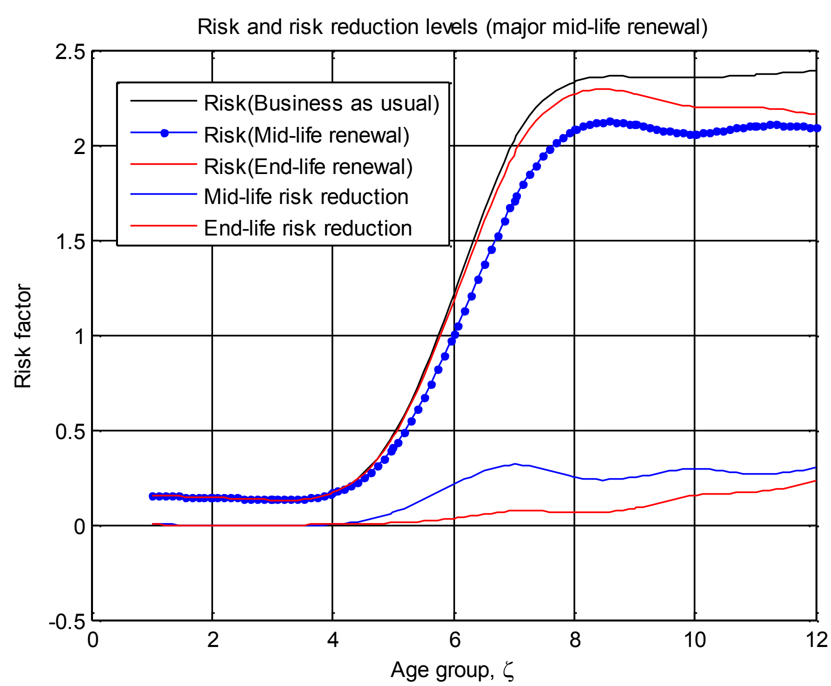


Figure 3-19: Applying the risk trending model to reactors (mid-life renewal)

As stated earlier on, the reactor curves presented in Figures 3-16 to 3-19 serve the purpose of demonstrating how the model can be used to model the risk of various types of physical assets if the failure functions or the life modelling parameters are known (determined). Just like power transmission transformers, failure of the reactors is age related. They do not portray any infantile mortality failure.

In this chapter, the failure risk of physical assets was modelled. Inferences from system dynamics, the Markov analysis, the Weibull distribution and the bathtub curve analysis were assembled to come up with the model. The power grid AM system was represented by causal loop diagrams from systems thinking. A subsystem with components operating in a high-load regime was expressed as a system in state-space transitions so as to enable the application of the Markov processes. System dynamics principles were used to adapt the inferences into a linear algebraic form of a risk trending model containing a failure risk function. The failure risk function was expressed in terms of parameters of the Weibull distribution. The parameters were estimated using the MLE. Only failure data was used to estimate the parameters according to methods in [35], [81]. The sensitivities of the risk factor to variations in the number of components renewed and the number admitted to or relieved from a high-operating-load regime during the lifespan were simulated. The focus of the sensitivity analysis was on the impact of major mid-life and end-life renewal strategies on the risk factor. The sensitivity analysis was applied to a set of AM systems made up of substation transmission transformers. This was able to track the magnitudes of risk amplifications and attenuations caused by the application of renewal strategies.

The use of the Weibull distribution made it possible to model with a few data sets, in this case, twelve sets. The Weibull distribution may be applied to model a wide range of distributions, provided the shape and scale parameters for a given set of data are known. The challenge that can arise when dealing with failure data is that some components may have been taken out of service before the end of their lifespan, or the number of failures may be small. In that case, [35], [81] recommend using the MLE for the parameter estimation. It is assumed that the transformers used in the present work had reached their end of lifespan because the DP was ≤ 200. Normally, a DP of ≤ 200 is an indication of complete loss of mechanical integrity of the insulation material [68], [96].

The model that has been advanced (proposed) successfully trended the failure risk of physical assets. It could be used as a planning tool and as a measure of improvements brought about by the application of strategies or technologies associated with the strategies. It is flexible because the shape and scale parameters that are estimated are unique to the type of failure data used. The parameter estimates can be used to show dominant failure modes during the component life cycle based on the plots of the PDF and hazard rates.

When using the model, analysts may choose any empirical failure function that best represents the failure data. For example, [15], [16] presented a transformer failure function based on Perks' formula that may be used as follows:

$$F(t) = \frac{A + \alpha_p e^{bt}}{1 + \mu_p e^{bt}} \tag{3.28}$$

where *F(t)* is the instantaneous failure rate, *A* represents the frequency of random events such as lightning and collisions, b, α_p and μ_p are constants estimated using the Bayesian method in [15], and t is the time of operation.

In this chapter, it was possible to assign modelling equations to systems thinking approaches in management. Most of these approaches lack quantitative capabilities [2], [26], [28], [33], [34]. The MLE of Weibull parameters, Markov processes, and bathtub curve inferences are well known, but their integration in the systems thinking philosophy is remarkable, as it enhances the quantitative capability of the philosophy. The integration was facilitated by the appropriate application of the dynamic hypothesis. This underscores the importance of the dynamic hypothesis in the successful advancement of system education.

Models are supposed to break down complexity [58]. The proposed model did that by utilizing a small number of times to failure for modelling component reliability and risk. In the power utility AM this is significant, because data unavailability is one of the main barriers to successful statistical analysis as alluded to in [2]. Application of the MLE for parameter estimation guaranteed accuracy in dealing with the small sample sizes encountered in the study. The MLE is also a reliable method when handling data that is censored [35], [81].

It is worth mentioning that systems thinking helps to reveal the root causes of problems so that optimization models can be applied to deal with the specific problems that have been identified. In this chapter, the MLE was the model used to optimize the Weibull distribution parameter estimates. The focus of the study (chapter) was on modelling of the risk profile changes (as opposed to maintenance optimization) with respect to the application of renewal strategies. This is very important in providing a strategic direction for a risk-based asset management planning process. It can be a useful tool for analyzing the risk level and to overcome some of the shortfalls of the risk matrix approaches which were examined in Section 2.5.2. When applying the model, asset managers may integrate models like SMDP or MDP, which were discussed in Section 2.6.3.2, in order to optimize other parameters like inspection rates and maintenance policies. These are beyond the scope of the current research, but will be the focus of future studies.

3.6 Chapter conclusions

In this chapter, inferences from the Markov processes, the bathtub curve analysis and the Weibull distribution have been integrated with systems thinking to form a risk trend monitoring model, also called a risk factor. These inferences are well known. Thus, what is original in the study is not the use of these inferences, but how they augment the quantitative capability of systems thinking to trend the risk. The risk factor has been expressed in terms of components that generally describe a set of power utility AM systems, and also contains a failure risk function expressed in terms of the Weibull parameters. The parameters were estimated using the MLE for a given set of failure data. Then the sensitivities of the risk factor with respect to the variation in the number of components renewed and the number admitted to or relieved from a high-operating-load regime during the life cycle were simulated. The model was able to monitor trends of risk amplifications and attenuations associated with the application of renewal strategies, thereby quantifying trends of the risk of failure. The model reinforces the capabilities of systems thinking approaches by providing modelling equations for the purposes of quantitative measurement and control of risk. The Weibull distribution and its parameter estimates were applied to make it possible to model reliability and risk with only a few data sets. Therefore, the model can prove useful in situations where data unavailability problems exist. The model may be applied to any physical asset, provided the failure likelihood function is determined, failure data are available, and component renewal probabilities are known. It can be applied in risk management, in refurbishment planning, in performance-based compensation schemes, and in advancing system education.

In Chapter three, a quantitative risk trend monitoring model was developed. This model has also been presented in [97]. However, the model did not quantify the cost benefits of the risk profiling. Hence, Chapter four evaluates the cost benefits of component risk trending to fill that gap.

CHAPTER FOUR

COST BENEFITS OF COMPONENT RISK TRENDING

4.1 Introduction

This chapter incorporates statistics into systems thinking in order to evaluate the cost benefits of risk trending, thereby extending the work in Chapter three, which was partly presented in [97]. The chapter applies some cost models to illustrate how the model that was developed in Chapter three can also be used for the cost benefit analysis. It is worth mentioning that systems thinking aids in establishing cause and effect and not in optimizing asset management (AM) systems. Optimization can be achieved through the use of analytical tools that can be integrated into systems thinking. In this case, the optimization of the model is achieved through the use of methods for optimizing statistical parameters. These methods include the maximum likelihood estimation (MLE) and method of moments (MOM).

Deregulation and globalization of electric energy supply under current economic environment compel power utility managers to consider both reliability and costs in the decision making process [55]. The major challenge asset managers face is the need to enhance reliability and at the same time to lower costs [2], [55]. These conflicting objectives, combined with legal and stakeholder requirements for supply reliability; stringent risk evaluation requirements as stipulated in ICE 31010 and 60300-3-9 standards (see, for example, Sections 2.5.1 and 2.5.2); and uncertainties associated with equipment life prediction, justify the application of a multi-method risk assessment or evaluation approach. In this case, the multi-method (multi-criteria) approach combines systems thinking with statistical analyses, parametric probability inferences and cost models.

The analysis of probabilities is viewed to be the best approach in tackling the uncertainties in the prediction of equipment life [55]. However, probabilistic and statistical inferences tend to falter when it comes to determining causation [35]. Systems science (thinking) enables analysts to understand how things are compounded and work together in integrated wholes [29]. Systems theory characterizes systems by typologies such as emergency (small things making complete wholes), interdependence, hierarchy, convergence and feedback [26], [28], [29], [33]. These typologies establish synergies and cause-and-effect relationships that may be too difficult to depict by mere analysis [33]. Analytical approaches can be applied to solve specific problems that have been determined by the root cause analysis of systems thinking [26].

Deterioration of assets and maintenance management systems can be represented by Markov process models [55], [97]. An AM system can be modelled based on the principle that the power grid consists of assets that are being maintained and refurbished [2]. In references [97] and [98], the grid was expressed as a system in state space transition, thus it enabled the application of Markov concepts to some parts of the system in the development of the risk trending model. This work superimposes a cost model on the risk trending model, in order to determine the cost benefits of risk amplifications and attenuations that were presented in Chapter three. Average annual maintenance cost data for 12 MVA transformers (Appendix B, Table B3) is used to illustrate how the risk trending model can be applied in the evaluation of the cost benefits (as renewal strategies are executed).

In Sections 4.2 to 4.6, the problem is formulated and a systems view of the AM is given. Furthermore, parameter estimation techniques are outlined, cost models are evaluated and primary data that is used for the modelling process is presented. Section 4.7 presents and discusses the results, Section 4.8 summarizes the model that has been developed, whereas Section 4.9 draws the conclusions from the chapter.

4.2 Problem formulation

This section demonstrates the use of systems thinking in problem formulation and in determining causation. Then, it shows how statistical and stochastic techniques can be integrated with systems thinking. Statistical inferences that were applied in computing optimized Weibull parameter estimates in Chapter three are utilized again. In addition, the MOM is incorporated. These are applied for the evaluation of cost benefits of component risk trending.

4.2.1 Systems view of power grid management

In this section, a systems view of power utility AM is presented in form of causal loop diagrams. Furthermore, adaptations of causal loop diagrams to Markov inference and risk models are demonstrated. Finally, statistical relationships required for the processing of the failure data, in order to optimize the Weibull parameters, are advanced.

The main objective of physical AM is to optimize life cycle business impacts of costs, performance and risk [1]. In order to achieve this, the power utility creates, operates and maintains the assets to yield returns on the investment through revenue generation. Most power utilities are resource constrained hence they manage assets that are designed for a 30-year cycle, but being replaced on a 100-year cycle [64]. This results in capacity constraints, which in turn leads to components operating at higher loads than they were designed for [97], [98]. This relationship was demonstrated in Figure 3-3, but it has been reproduced in a more elaborate form, for ease of reference, as outlined in Figure 4-1. For this reason, the systems or subsystems have been merged, as opposed to the way they were separately presented in Chapter three.

The top of Figure 4-1 represents a subsystem of operating constraints. It shows that capacity constraints cause deferred maintenance and refurbishment while increasing the number of components operating at the high-load regime. Operations, maintenance and investment subsystem is enclosed in the dotted loop. It shows that improvement of asset condition increases revenue, which in turn increases CAPEX for investment. It also increases OPEX for the application of AM technologies. It further shows that as the application of AM technologies increases, it reduces the number of components that operate at the high-load-regime.

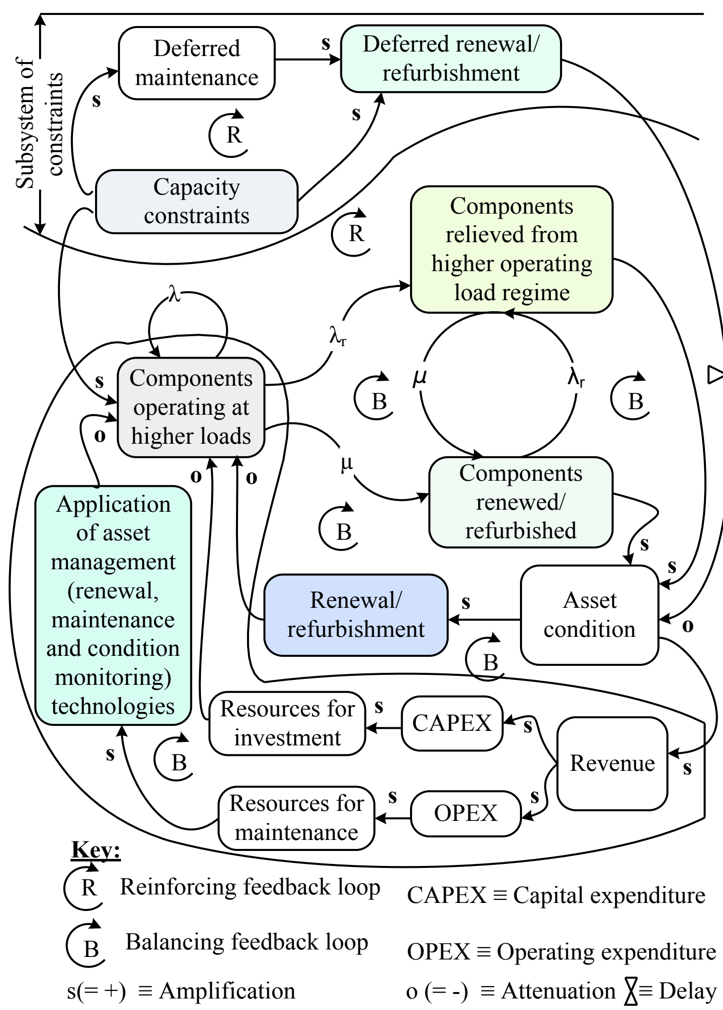
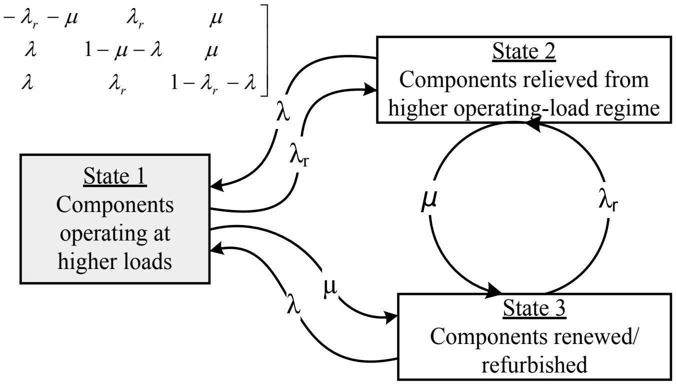


Figure 4-1: Power grid management system as a system of subsystems

The emphasis of Figure 4-1 is on the impact of capacity constraints on component overload and on the application of AM strategies to relieve the components from the overload. The middle of

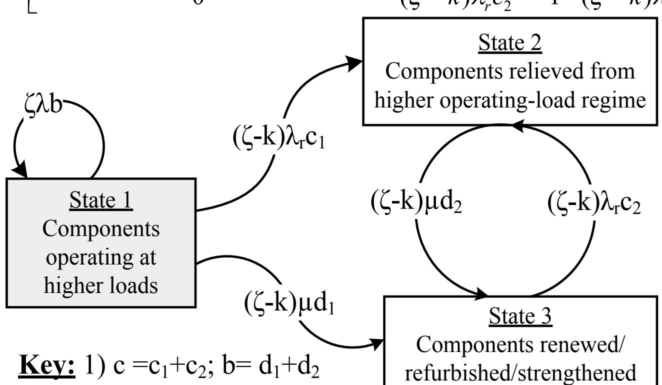
Figure 4-1 is a subsystem in state space transition (same as Figure 3-7) with transitional probabilities λ, λ_r and μ as shown in [97]. The term λ stands for the probability at which components are admitted and operated at a high-load regime; λ_r is the probability at which they are relieved from the high-load regime; and μ is the probability of renewal or refurbishment or major overhaul. It was shown that by representing the subsystem in that way, Markov concepts can be incorporated in the causal loop diagrams in order to model the impacts of maintenance and renewal strategies on the failure risk of physical assets [97]. It was further shown that the generalized Markov process can be modified by adapting system dynamics principles. As demonstrated in Figures 4-2 (a) and (b), the space transitions from the generalized and modified Markov processes have distinct contrasts. Transitional probability matrices *P1* [that is, from equation (3.6)] and *P2* [that is, from equation (3.7)] are obtained from Figure 4-2 (a) and Figure 4-2 (b), respectively. These matrices lead to Figure 4-3 and Figure 4-4, respectively [97].

$$P1 = \begin{bmatrix} 1-\lambda_r-\mu & \lambda_r & \mu \\ \lambda & 1-\mu-\lambda & \mu \\ \lambda & \lambda_r & 1-\lambda_r-\lambda \end{bmatrix}$$



(a) Generalised form and its state space matrix, P1

$$P2 = \begin{bmatrix} \zeta\lambda b - \left[(\zeta-k)\lambda_r c_1 + (\zeta-k)\mu d_1\right] & (\zeta-k)\lambda_r c_1 & (\zeta-k)\mu d_1 \\ 0 & 1-(\zeta-k)\mu d_2 & (\zeta-k)\mu d_2 \\ 0 & (\zeta-k)\lambda_r c_2 & 1-(\zeta-k)\lambda_r c_2 \end{bmatrix}$$



Key: 1) c = c_1+c_2; b= d_1+d_2
2) c and d refer to eq.(1)

(b) Modified form and its state space matrix, P2

Figure 4-2: State space diagram: (a) Generalized Markov (b) Modified form

Figure 4-3 outlines the transient probabilities from the generalized Markov model, where 1-State1, 1-State 2 and 1-State 3 represent the unavailability of State 1, State 2 and State 3, respectively. Figure 4-4 shows the effect of industrial system interactions, such as aging and number of components renewed or repaired, on transitional probabilities [97].

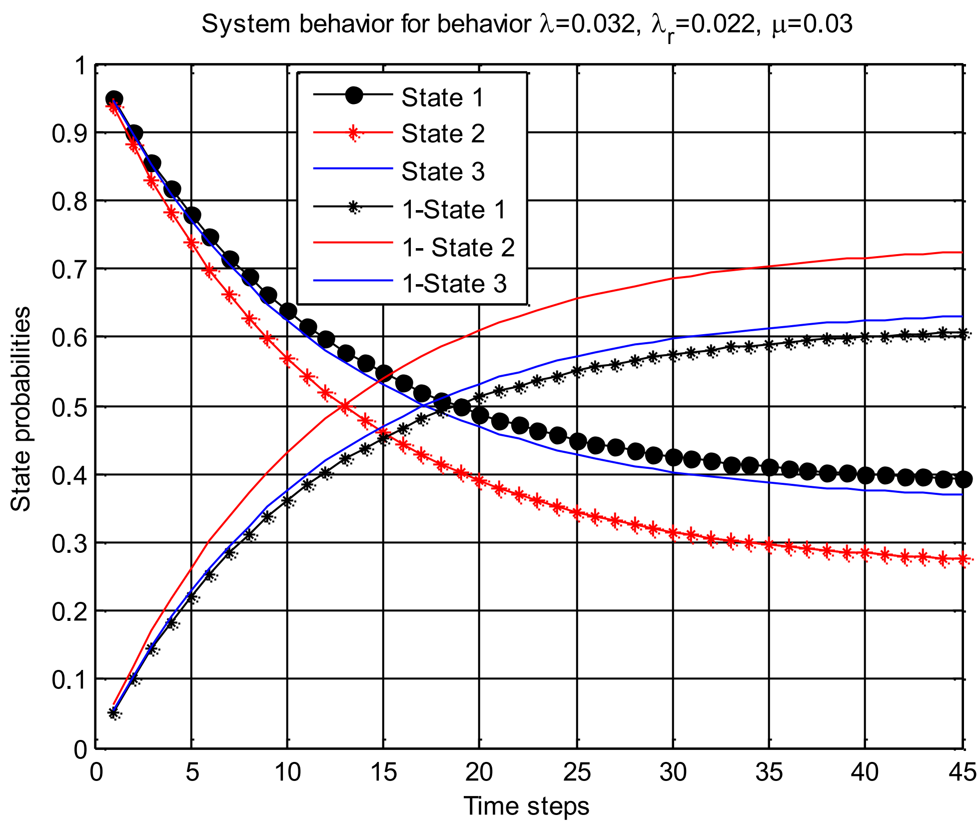


Figure 4-3: Generalized Markov transitional probabilities

In Figure 4-3, the states do not reduce to zero, but tend to reach some limiting values. In contrast, Figure 4-4 is able to show oscillations and attenuations caused by interaction of industrial system elements. For example, state 1 is attenuated to zero in seven time steps whereas other states decay to some steady state value within the same time steps. This effect is similar to what was shown in [29] and [93], but using algebraic equations instead of the matrices.

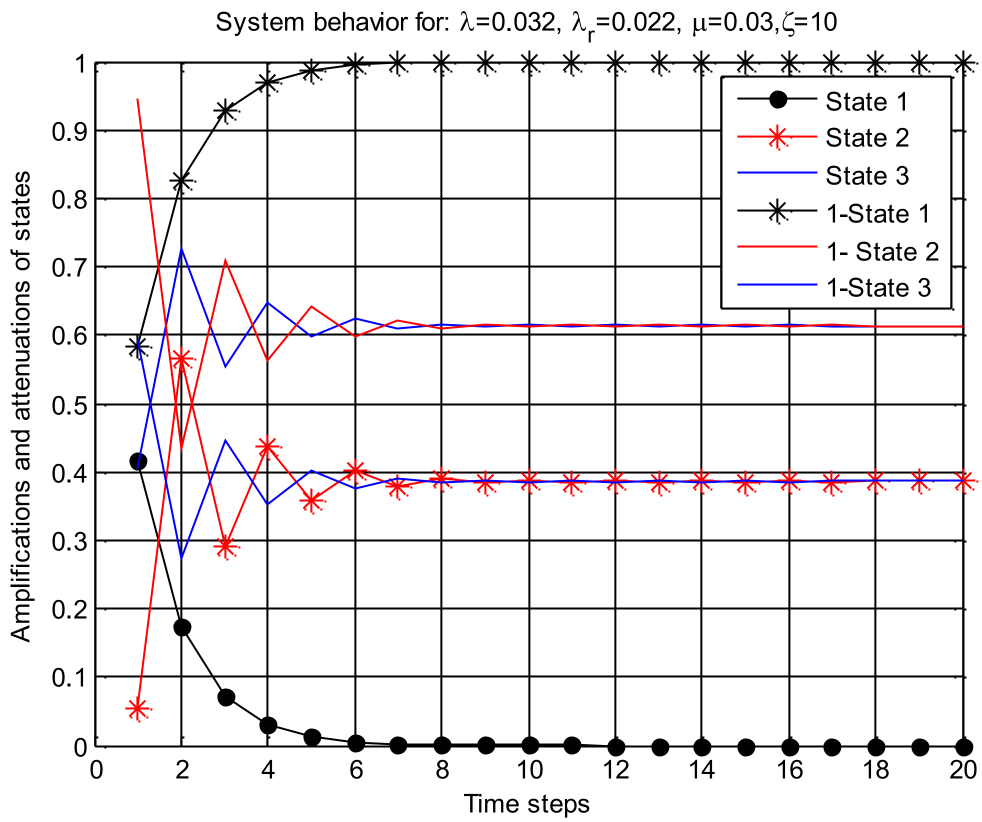


Figure 4-4: Modified transitional probabilities (dynamic system) showing oscillations

A component risk trending model can be expressed as follows [97]:

$$RF = \frac{\phi}{\gamma} + \frac{F(\zeta)}{\phi}\{\sigma + [\zeta\,\lambda\,\rho] - [(\zeta-1)\lambda_r\,\tau] - [(\zeta-1)\mu\omega]\}\,|1<\zeta<{}^{t}\!/_{n}, \phi>0 \tag{4.1}$$

where ϕ, γ, σ, ρ, τ and ω stand for critical number of components, total number of components, components operating at a high-load regime, components being admitted into the high-operating-load regime, components being removed from the high-operating-load regime, and components renewed, respectively. The term ζ is the asset age group, λ, λ_r and μ are the probability of being admitted into the high-load regime, the probability of being removed from the high-load regime and the probability of being refurbished, respectively; t is the technical life and n is the number of years from which ζ is determined (for more details, see Chapter three, Section 3.4.2.3). The term $F(\zeta)$ is failure risk or likelihood function, obtained by integrating the probability density function (PDF).

Asset managers are not only concerned with the risk trending, but also with the impact of the risk on cost [1]. In order to model the cost benefits of the risk trending, the term $F(\zeta)$ in equation (4.1) is replaced by a cost model derived from a two-parameter Weibull function. The advantages of the two-Weibull function were given in Chapter three. As stated in the Section 4.1, only preventive maintenance costs are considered for the purpose of illustrating the fundamental concepts that are applied in the model.

Section 4.2.2 gives an overview of the parameter estimation methods. The section also extends the MLE parameter estimation approach that was presented in Chapter three by including the MOM.

4.2.2 Parameter estimation methods

In Chapter three, it was stated that the most commonly used Weibull parameter estimation methods for equipment failure modelling are the least squares method (LSM) and the MLE. Furthermore, it was shown that when the number of failures is small and the data is censored, the MLE gives more accurate results than the LSM [35], [81], [99]. The MLE can be used to improve the estimates of the parameters obtained by the LSM. The MLE is viewed as a best theoretical solution for estimating parameters when uncertainties associated with observed or calculated data exhibit some type of a distribution. On the other hand, when these uncertainties are normally distributed or when the normal distribution is approximately correct, the MLE reduces to the LSM [82].

A Randomized Neighborhood Search (RNS) method was applied to evaluate severity of fire accidents in insurance companies and is claimed to give better results than the LSM and MLE, but the MLE came next to the RNS (i.e., in terms of accuracy) [100]. In one study, it was shown that by applying the Weibull distribution to failure data, the MOM gave accurate results for a greater number of times than the MLE and the LSM [101]. Generally, it has been shown that results from the MLE and MOM are usually so close to each other that they may be applied interchangeably [102]. From what is advanced, it is inferred that the MLE may be reliably used for parameter estimation, whereas the MOM may be applied to validate the results of the MLE [99]-[102].

In view of the foregoing background, this chapter applies the MLE to estimate the parameters and then compares the results with those obtained from the application of the MOM. Since the MLE was dealt with in Chapter three, the section that follows tackles the MLE only briefly, just to recap some concepts, but it illustrates the mathematical concepts that pertain to the MOM in greater depth.

4.2.2.1 The MLE

If x_1, …., x_n are random samples for a distribution, the likelihood function L is defined from the PDF as follows [84]:

$$L(x_1,...,x_n,\theta) = f(x_1,\theta)\cdot ...\cdot f(x_n,\theta) \tag{4.2}$$

where θ is the parameter to be estimated.

For the two parameter Weibull function, $\theta = \beta,\ \eta$. Therefore, from Chapter three, the likelihood function of the two-parameter Weibull PDF becomes:

$$L(x_1,...,x_n;\beta,\eta) = \prod_{i=1}^{n}\frac{\beta}{\eta}\left(\frac{x_i}{\eta}\right)^{\beta-1}.\exp\left[-\left(\frac{x_i}{\eta}\right)^{\beta}\right] \tag{4.3}$$

From equation (4.3), it can be shown that:

$$\eta = \left[\frac{1}{n}\sum_{i=1}^{n}x_i^{\beta}\right] \tag{4.4}$$

$$\beta = \left[\frac{\sum_{i=1}^{n}(x_i)^{\beta}\ln x_i}{\sum_{i=1}^{n}(x_i)^{\beta}} - \frac{1}{n}\sum_{i=1}^{n}\ln x_i\right]^{-1} \tag{4.5}$$

By applying iterative numerical methods like Newton-Raphson to equation (4.5), β can be obtained and by substituting its value in equation (4.4), η can also be determined. The Newton-Raphson is of the following form:

$$\beta_{i+1} = \beta_i - \frac{f(\beta_i)}{f'(\beta_i)} \tag{4.6}$$

where

$$f'(\beta_i) = \sum_{i=1}^{n}x_i^{\beta}(\ln x_i)^2 - \frac{1}{\beta^2}\sum_{i=1}^{n}x_i^{\beta}(\beta\ln x_i - 1) - \left[\frac{1}{n}\sum_{i=1}^{n}\ln x_i\right]\left[\sum_{i=1}^{n}x_i^{\beta}\ln x_i\right] \tag{4.7}$$

4.2.2.2 The MOM

The moment-generating function of the random variable X is given as an expected value as follows [84]:

$$M_X(t) = \mathrm{E}(e^{tX})\begin{cases}\sum_{\infty} e^{tx}f(x), & if\ x\ discrete\\ \int_{-\infty}^{\infty} e^{tx}f(x)\,dx, & if\ x\ continuous\end{cases} \tag{4.8}$$

If the expected value of a function $h(X) = X^r$ for r = 1, 2,… n, and assuming that the inside of the summation and the integral in equation (4.8) can be differentiated, then the rth moment can be given as follows:

$$\left.\frac{d^r M_X}{dt^r}\right| = \begin{cases}\sum_{\infty} x^r e^{tx}f(x), & if\ x\ discrete\\ \int_{-\infty}^{\infty} x^r e^{tx}f(x)dx\,, & if\ x\ continuous\end{cases} \tag{4.9a}$$

$$\therefore \left.\frac{d^r M_X}{dt^r}\right|_{t=0} = \begin{cases} \sum_{\infty} x^r f(x) \\ \int_{-\infty}^{\infty} x^r f(x) dx \end{cases} \tag{4.9b}$$

$$\therefore \left.\frac{d^r M_X}{dt^r}\right|_{t=0} = E(X^r) = \mu_r' \tag{4.9c}$$

where t is the real variable, μ_r' is an expected value or the rth moment about the origin of the random variable X.

From equation (4.9), moments for a given PDF can be generated. For the Weibull PDF, μ_r' can thus be obtained by letting $f(x)$ be $f(x;\theta)$ as in equation (4.2). Thus:

$$f(x;\beta,\eta) = \left(\frac{\beta}{\eta}\right)\left(\frac{x}{\eta}\right)^{\beta-1} e^{-\left(\frac{x}{\eta}\right)^{\beta}} \quad , \quad x > 0 \tag{4.10}$$

Applying equation (4.10) according to equations (4.9 b and c) yields the following:

$$E\left(X^r\right) = \int_0^{\infty} x^r \beta \left(\frac{1}{\eta}\right)^{\beta} x^{\beta-1}\, e^{-\left(\frac{x}{\eta}\right)^{\beta}} dx \tag{4.11}$$

By letting $\left(\frac{x}{\eta}\right)^{\beta} = v$ it results in the following [103]:

$$E\left(X^r\right) = \int_0^{\infty} \left(\frac{1}{\left(\frac{1}{\eta} \right)} v^{\frac{1}{\beta}} \right)^r e^{-v} dv \tag{4.12}$$

$$E\left(X^r\right) = \eta^r \int_0^{\infty} v^{\left(1+\frac{r}{\beta}\right)-1} e^{-v} dv = \eta^r \Gamma(r) \tag{4.13}$$

$$= \eta^r \Gamma\left(1 + \frac{r}{\beta}\right) \tag{4.14}$$

The first and second moments can be derived in a similar fashion, respectively, as follows [77], [101]-[103]:

$$\mu_1' = \left(\frac{1}{\eta}\right)^{\frac{1}{\beta}} \Gamma\left(1 + \frac{1}{\beta}\right) \tag{4.15}$$

$$\mu_2' = \left(\frac{1}{\eta}\right)^{\frac{2}{\beta}} \left\{ \Gamma\left(1 + \frac{2}{\beta}\right) - \left[\Gamma\left(1 + \frac{1}{\beta}\right)\right]^2 \right\} \tag{4.16}$$

The parameter estimates can be derived from the coefficient of variation, CV as follows:

$$cv = \sqrt{\left(\mu_2'\right) \Big/ (\mu_1')^2} = \frac{\left[\Gamma\left(1+\dfrac{2}{\beta}\right) - \Gamma^2\left(1+\dfrac{1}{\beta}\right)\right]^{1/2}}{\Gamma^2\left(1+\dfrac{1}{\beta}\right)} \tag{4.17}$$

Statistical software or tabulation methods can be applied to equation (4.17) in order to compute the estimate of β (i.e. $\hat{\beta}$), which in turn can be used to compute the estimate of η (i.e., $\hat{\eta}$) from the following:

$$\hat{\eta} = \left[\frac{\bar{x}}{\Gamma(1/\hat{\beta}+1)}\right]^{\hat{\beta}} \tag{4.18}$$

where $\bar{x}$ is the mean of the data.

4.3 Cost models

This section evaluates the merits of various cost models in order to establish the reason for the selection of the model that is superimposed on the risk trending model that was developed in [97].

The Weibull function is generally used to treat failure time related to aging of transformer insulating materials under combined electrical, mechanical and thermal stresses [60]. It is also applied for processing failure times of most industrial equipment, whereby the likelihoods of survival and failure are the core parameters used in modelling equipment risks and costs [35], [81].

This chapter has considered two common approaches that are used in modelling costs, based on the convenience with which the estimated Weibull parameters can be applied. The first one is based on renewal theory, whereby the maintenance cost rate is determined according to [59]. The second one expresses planned preventive and unplanned maintenance costs as functions of the survival and failure likelihoods [35], [81].

The maintenance cost rate C (τ), based on the renewal theory, can be expressed as follows [59]:

$$C(\tau) = c_r N_r(\tau) + c_c N_c(\tau) + c_p \tag{4.19}$$

where c_r, c_c and c_p are imperfect, corrective and preventive cost rates, respectively; τ is the interval time; N_r and N_c are number of components under repair and corrective maintenance, respectively.

In implementing equation (4.19), the failure likelihood function *P (L)* is employed. It is derived from the Inverse Power Law and the Arrhenius model given as follows [59]:

$$P(L) = 1 - \exp\left[-\left(\frac{E}{E_o}\right)^{\alpha(n-bT)}\left(\frac{M}{M_o}\right)^{m\alpha}\left(\frac{L}{L_o}\right)^{\alpha}\right]e^{\alpha BT}; T = \frac{\theta-\theta_o}{\theta_o\theta} \tag{4.20}$$

where E, M, T are the electrical, mechanical, and thermal stresses, respectively; L is lifetime; E_o and M_o are the scale parameters for the lower limit of electrical and mechanical stresses, respectively;

and L_o is the corresponding lifetime; α, n, m and B are the shape parameter, the voltage endurance coefficient, the mechanical stress-endurance coefficient, and the activation energy of thermal degradation reaction, respectively. Finally, b is the correction coefficient that takes into account the reaction of materials due to combined stress application; and θ and θ_o are absolute and reference temperatures, respectively.

The total cost per year can be obtained by expressing planned preventive and unplanned maintenance costs as functions of the survival and failure likelihoods as follows [35], [104]:

$$C_y = \frac{Y_{NS}.\$_p}{m} + \frac{Y_{NS}.\$_u}{m}\left\{1 - \exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right]\right\} \tag{4.21}$$

where Y_{NS} is the number of maintenance hours in a year, m is the preventive maintenance interval; $\$_p$ and $\$_u$ are planned and unplanned preventive maintenance cost rates, respectively; t is the lifetime (time to failure); η and β are as defined earlier on.

The first term in equation (4.21) represents scheduled preventive maintenance costs when maintenance is conducted at m hourly intervals. The second term stands for unplanned costs. The model assumes that preventive replacement or maintenance is constant regardless of the number of components surviving at a given time.

The preventive maintenance cost per unit time can also be presented as follows [81]:

$$C_T = \frac{£_u.\left(1 - e^{-\frac{t}{\eta}}\right) + £_p.R(t)}{\int_0^T R(t)dt} \tag{4.22}$$

where, $£_u$ is cost of unscheduled maintenance due to downtime, and the term in the parenthesis represents failure likelihood; $£_p$ is the cost of planned maintenance, whereas $R(t)$ is the survival likelihood (reliability function).

4.4 Evaluation of cost models

Equation (4.19) is an excellent model for evaluating imperfect, corrective and preventive maintenance costs. However, its application requires a lot of failure statistics which may not be readily available [50], [59]. As stated earlier on, one of the objectives of this study is to develop a model that utilizes small sample sizes so as to overcome data unavailability problems, as alluded to in [2]. In addition, the focus of the study is on preventive maintenance. Henceforth, for modelling only preventive maintenance with small sample sizes, equations (4.21) and (4.22) are ideal and suffice. Equation (4.21) assumes that the number of preventive maintenance activities are limited to a year, whereas equation (4.22) is flexible to the lifetime of equipment. Due to its flexibility, equation (4.22) is preferred to equation (4.21) and it is adopted for further analysis. However, modifications are implemented by removing the denominator so that it reflects the total cost of the items in a given sample, and by adding β to the exponent to adapt it to the application of the Weibull distribution. The modified form of equation (4.22) is given as

$$C_T = £_u \cdot \left\{ 1 - e^{\left(-\frac{t}{\eta}\right)^{\beta}} \right\} + £_p \cdot R(t) \tag{4.23}$$

Equation (4.23) is used to compute costs related to preventive maintenance regimes as a function of instantaneous failure and survival probabilities.

Section 4.5 outlines a generalized risk and cost trending model, whereas Section 4.6 presents the data that is used for the sensitivity analysis needed to generate the results that are presented in Section 4.7. Finally, Section 4.8 presents the conclusions.

4.5 Risk and cost trending

This section provides a generalized form of cost and risk trending model which is a modification of equation (4.1), whereby the function *F (ζ)* is replaced by Ω_T . Therefore, equation (4.1) becomes:

$$RF = \frac{\phi}{\gamma} + \frac{\Omega_T}{\phi} \{\sigma + [\zeta \lambda \rho] - [(\zeta - 1)\lambda_r \tau] - [(\zeta - 1)\mu \omega]\} \, |1 < \zeta < t/n, \phi > 0 \tag{4.24}$$

When trending the risk, the generalized form of the failure likelihood, *F (t)* = ψ_T (t) and the hazard rate, *h (t)* for the Weibull distribution are, respectively, as follows [98]:

$$\psi_T(t) = \int_0^t f(t)\,dt = 1 - \exp\left[-\left(\frac{t}{\eta}\right)^{\beta} \right] \tag{4.25}$$

$$h(t) = \frac{f(t)}{R(t)} = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \tag{4.26}$$

where *f(t)* is the PDF, *h(t)* represents the conditional probability that equipment will fail in a given time interval, given that it survived up to that time interval.

The term Ω_T in equation (4.24) can be used to represent both the cost function, that is, equation (4.23) and the failure likelihood, that is, equation (4.25). This is achieved by substituting equations (4.23) and (4.25) into equation (4.24) one at a time, provided that β and η are known. The value of *n* in equation (4.24) was set to five as advanced in [97].

4.6 Primary failure and cost data

This section presents primary data for times to failure and costs for power transmission (12 MVA) transformers. The times to failure are used to compute the Weibull parameters, which in turn are fitted in the expressions for risk and cost models.

Table 4-1 is extracted from Table 3-2. It outlines times to failure of the 12 MVA transformers. Table 4-2 lists average costs of preventive and unplanned maintenance. The source of all the transformer data is Appendix B.

Table 4-1: Times to failure for 12 MVA transformers (10^5 hrs.)

1.892	4.188	3.925	1.971
2.182	1.971	4.366	2.365
2.418	4.03	2.31	3.715

Table 4-2: Annual maintenance costs for 12 MVA transformers (US$)

Planned preventive cost ($£_p$)	Unplanned (downtime) cost ($£_u$)
17,466.7	30,000

Section 4.7 presents and discusses the results, whereas Section 4.8 provides the conclusion.

4.7 Results and discussion

This section presents and compares the Weibull parameters that were computed using the MLE and MOM. It further analyses and discusses cost benefits of risk trending. The computed parameters are used to evaluate reliability functions. They are also fitted in the likelihood functions in the risk and cost models in order to plot the risk profiles. The cost benefits are derived from the difference between risks at business as usual and risks with AM renewal interventions at mid-life and/or end-life.

4.7.1 Comparison of parameter estimates

The shape (β) and scale (η) parameters were computed from times to failure that were presented in Table 4-1 by coding formulae for the MOM, that is, equations (4.4) and (4.5); and the MLE, that is, equation (4.17) in R-Statistical software. Results from the two methods are compared as shown in Table 4-3. Standard errors (se) for the computed parameters are also indicated.

Table 4-3: Parameter estimates with comparison using standard error (se)

Parameter	MLE	MOM
β	3.434	3.4988
	(se: 0.7888)	(se: 0.6697)
η [x10^5 hrs]	3.2897	3.2786
	(se: 0.293)	(se: 0.3025)

Kolmogorov-Smirnov (K-S) test was used to check if the data really came from the purported Weibull distribution based on the p-value. The acceptance of the hypothesis was based on $p > 0.05$. The p-value was 0.2185, supporting that the results indeed came from the Weibull distribution with the specified parameters.

4.7.2 Probability plots and sensitivity analysis

This section presents results of probability plots and sensitivity analysis, that is, sensitivity of the risk factor with respect to operations and maintenance (O & M) costs. The MLE parameters from Table 4-3 were applied to compute and plot the PDF, CDF, hazard rate and risk-cost trends. The computed parameters were fitted in the term Ω_T in equation (4.24) in order to plot the cost and risk trends.

Plots of the PDF and CDF are presented in Figure 4-5, whereas the hazard rates (risks of failure) are shown in Figure 4-6. Figure 4-5 shows that the PDF and CDF are slightly skewed to the right with the point of inflection for the CDF occurring at 33.7 years of age. The hazard rate corresponding to that age (point of inflexion) is 0.07. The PDF is zero when the CDF is equal to unity; signifying the end of technical life (lifespan), with probability = 1 at 67 years of age. Thus by determining the CDF and PDF from parameter estimates, analysts can predict the life span of assets such as transformers.

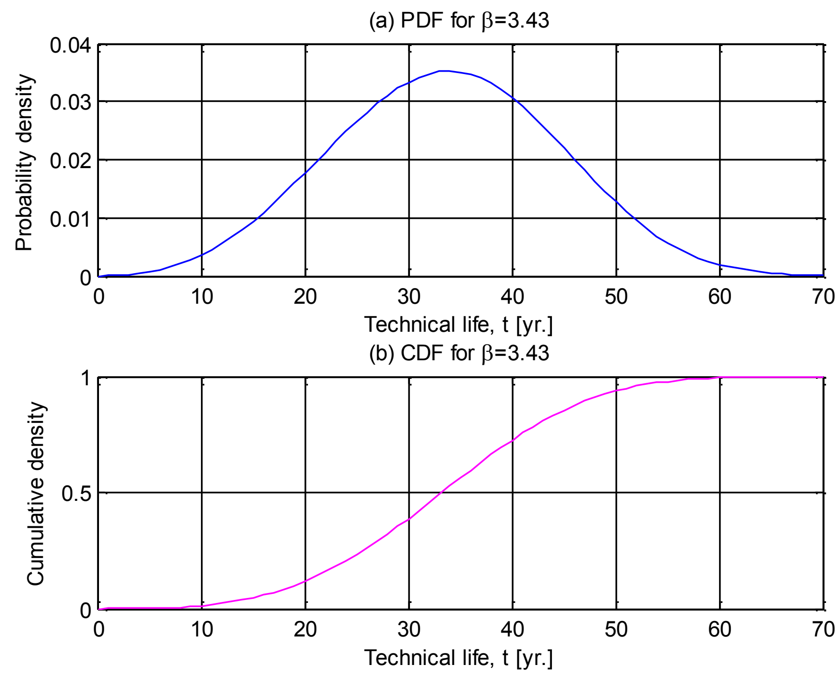


Figure: 4-5. Plots of (a) PDF and (b) CDF

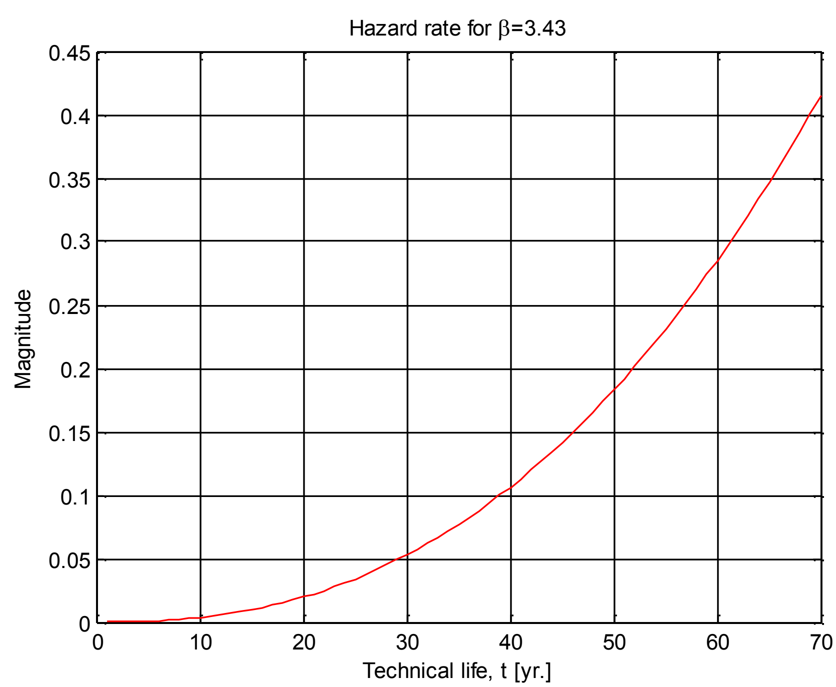


Figure: 4-6. Hazard rate characteristics

In another study on the degradation of the degree of polymerization (DP) of transmission transformer insulation paper, a life span of 70-80 years was projected [72]. These transformers were definitely under different operating conditions to the ones being studied in the current research, but their results portray the average life expectancy of the transformers in most electric grids.

Trends of planned and unplanned maintenance costs are displayed in Figure 4-7, showing the intersection of the two curves at point A. The data that was used for the computation of the costs came from Table 4-2 (Appendix B, Table B3 is the source of the data).

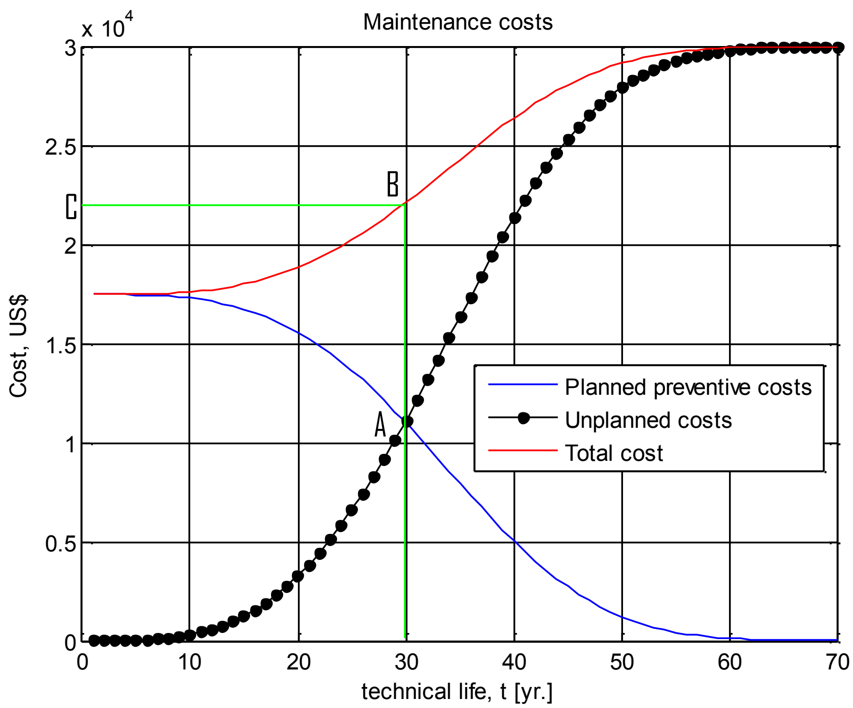


Figure 4-7: Maintenance cost profiles

Figure 4-7 demonstrates how maintenance costs vary with time. The planned costs are equal to unplanned costs at 29.9 years of age; shown as point A. Point B on the total cost curve that is overlaid on the figure is the total cost for point A. After point A, unplanned costs exceed the planned costs because the number failing due to the aging of items is higher than that of surviving items.

The point A in Figure 4-7 is very significant in the timing of refurbishment and major maintenance strategies. It points to the fact that the refurbishment strategies should be implemented just before point A, that is, before the breakdown maintenance costs exceed the planned maintenance costs. The timing represents 44.6% of the lifespan or just before mid-life-span. This is a simplified and innovative way of forecasting asset replacement and refurbishment timing and could be a valuable tool for power utility AM planning. The actual refurbishment could be planned to commence earlier, say at 40% of the lifespan.

Cumulative maintenance costs are presented in Figure 4-8. The two cost-curves intersect at 52.4 years of age (point B). At that time, decisions regarding end-of-life strategies like refurbishment and disposal should have been made so that breakdown costs are reduced (i.e., before they exceed the costs of preventive maintenance).

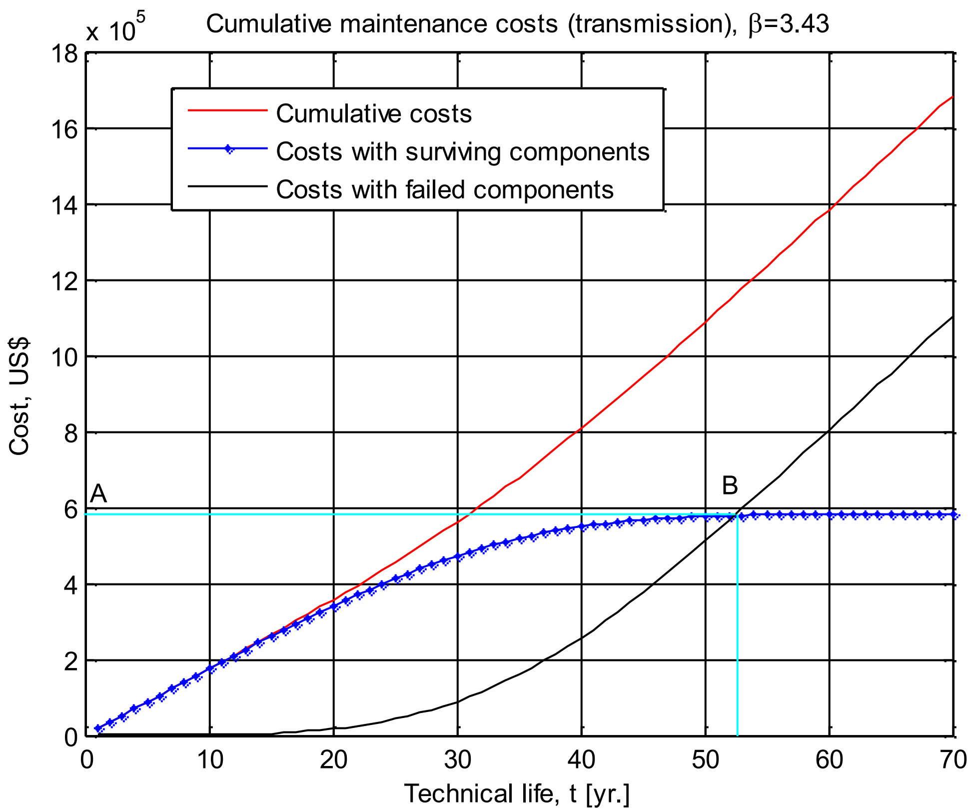


Figure 4-8: Cumulative maintenance costs over the lifetime

The rest of this section shows how the model, that is, equation (4.24), was applied in trending the risk and costs for the following three scenarios: risk with business as usual (unmitigated risk), risk with mid-life refurbishment/renewal, and risk with end-life refurbishment. The values used in the analysis were as follows: $\phi = 3$, $\gamma = 20$, $\sigma = 6$, $\lambda = \lambda_r = 0.02$, and $\mu = 0.03$. Then, the sensitivity of the risk factor to changes in ρ, τ and ω were analyzed.

Risk trends for the three scenarios are presented in Figures 4-9 and 4-10, with plots of risk reductions due to the application of the strategies provided beneath them. It is worth noting that the abscissa of the plot of risk trends is given in age group ζ as explained in Chapters three and four [97]. The reason for this is that the key lifecycle decisions and actions in AM are not done yearly, but, on average, in five-year strategic time frames [94], [97].

Figure 4-9 shows the plots of risk trends (on top) and magnitudes of risk reductions (beneath) for a case where major end-life renewal efforts are implemented.

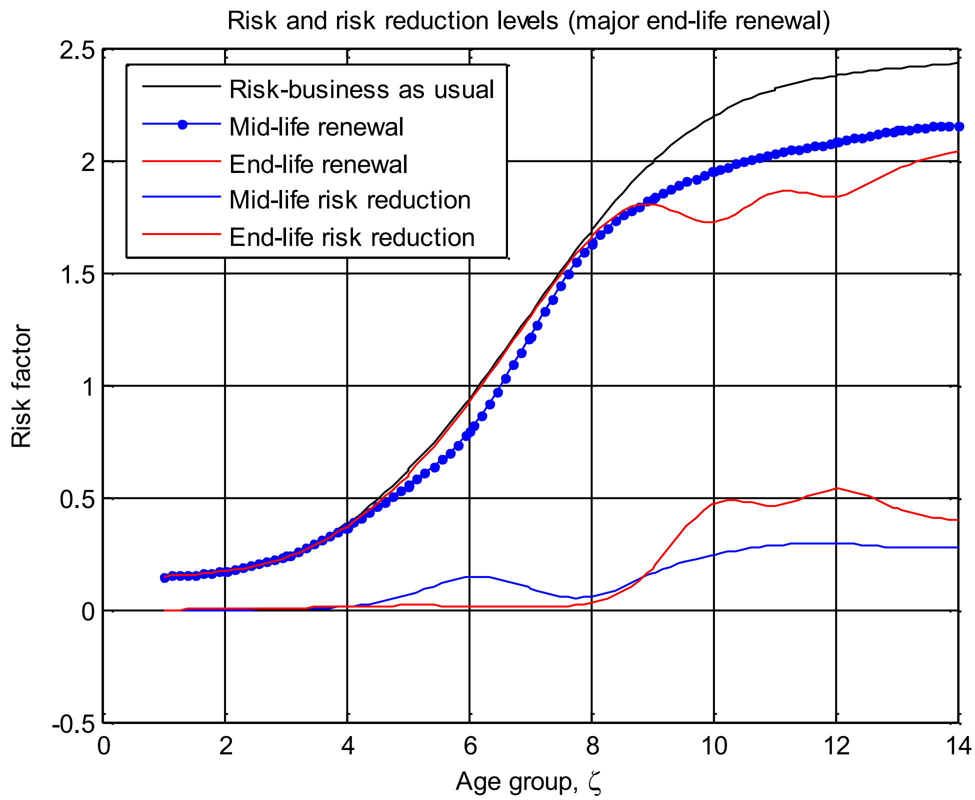


Figure 4-9: Risk profiles and reductions (for end-life strategies)

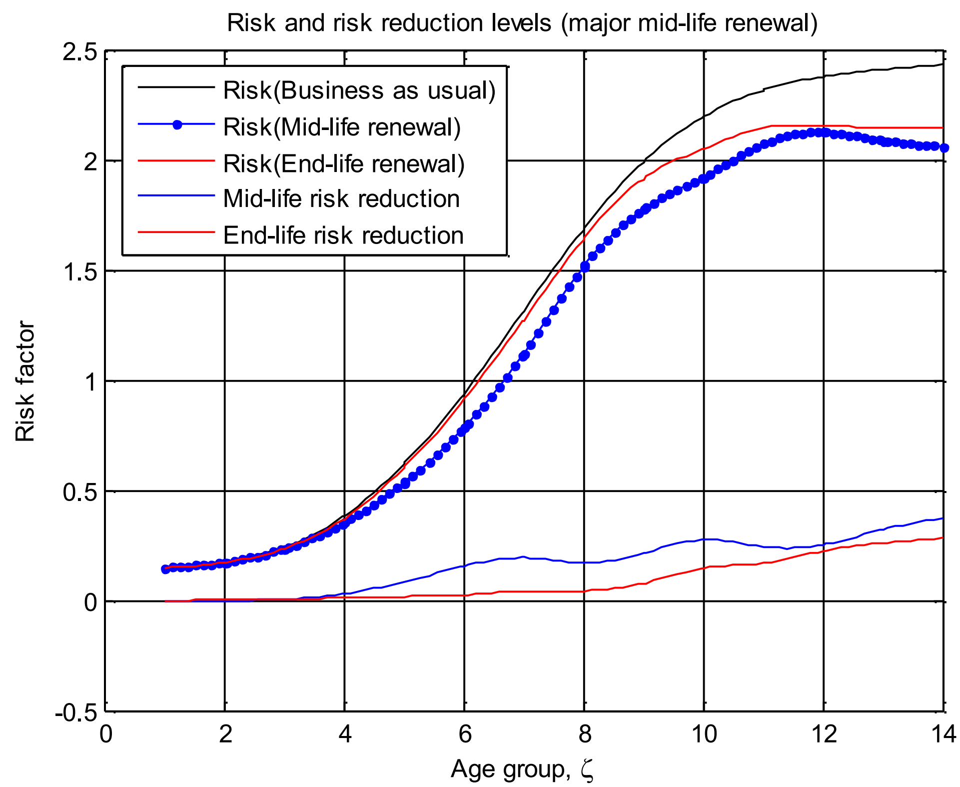


Figure 4-10: Risk profiles and reductions (for mid-life strategies)

Figure 4-10 indicates plots similar to those in Figure 4-9, but for a scenario where major mid-life renewal efforts are applied. The risk reductions are of prime importance as they measure the magnitudes of risk mitigation required by asset managers in order to invoke AM decisions.

Figure 4-11 shows the risk reductions that were presented beneath Figures 4-9 and 4-10 as well as their cumulative values. Later on (in Figures 4-12 and 4-13), these risk reductions are expressed in terms of cost benefits of risk mitigation (attenuations). This is achieved by superimposing the cost model, that is, equation (4.23) onto the risk trending model, that is, equation (4.24) as demonstrated in Figures 4-12 and 4-13. This is of great significance to the asset manager as it quantifies the impact of the risk-profiling (trending) in monetary terms, which is more meaningful than using the risk factors only.

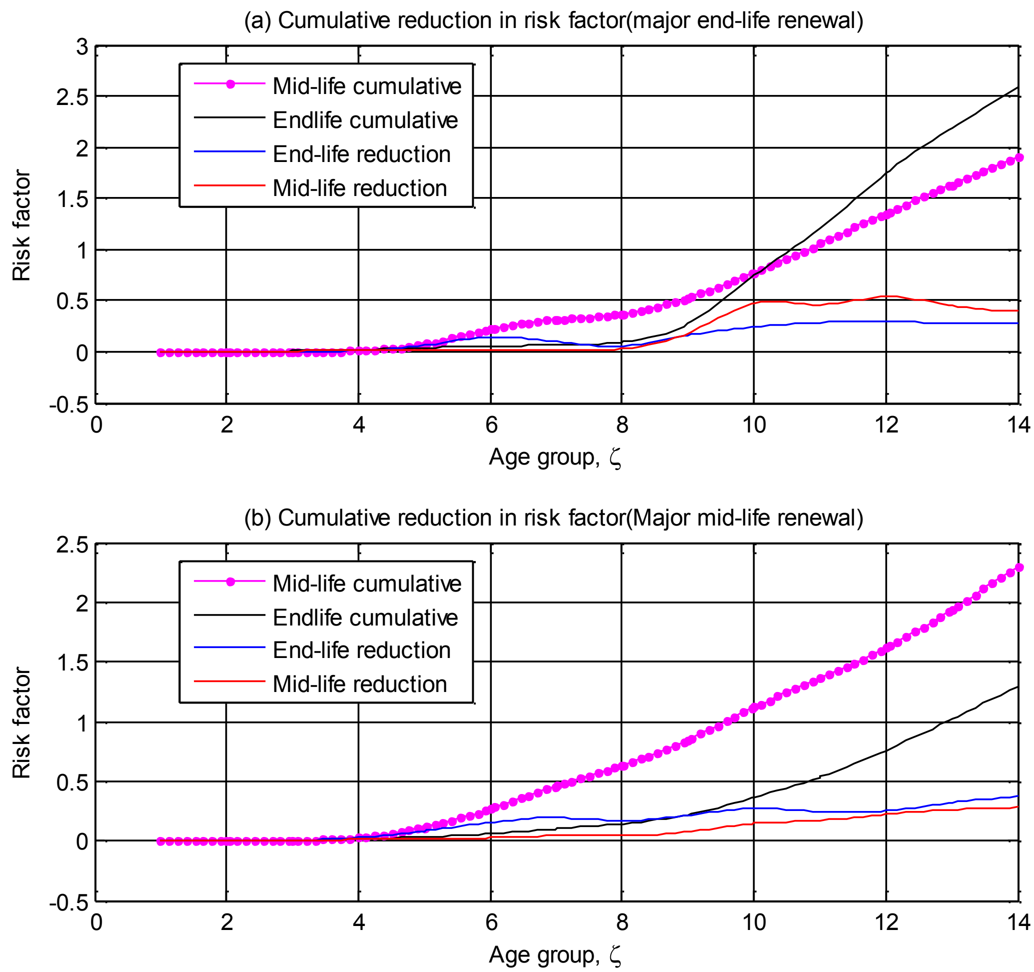


Figure 4-11: Risk reduction and cumulative values (a) end-life (b) mid-life

Figures 4-12 and 4-13 outline trends of risk as well as the cost benefits associated with the various AM strategies. Figure 4-12 shows the cost benefits accrued when the major end-life renewal strategy is carried out, whereas Figure 4-13 indicates the cost benefits associated with the major mid-life renewal.

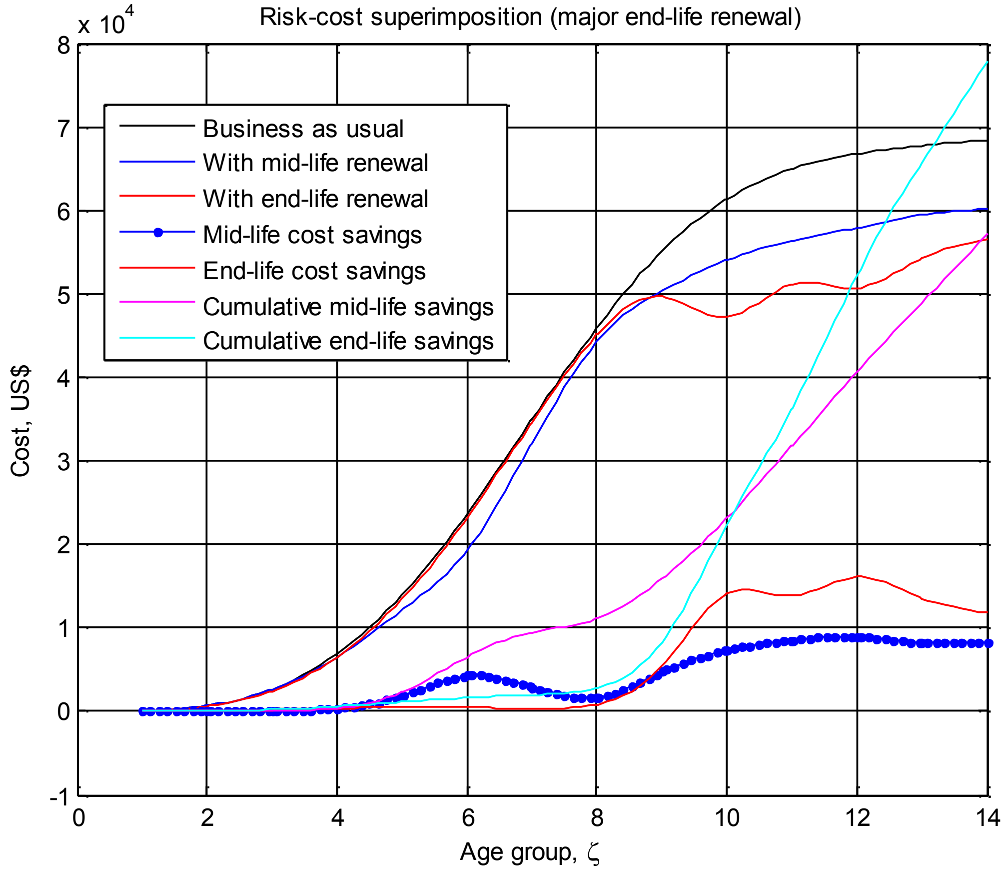


Figure 4-12: Risk-cost trends (major end-life renewal strategies)

Figure 4-12 shows that end-life renewal strategies yield substantial cost benefits (savings), but the benefits are accrued late in the lifecycle. In contrast, Figure 4-13 portrays that mid-life renewal strategies accrue cost benefits early enough to be re-invested in the business. From an AM point of view, the mid-life renewal case is the best option. The model is vital for a risk-based power distribution AM as it expresses the risk profile in terms of savings in O & M costs. Since the financial benefits of refurbishment are hard to show, the findings from this study can be used to emphasize the importance of refurbishment strategies. The study shows that although refurbishment does not necessarily add capacity that is required for generating more revenue, it is a means of achieving tangible financial benefits in the form of O & M savings.

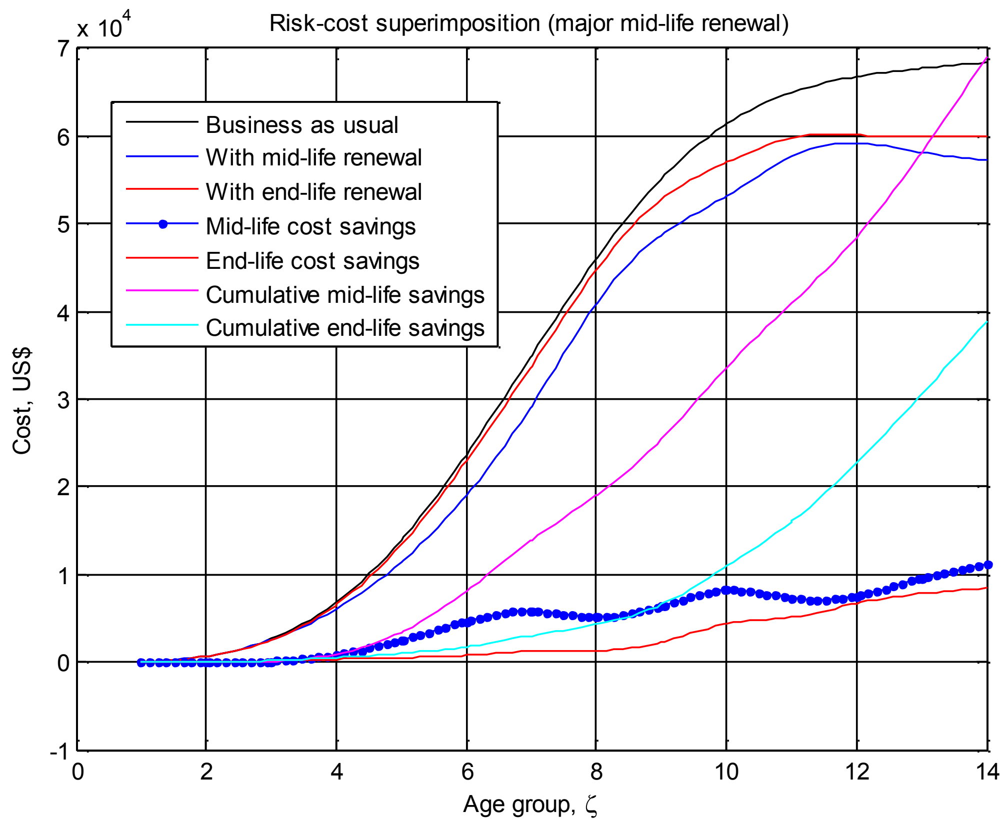


Figure 4-13: Risk-cost trends (major mid-life renewal strategies)

In this chapter, systems thinking (theory) (extended from Chapter three) was used in determining cause and effect relationships in a complex power utility AM system. Causal links that are difficult to detect by statistical or analytical techniques were determined by systems thinking. That augmented the capability of statistical inferences. It validated the notion that statistics may show correlations, but not necessarily causality [35]. Furthermore, equipment failure data was applied to compute the Weibull parameters using the MLE and MOM. Then, the parameters were employed in reliability analysis and in risk-cost trending. That was done in order to evaluate the cost benefits of component risk trending.

Therefore, the risk trending model was successfully applied to evaluate the cost benefits of the risk trending process. This is of great significance as the quantitative capability of the model can help physical asset managers in exploring, treating, monitoring and reviewing risks associated with their physical assets over the entire lifespan. The ability to show the quantitative benefits of refurbishment (renewal) can change the managers' perception of refurbishment projects, so that the projects are seen as adding economic value in terms of the O & M cost-savings. In order to augment the model, asset managers may conduct a comparative NPV analysis for the three strategic options, namely: business as usual, mid-life renewal and end-life renewal as advanced by [64].

The multi-criteria risk evaluation approach presented in this chapter has only considered preventive and breakdown maintenance costs in the cost benefit analysis. Future research should explore ways of adopting other types of costs. The model developed could assist asset managers in the assessment of their physical assets during the lifecycle. Section 4.8 provides a summary of the overall model formulation process.

4.8 Overview of the Model Propounded

This section presents an overview of the model that has been developed and discussed in this chapter. This is schematically outlined in Figure 4-14. Legal and stakeholder objectives as well as the firm's vision, mission, objectives, and strategy for the asset portfolio form the main reference point (input) at the start of the risk management process.

This chapter has demonstrated how the systems thinking and parametric-probability-distribution concepts can be integrated to model cost benefits of component risk trending. The cost benefits were expressed in terms of savings in O & M costs. This was implemented by superimposing cost models on a risk trending model in order to convert the risk trends into cost trends. In both the risk and cost trending processes, a two-parameter Weibull distribution was employed to take advantage of its core advantages, which include versatility (the ability to model a variety of other distributions) and the ability to model with a few data sets, taking cognizance of the fact that the data unavailability is one of the key challenges in the power utility AM.

Just as in most existing models for evaluating the risk level, such as the risk-matrix methods, the model presented is aimed at forecasting the risk level by trending the failure risk profile rather than optimizing the strategies. However, in the strategy mix during the implementation of asset management processes, asset managers may employ methods for optimizing specific maintenance and inspection undertakings, such as the MDP and SMDP models that were highlighted in Chapter two. They may also assimilate the traditional risk-matrix techniques, on a yearly basis, as part of their tactical and operational measures to mitigate the risk for specific asset operating periods (years or lifecycle phases) under consideration.

Any type of risk impact category; whether financial, environmental or technical, is as a result of component or system failure. Hence, monitoring and evaluating the trend of the failure risk in this chapter is envisaged to be the best way of getting a holistic perception of the risk profile of assets in industry, as the consequences of the failure risk can affect all the impact categories.

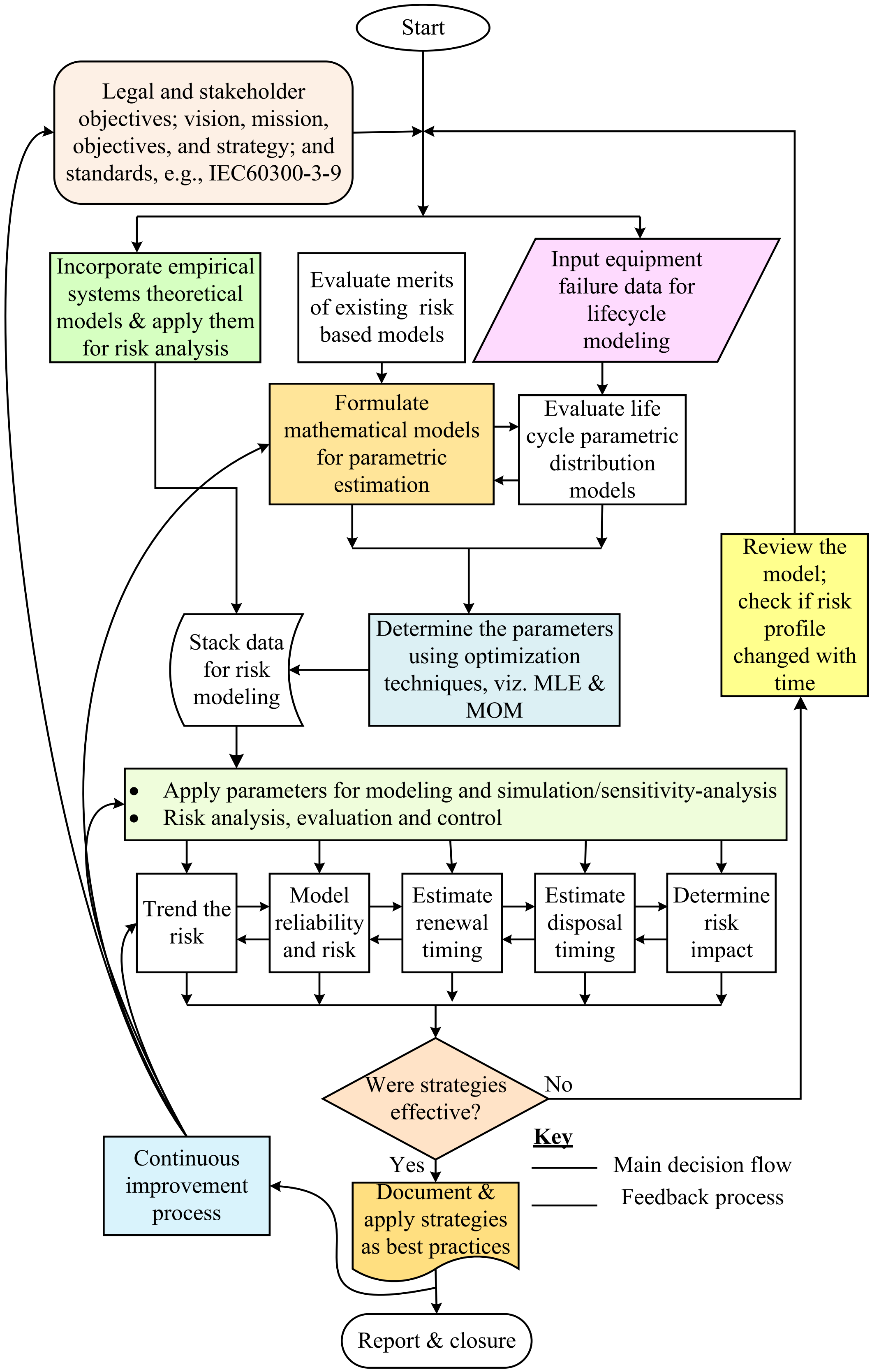


Fig. 4-14. The proposed multi-criteria risk analysis model

Accurate estimation of the parameters is central to the correct application of the model that has been advanced. This was achieved by using parameter optimization techniques, namely: the MLE and MOM, as shown in the middle of Figure 4-14. Since the case study data employed for the modelling process was assumed to be singly censored, the analytical approach used was chosen to suit that type of data. For non-singly censored data, reference can be made to other sources, such as that presented in [77]. Once the parameters have been computed, empirical equations (relationships) can be used to simulate or model the component life cycle characteristics.

The MLE and MOM provide accurate parameter estimates even where small sample sizes are involved or when data is truncated (censored). However, it was noted that the MLE and MOM yield almost the same and equally accurate parameter estimates when the magnitude of the time to failure is large. However, when the time to failure values are small (regardless of the sample size), the MLE yields more accurate results than the MOM (see, for example, Table 4-3; and the comparison presented in Table 6-3).

Results from reliability plots, preventive and downtime maintenance costs, and risk-cost-trending models were capable of projecting that the best refurbishment timing was just before 46.6% of the asset life. Allowing for delays in logistics associated with the renewal, the refurbishment works could commence, say, at 40% of the asset life.

The bottom of Figure 4-14 shows that if the metrics (risk factors and lifecycle-modelling parameters), derived by the proposed methodology, indicate that the measures effectively reduced the risk, or seem to project that certain types of strategies will have reduced the risk level, then they should be documented as the best practices. Thereafter, a continuous improvement process should be carried out. Otherwise, a review should be carried out to improve the model design and configuration. The review could also be used to check if the risk profile changed with time.

4.9 Chapter conclusions

This chapter has shown how systems thinking typologies (causal relationships) and system dynamics concepts can be applied to determine root causes of capacity constraints and component overloading. It has further demonstrated how the problems identified can be solved using analytical, statistical and stochastic inferences. These inferences have the ability to show correlations, but they falter in showing causation, where systems thinking is strong. Systems typologies helped in presenting a power grid asset management system as a system-of-systems or subsystems with capacity constraints leading to components operating at higher loads than others. The chapter revealed how causal relationships can be exploited to formulate the problem as a

Markov process, where transitional probabilities are used in modifying the risk trends. Cost models were superimposed on a risk trending model in order to convert the risk trends into cost trends for the cost benefit analysis to be effected. Accurate estimation of the Weibull parameters is central to the correct application of the model that has been advanced. Once the parameters have been computed, the component life cycle characteristics can be simulated or modelled. Time to failure data was applied to estimate the Weibull parameters using the MLE and MOM. The MLE and MOM provide accurate parameter estimates even where small sample sizes are involved or when data is truncated (censored). In terms of statistical inference, the methods were viewed as equally accurate, but results of the MLE were adopted for consistency with what was presented in Chapter three (since Chapter four is an extension of Chapter three). On the other hand, the MLE provided better results for the scale parameter, η that is crucial for modelling the spread of the PDF plots. Results from reliability plots, preventive and downtime maintenance costs, and risk-cost-trending models were capable of projecting that the best refurbishment timing was just before 46.6% of the asset life. The results also quantified the cost benefits of risk reductions associated with the application of AM strategies. The cost benefit analysis can help asset managers in the following decision making processes: exploring cause, consequence and impact of risk; and monitoring and reviewing risk profiles, in time series. The capability to model with small sample sizes makes the model useful in cases of data scarcity or unavailability.

The application of the risk trending models presented in Chapters three and four does not mean that the existing risk assessment methods (for example, the RCM) should be side-lined. It is worth noting that the RCM is a dominant emerging risk assessment philosophy in the power sector and in the physical AM in general. Therefore, Chapter five takes cognizance of that fact and it uses the literature review to examine the strengths and weaknesses of the RCM and develops models to improve some aspects of the RCM.

CHAPTER FIVE

TRANSFORMER RISK MODELLING BY STOCHASTIC AUGMENTATION OF RELIABILITY-CENTERED MAINTENANCE

5.1 Introduction

This chapter reviews the literature and then applies power transformer case studies to develop a risk assessment model that augments the probabilistic capabilities of the Reliability-centered maintenance (RCM). Many electric power utilities install RCM programs to establish maintenance requirements [10], [105]. Much data and long (vast) experience is needed to successfully conduct the RCM [90]. Despite being around for a long time, its application in the power sector is still at an infancy stage [68].

Significant changes in business environment make electric power utility decision making and risk management, especially the need for improved risk characterization, increasingly challenging [64]. Every stage of the physical AM process should incorporate and build on the best attributes of the RCM for the process to succeed [25], [26].

Section 5.2 provides a critical examination of the RCM and challenges faced during its implementation with respect to risk characterization, data requirements and reliability modelling. Then, Section 3 outlines the methodology. Thereafter, Section 4 presents and discusses the results. Finally, Section 5 provides the conclusions.

5.2 Critical review of the RCM

5.2.1 Merits, demerits and opportunities

The RCM, initially applied in the aviation industry, establishes maintenance and refurbishment needs in complex, critical assets [26], [105] based on constant failure and repair rates [59]. Critical assets are those for which the financial and service level impacts of failure justify proactive assessment and restoration [10]. The main value of the RCM is in answering the seven questions about the functions, functional failures and their causes as well as remedial actions needed to determine the most appropriate maintenance strategies [105]-[107]. In order to answer the questions, detailed decision algorithms must be formulated, which can be very tedious. For that reason, asset managers tend to either reduce the failure modes or to prioritize the implementation of the RCM to critical assets. The determination of critical equipment involves a decision algorithm which can be summarized in the form shown in Figure 5-1.

The RCM has been described as a structured methodology and maintenance organization or process for establishing the most cost effective level of reliability [57], [106]- [108]. The RCM is claimed to reduce 11 kV transformer maintenance costs by 30 to 40% and routine preventive maintenance costs by up to 50% [109]. The US navy reported the following tangible benefits of the RCM: life cycle cost reductions of 15%, representing $1.7 billion; increased availability by 17%; and extended ship lifecycle by 8 years [25].

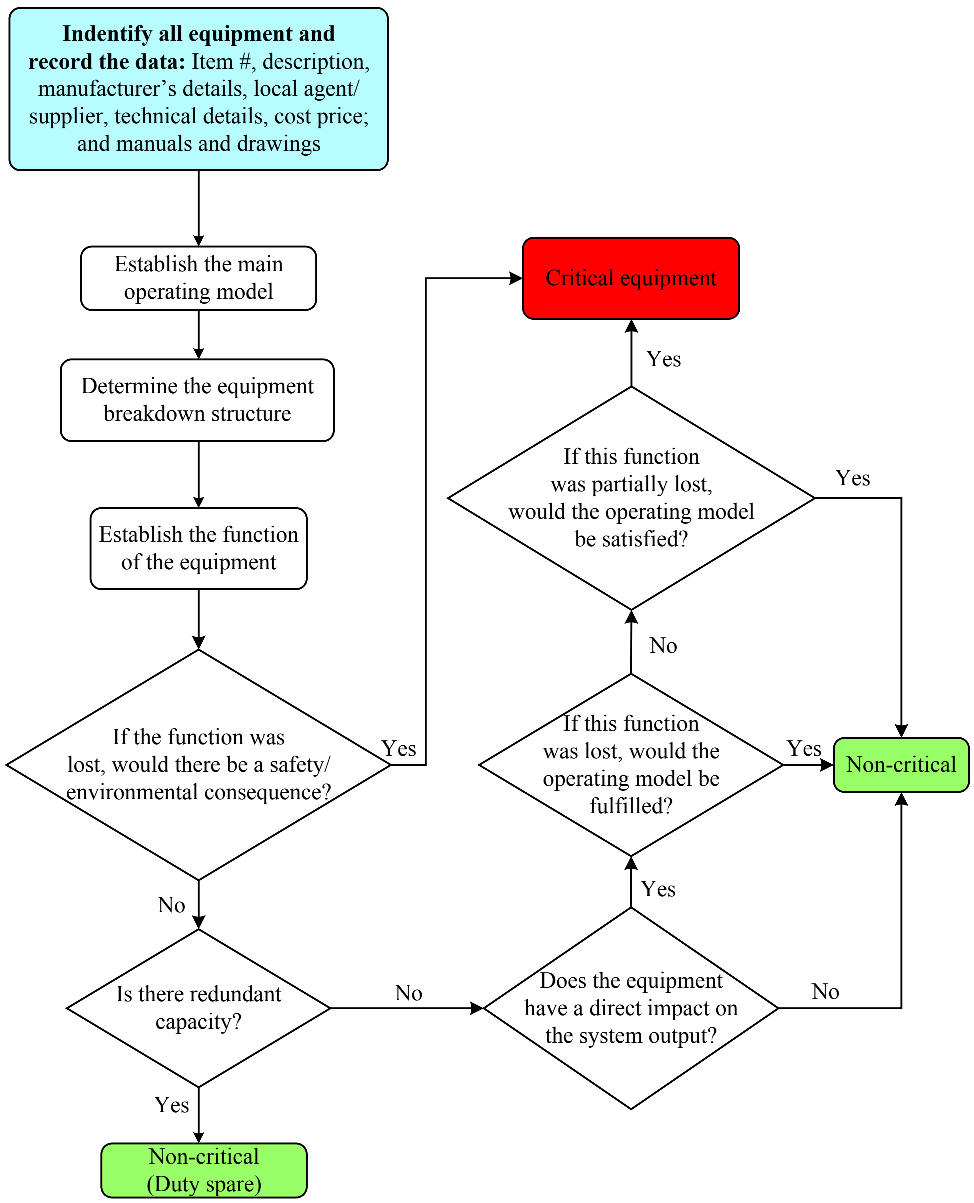


Figure 5-1: Equipment criticality determination (adapted from [10])

The major flaws of the RCM are as follows: it lacks prioritization needed for general industrial application [25], it is costly to implement and requires components of Total Productive Maintenance (TPM) to sustain its full capability [110]. Furthermore, it lacks the flexibility and full merits of probabilistic models [111]. Finally, it is unable to quantify the benefits of maintenance on system reliability and costs [112], [113].

The Risk based inspection (RBI) may be incorporated in the RCM to fortify it [10], [64]; thereby helping to select appropriate condition monitoring methods [57]. However, the RBI is neither able to quantify costs of inspection/condition monitoring nor indicate the alternative risk treatment options [57]. The RCM's fault root cause analysis usually comprises a Failure mode effect analysis (FMEA) which is used to analyze potential failure modes and their impacts; and the Failure Mode Effect and Criticality Analysis (FMECA) which extends the FMEA to include measures to rectify the faults [114]. The major concerns about the FMECA are the tendency to eliminate cascade failures [33], and the use of simple uptime or downtime data to compute risk indexes which can affect the validity of the results [91]. For power transformers, a risk index is given as the product of consequence factor and failure probability [4], [76]. Sections 5.2.2, 5.2.3 and 5.2.4 critically examine challenges pertaining to the risk characterization, data requirements and reliability modelling, respectively.

5.2.2 Risk characterization

Physical AM centers on optimization of risks, cost and reliability [1]. The risk management process consists of the following seven stages that are presented in Figure 5-2 [10]: risk contextualization, risk identification, risk exploration, risk assessment, risk treatment, risk monitoring and review, and risk reporting. Risk characterization refers to a synthesis of the seven stages, to provide a conclusion about the risk, the nature of the inherent and residual risk; and a rethink in strategy or policy due to changes in the risk profile over time.

The success of the risk characterization process requires a comprehensive database of faults, failures, operations, and maintenance as in a surveyed breakdown strategy; whereby a fault and damage database is combined with SCADA, ERP software and GIS [2]. The cost implications and integration challenges tend to limit the application of such strategies in the power sector. Hence, the asset managers tend to solely rely on soliciting opinions on how to determine the probability of failure or the end of life from experts in the field. For the power transformer risk management, the sourcing of opinions from the experts involves consultations with designers and chemists along with a rigorous inspection and an extensive testing procedure [76]. This is both time consuming and very costly. The foregoing scenario highlights the need to develop models that can eliminate some of the steps in the risk characterization process in order to reduce the time and costs.

Figure 5-2 outlines the key elements of an integrated risk management process, showing the contribution of the RCM in the process. The Top-down and Bottom-up techniques shown in the figure are tools used in the development of lifecycle management and maintenance plans for the assets [10].

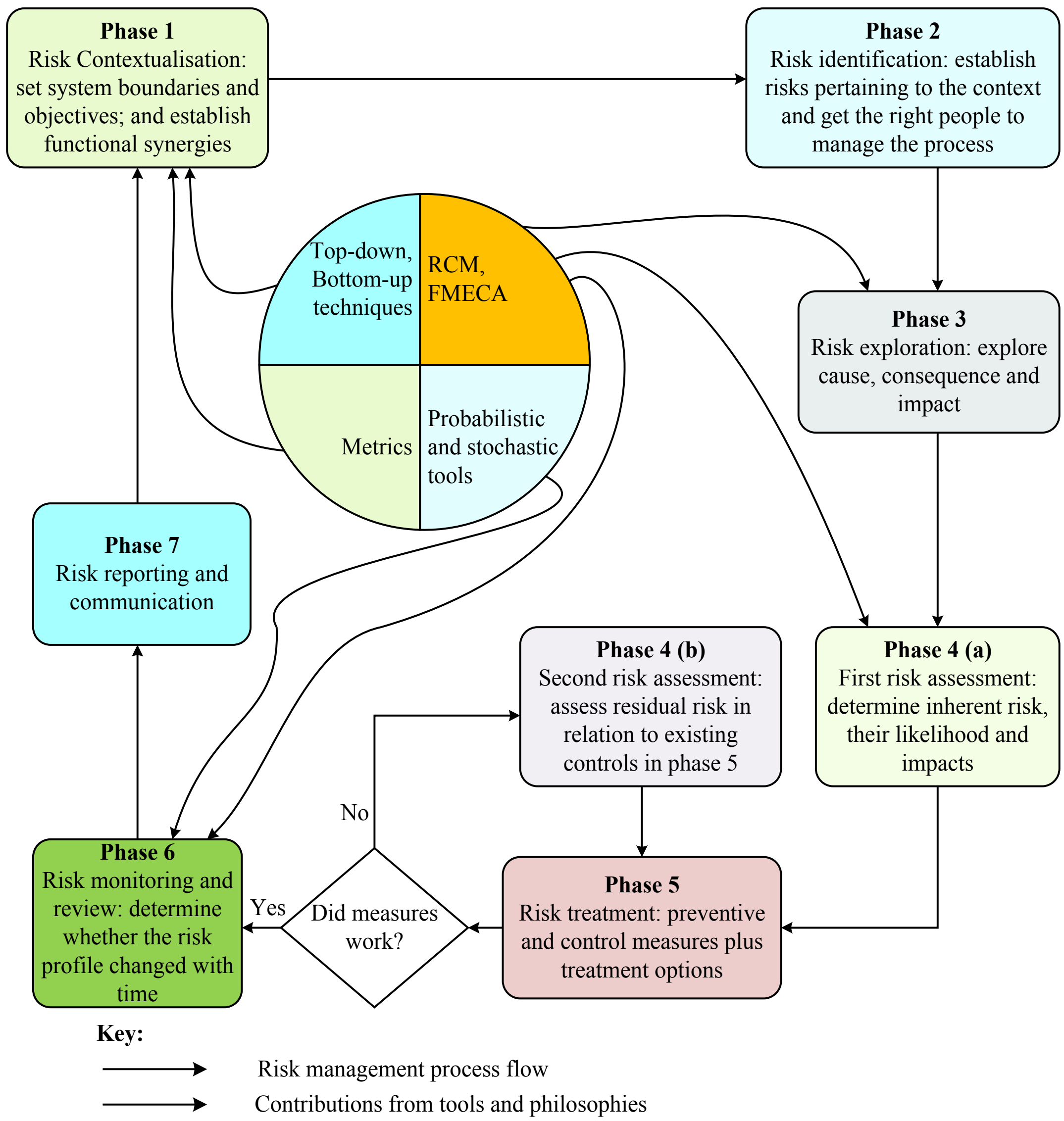


Figure 5-2: A systems view of the RCM and risk management process (adapted from [9])

5.2.3 Data requirements

This section highlights key issues pertaining to the data requirements in the risk management process. The RCM is one of the proactive equipment management practices, with probabilistic inferences, that have characterized the current risk-based techniques and AM paradigms [2], [26]. Data requirements for probabilistic concepts are huge, and it is usually difficult to get the data [2], [90]. The validity of the risk evaluation processes by line managers, who normally conduct the risk analysis [55], can be adversely affected by the data unavailability.

Parameters for probabilistic models include mean times to failure, inspection rates and probabilities of state transitions [5], [92]. ICT models are useful for capturing these parameters, but power utilities have applied the models inconsistently, in a fragmented way and face challenges in integrating them in the data mining process [66]. OSA-CBM and MIMOSA initiated the integration of standard ICT protocols in condition monitoring and maintenance, but most organizations have not embraced their use [25], [66]. The IEEE standardized the protocols to incorporate condition monitoring transducers [25]. It also developed a standard for the FMECA and fault root cause analysis [4].

5.2.4 Reliability modelling

This section explores ways of integrating stochastic processes in the RCM in order to simplify its process of quantifying the effects of maintenance on reliability, and to augment its probabilistic capabilities. Models that quantify effects of maintenance on reliability in the power systems are few, hence the need for research to focus in this area [5]. Many electric power utilities install RCM programs as risk prioritization tools for critical systems and equipment that have experienced problems [25]. However, the RCM approach is heuristic and its application requires judgment and experience which can take long before enough data is collected for the decision making purposes [90]. It is envisaged that the Markov analysis can be used cost effectively (with a few data sets) to derive the MTTFF, to model reliability and to measure the effectiveness of strategies, provided component failure and repair rates are known [27]. In modelling reliability, Markov processes treat equipment failures and repairs as constant or as exponentially distributed [5], [92]. The treatment of failure and repair rates as constant is the major criticism of the Markov approach [81]. However, the treatment simplifies the analytical process [115], [116]. Section 5.3 presents an analytical model that exploits the opportunities, and addresses the challenges that have been outlined in Section 5.2.

5.3 Risk modelling methodology

Based on the background presented in Section 5.2, Section 5.3 proposes a multi-method approach involving statistical data analysis and simulation using stochastic Markov processes, as a way of determining probability of failures without the need for physical equipment inspection and testing; and even where only a few data sets are available. The probabilities determined can be used to compute risk indexes within the FMECA stage of the RCM.

The overall methodology consists of two analytical approaches which are chosen based on time horizons considered for the data collection process. The approaches are the MOM, for estimation of the Weibull parameters; and the Markov analysis, for simulation of transient probabilities. For long time horizon (for equipment with long historical data), the MOM utilizes failure statistics from historical records to compute the Weibull parameters which are needed for reliability modelling (alternatively, the MLE may be used instead of the MOM). Then, the parameters are applied in determining failure probabilities that are input into the FMECA in order to evaluate the risk factors or indexes. In case of short planning horizon (i.e., 1 to 3-year time horizons), the Markov process applies annual failure and repair rates to generate state-space transitional probability matrices, to plot transient probabilities and to compute the MTTFF.

5.3.1 Overall approach

This section presents the overall methodological approach applied. This involves statistical data analysis and simulation of the MTTFF using stochastic Markov processes, as a way of determining probability of failures with reduced level of physical inspection, and even when only limited data is available. The probabilities thus determined can be used to compute risk indexes within the FMECA stage of the RCM. Figure 5-3 outlines the methodology. The figure shows that, at the beginning, the risk analyst must decide whether the equipment has a long history or not. If it has a long history, with a reasonable quantity of data, then the MOM or the MLE should be used. Otherwise, the Markov simulation model should be used.

Figure 5.3 also shows that, for effective risk assessment, spare part contingency plans should be made and the optimum number of spares determined to reduce the MTTR [4]. A new way of determining the optimum quantity of spares uses the Poisson distribution to satisfy the minimum requirements on MTBF, reliability and statistical economics [65]. The statistical economics is reported to be the best method as it reduces the total system costs and the cost of spares carried in the system. Besides, aging failure probabilistic modelling should be incorporated to accurately evaluate the system reliability [21].

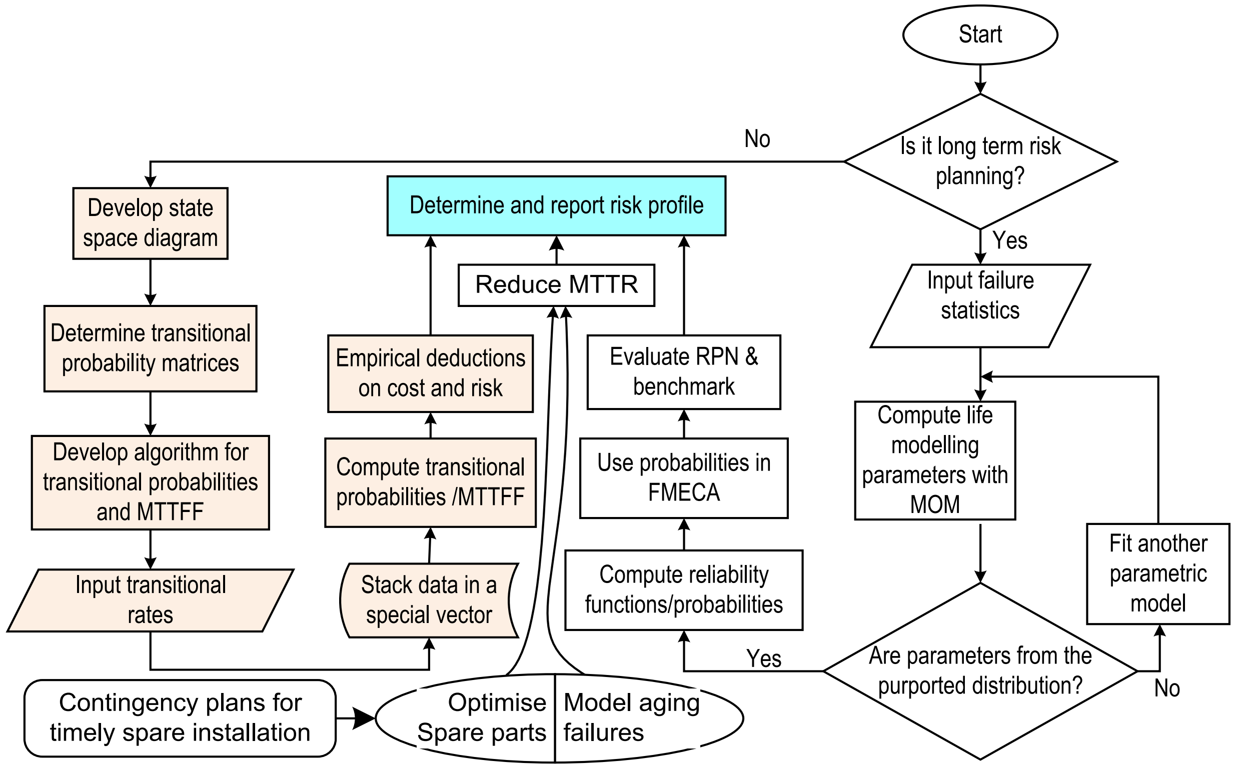


Figure 5-3: Overall risk assessment methodology

Section 5.3.2 presents the analytical method employed. Section 5.4 presents and discusses the results from the application of the analytical approaches.

5.3.2 Analytical approach

Chapter four demonstrated how the MOM can be applied to failure statistics in order to generate parameters for reliability modelling and risk mitigation. It further showed that three methods are normally used to compute the Weibull parameters, namely: the MOM, MLE and LSM. The LSM gives accurate results for large sample sizes and for non-censored data, whereas the MOM and MLE provide accurate results for all sample sizes and even for censored data [35]. Based on standard errors and confidence intervals of the parameter estimates, the MOM is considered to be as accurate as the MLE (especially when the times to failure are not too small), thus it is normally used to validate the results of the MLE [103]. When the times to failure become too small, the MLE gives better results than the MOM. The magnitudes of the times to failure used in this chapter are large, hence either the MLE or MOM can be used, but the MOM is applied as an illustrative case.

This section integrates some of the results from Section 4.7.1 with the Markov process to compute the MTTFF and the state transitional probabilities that are applied in the risk assessment model.

5.3.3 Method of moments (MOM)

In order to apply the MOM, data must be applied to a known type of distribution. This section applies the Weibull distribution to the MOM. In Chapter four, time to failure data (see Table 4-1) was processed using the MOM in order to determine the Weibull parameters. Since the type of distribution was imposed on the MOM, it was necessary to carry out a statistical hypothesis to prove that the data really conformed to the chosen distribution [117]. This test was implemented using the R-Statistical software package as explained in Section 5.4.1. The application of the Weibull distribution offers these merits: the capability to model different types of distributions with small sample sizes and the ability to relate its shape parameter to the bathtub curve [35].

The parameters estimated can be used to model different distribution functions, for example, the PDF, CDF and hazard rate *h(x)* which are, respectively, expressed as follows [35], [81]:

$$PDF = f(x) = \frac{\beta}{\eta}\left(\frac{x}{\eta}\right)^{\beta-1} \exp\left[-\left(\frac{x}{\eta}\right)^{\beta}\right] \tag{5.1}$$

$$CDF = \int_{0}^{x} f(x)\,dx = 1 - \exp\left[-\left(\frac{x}{\eta}\right)^{\beta}\right] \tag{5.2}$$

$$h(x) = \frac{f(x)}{R(x)} = \frac{\beta}{\eta}\left(\frac{x}{\eta}\right)^{\beta-1} \tag{5.3}$$

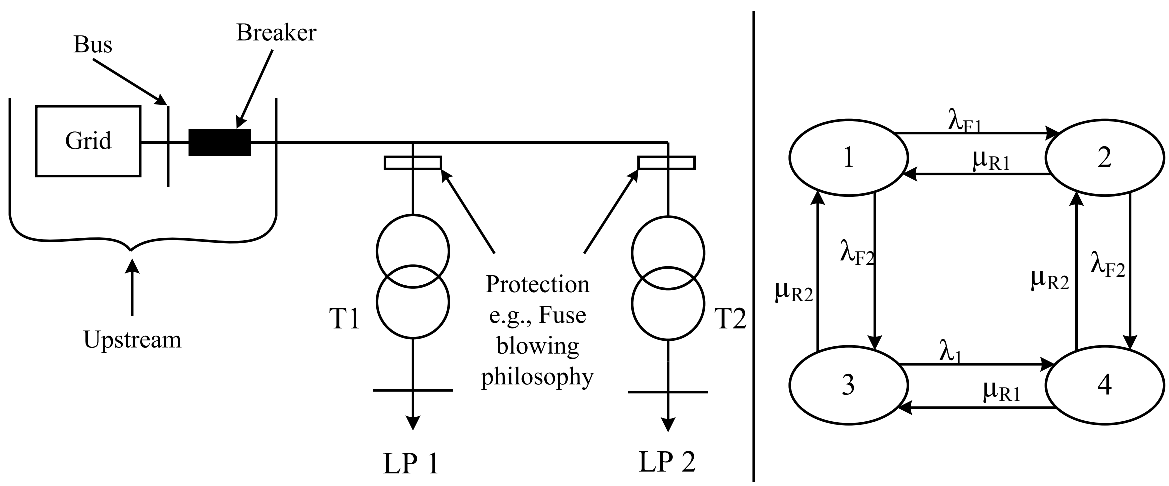
where β = shape parameter, η = scale parameter, x = random variable, and $R(x)$ = reliability function. The $h(x)$ represents the probability that an item that has survived up to time x will fail after that time.

Section 5.3.4 shows how the Markov approach is used to compute the transitional probabilities and the MTTFF.

5.3.4 Markov and the MTTFF

If a repairable system or component can be in either a failed or a non-failed state, probabilities associated with these states can be defined using a discrete or a continuous Markov process [115]. Failure and repair rates are key parameters used in the Markov process. These rates can be used to determine the optimum maintenance policy or strategy for physical assets [2], [7]. The Markov analysis applies state-space diagrams to produce stochastic transitional probability matrices that can be used in reliability modelling [81], [115]. The probabilities derived from the matrices can also be used to reinforce the stochastic capabilities of the RCM philosophy [118].

Figure 5-4 shows a case of two independent, non-identical components (T1 and T2) with four states. The case is chosen for modelling and simulating the transient probabilities and the MTTFF. In the figure, λ_{F1} and λ_{F2} are failure rates 1 and 2, respectively; whereas μ_{R1} and μ_{R2} are repair rates 1 and 2, respectively. Numbers 1, 2, 3, and 4 in Figure 5-4 (b) represent States 1 to 4 (that is, P_1 to P_4), respectively. It is assumed that the upstream reliability is perfect and that a fuse blowing philosophy applies to the system.



(a) Two-component system model (perfect upstream reliability) (b) State-space transitions

Figure 5-4: Two-component-four-state model

The general Markov process assumes conditional probabilities of events. Transition from *i* to *j* can be generalized by [115]:

$$p_{i,j}(x) = P(Z(t+x)) = j \big| z(t) = i\,; 0 \le p_{i\,j} \le 1 \tag{5.4}$$

$$p_{i,j}(t+x) = \sum p_{ik}(t) p_{kj}(x) \tag{5.5}$$

$$\sum_j p_{ij}(x) \le 1, \text{ for all } i \text{ and } j. \tag{5.6}$$

where t = time and x = incremental time.

The stochastic transitional probability (state-space) matrix for the four states, that is, Figure 5-3 (b), is determined from the rates of arrival and departure by the following matrix:

$$P=\begin{bmatrix} 1-\lambda_{F1}\Delta t-\lambda_{F2}\Delta t & \lambda_{F1}\Delta t & \lambda_{F2}\Delta t & 0 \\ \mu_{R1}\Delta t & 1-\lambda_{F2}\Delta t-\mu_{R1}\Delta t & 0 & \lambda_{F2}\Delta t \\ \mu_{R2}\Delta t & 0 & 1-\lambda_{F1}\Delta t-\mu_{R2}\Delta t & \lambda_{F1}\Delta t \\ 0 & \mu_{R2}\Delta t & \mu_{R1}\Delta t & 1-\mu_{R1}\Delta t-\mu_{R2}\Delta t \end{bmatrix} \tag{5.7}$$

The probability of being in a given state after n time steps is expressed as:

$$P^{(n)} = P(0)P^n \tag{5.8}$$

$$\lim_{n \to \infty} P^{(n)} = \alpha \tag{5.9}$$

$$\alpha P = \alpha \tag{5.10}$$

where $P(0)$ is the initial state vector and α is the limiting probability vector.

Processing equation (5.7) according to equation (5.10), assuming that Δt is implicit and $\alpha = [P_1\, P_2\, P_3\, P_4]$, yields the following:

$$[P_1\ \ P_2\ \ P_3\ \ P_4]\begin{bmatrix} 1-\lambda_{F1}-\lambda_{F2} & \lambda_{F1} & \lambda_{F2} & 0 \\ \mu_{R1} & 1-\lambda_{F2}-\mu_{1} & 0 & \lambda_{F2} \\ \mu_{2} & 0 & 1-\lambda_{1}-\mu_{2} & \lambda_{1} \\ 0 & \mu_{R2} & \mu_{R1} & 1-\mu_{R1}-\mu_{R2} \end{bmatrix}=[P_1\ \ P_2\ \ P_3\ \ P_4] \tag{5.11}$$

From equation (5.11), time and frequency domains (treating the problem as an initial value problem) can be computed and limiting state probabilities obtained for each state. For example, for state one, the time (t) and frequency (s) domains are as follows:

$$P_1'(t) = -\lambda_{F1}P_1'(t) + \mu_{R1}P_2'(t) + \mu_{R2}P_3'(t) \tag{5.12}$$

$$sP_1(s) = -\lambda_{F1}P_1(s) + \mu_{R1}P_2(s) + \mu_{R2}P_3(s) \tag{5.13}$$

The other states can be derived in a similar manner. Four constant limiting states (*P_1 to P_4*) independent of initial conditions arise from the analysis of either time or frequency domains as follows:

$$P_1 = \frac{\mu_{R1}\,\mu_{R2}}{(\lambda_{F1} + \mu_{R1})(\lambda_{F2} + \mu_{R2})} \tag{5.14 a}$$

$$P_2 = \frac{\lambda_{F1}\,\mu_{R2}}{(\lambda_{F1} + \mu_{R1})(\lambda_{F2} + \mu_{R2})} \tag{5.14 b}$$

$$P_3 = \frac{\mu_{R1}\,\lambda_{F2}}{(\lambda_{F1} + \mu_{R1})(\lambda_{F2} + \mu_{R2})} \tag{5.14 c}$$

$$P_4 = \frac{\lambda_{F1}\,\lambda_{F2}}{(\lambda_{F1} + \mu_{R1})(\lambda_{F2} + \mu_{R2})} \tag{5.14 d}$$

(5.14)

In order to compute the MTTFF, number of steps from S_i to reach an absorbing state S_j must be determined. If S_k is a transient set of states with matrix G obtained by truncating P , that is, by deleting the Mth row and the Nth column, the mean number of times the process is in S_j before absorption, if it started in S_i, is given by [92], [115] as follows:

$$S(N_{ij}) = n_{ij} \leq |S \in S_k \tag{5.15}$$

$$N = (I - G)^{-1} \tag{5.16}$$

where n_{ij} are the elements of N and I = identity matrix.

Alternatively, the MTTFF can be obtained using a mean first passage time (MFPT) matrix [5], [115]. If M_Z is a fundamental matrix and $\bar{T}$ be the MFPT matrix, then:

$$M_Z = [I - (P - A)]^{-1} \tag{5.17}$$

$$\bar{T} = [I - M_Z + UM_D]D \tag{5.18}$$

where $I = U$ = identity matrix, P = transition matrix, A = matrix each row of which is the limiting probability vector, $\alpha = (\alpha_o, \alpha_1, ..., \alpha_n)$; M_D = a diagonal matrix of M_Z, $\bar{T}$ is such that $\bar{t}_{ij}$ represents the MTTFF or mean number of steps from state i to j, and D = diagonal matrix such that $d_{ii} = 1/\alpha_i$.

Expected failure cost per year can be presented in terms of the MTTFF as [5]:

$$C_F = \frac{F_C}{T_R + MTTFF} \tag{5.19}$$

where C_F is the expected failure cost per year, F_C is failure cost, and T_R is repair time.

Section 5.4 presents and discusses results of the estimated parameters, probabilities, hazard rates, simulated transient probabilities, and the MTTFF. It also shows how the probabilities are applied in the FMECA stage of the RCM.

5.4 Results and discussion

In this section, results are presented and discussed. Section 5.4.1 presents the parameters that were estimated using the MOM in Chapter four and shows how they are applied in this stage of the risk model. Section 5.4.2 presents and discusses the Markov transient probability simulation and the MTTFF results.

5.4.1 Parameter estimates and reliability modelling

Table 5-1 presents the results of the MOM extracted from Section 4.7.1. In Section 4.7.1, it was shown that Kolmogorov Smirnov (K-S) test was implemented to test the hypothesis that the data really came from the purported Weibull distribution. The test accepted the results for the specified parameters (that is, β and η) of the Weibull distribution. The parameter estimates also fitted within the confidence intervals; hence the null hypothesis could not be rejected.

Table 5-1: Estimates of parameters β and η by the MOM

Weibull Parameters	β	η [x10^5 hrs.]
Estimated parameter values	3.4988	3.2786
Standard error (se)	0.6697	0.3025
Confidence interval (2.5%), (97.5%)	(2.9048),(4.5105)	(2.7049), (3.828)

In this section, equations (5.1) to (5.3) have been applied, based on the values of β and η from Table 5-1, to generate plots of the CDF, the hazard rate and the PDF. The plots are presented and annotated in Figure 5-5. Figure 5-5 is referred to as a comparative model because it can be used to compare or benchmark results from other, but similar asset populations.

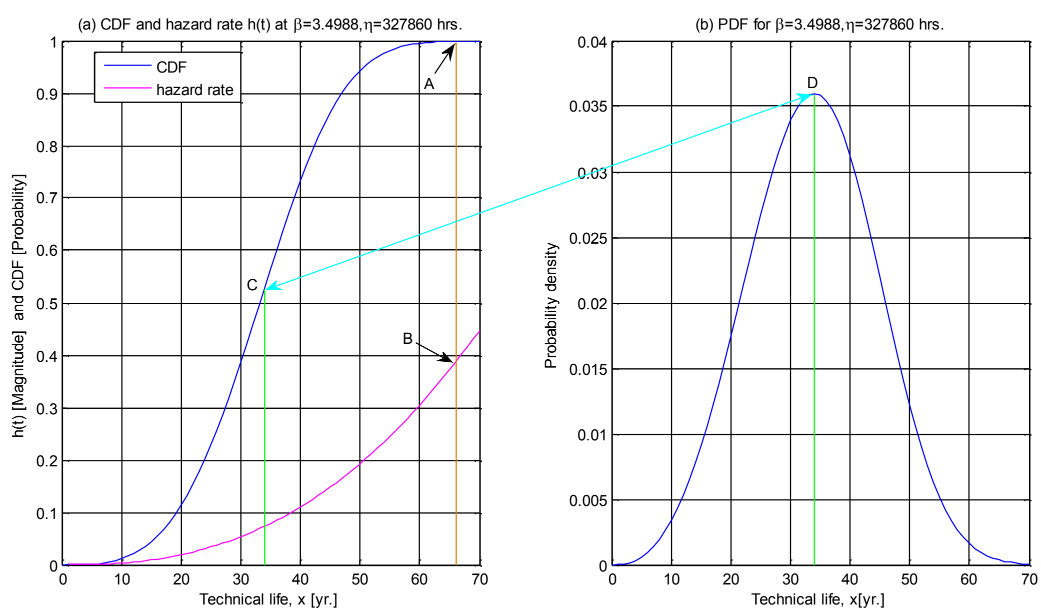


Figure 5-5: Comparative model of (a) CDF and hazard rate; and (b) PDF

The CDF is a failure distribution function; hence it can be used to represent the failure probability [35]. It stands for the chance that the equipment will have a lifespan of up to time x [14]. Thus, Figure 5-5 (a) can be used as a model from which the failure probabilities to be used for risk modelling can be extracted. It can also be used to compare with or benchmark against failure probability trends of similar assets currently in operation. Point A on Figure 5-5 (a) signifies the end of life, whereby the CDF = 1 and the asset age is 67 years. Point B corresponds to point A, where $h(x) = 0.384$. On the other hand, the PDF shows the chance of equipment failing at the age of x. Point D on Figure 5-5 (b) (the PDF curve) corresponds to the steepest slope on the CDF plot (point C) and it occurs at 34 years of age. In terms of risk mitigation, point C indicates that refurbishment of these transformers should be done before the age of 34 years. The scale parameter (η) represents the age at which 63% of equipment will have failed [35], [81]. For these transformers, η is 327860 hours or 37 years. The probabilities in Figure 5-5 (a) can be used as inputs into the FMECA within the RCM.

The FMECA is normally conducted in two stages, namely: the first stage involving current actions (measures) and the second one after proactive measures are taken to reduce the risk [26]. Table 5-2 (a) shows the first stage, whereas Table 5-2 (b) presents the second stage. The computed failure probabilities are incorporated in the second stage of the FMECA. For example, from Figure 5-5, at 30 years the probability is 0.387. This is inserted in column F of Table 5-2 (b), and the risk priority number (RPN) is given as the product of columns F, G and H (see column I). By comparing the RPN under the current actions (business as usual) with that after proactive actions are taken, the asset manager can determine whether the strategies implemented were effective in mitigating the risk or not.

Table 5-2 (a): FMECA Stage 1 [from system to failure mode]

A	B	C	D
System	Function	Functional failure	Failure mode
Transmission transformer	To transmit power	Failure to transmit power	Decrease of mechanical, thermal and electrical strength

Table 5-2 (b): FMECA Stage 2 [from current measures to risk priority number (RPN)]

E	F	G	H	I
Current measures to rectify failure	Probability	Severity (1-10)	Detection (1-10)	RPN (F x G x H)
Planned maintenance	0.387	3.35	3	3.889

The heading of column E in Table 5-2 (b) will change to reflect the type of strategy applied. For example, if CBM is conducted as the proactive measure that is needed to reduce the RPN, the heading will change to proactive measure and the CBM will be listed under it as shown in Table 5-2 (c). Table 5-2 (c) shows that the RPN reduces to 1.34 (from 3.889 to 1.34), which means the measures that were taken were effective.

Table 5-2 (c): FMECA after applying proactive measures

E	F	G	H	I
Proactive measures to rectify failure	Probability	Severity (1-10)	Detection (1-10)	RPN (F x G x H)
CBM	0.2	3.35	2	1.34

The severity (consequence) depends on the impact of the equipment on system reliability, criticality of customer and type of public service served [76]. Detection shows the relative difficulty (in terms of the skill needed) in which a failure mode is detected on a scale of 1 to 10 [9]. For an objective risk analysis, the RPN must be computed for each failure mode that can be identified. It is worth noting that probabilities and detection are likely to change, whereas the severity will always remain the same.

It is also worth noting that stage one of the FMECA can be recorded in the RCM information worksheet according to [105]. A typical RCM worksheet would also give details of the failure effects and whether the failures are evident or hidden. Since the LV network has numerous components and most of which are small, the best practice is to group the small components and then to do a failure finding exercise for the group, rather than to deal with the individual components. Thereafter the degree of failure is quantified. If the components go through partial failure before total failure, the probability of failure could be calculated from the time of partial failure to the total failure.

Different assets will have different failure probabilities due to the varying operating environments they are subjected to. For example, the following values of failure probabilities at the equipment age of 30 years were derived using the Inverse Power Law and the Arrhenius model [59]: transmission transformers, 25%; distribution transformers, 21%; switch gears, 14%; contact breakers, 37%; and load interrupters, 20%. This kind of information can be compared with the results that are plotted in Figure 5-5.

Section 5.4.2 demonstrates how the Markov process analyses transitional probabilities and the MTTFF. In the process, failure and repair rate data is applied to the state-space model that was presented in Figure 5-4 (b). The fundamental purpose of this section is two-fold. First, to develop a model that simplifies the risk analysis, using only a few data sets from a short time span. Second, to apply the MTTFF in conducting the RCM. This will help to model the impact of maintenance strategies on costs.

5.4.2 Simulation of MTTFF and transient probabilities

5.4.2.1 Application of failure and repair data in MTTFF analysis

In order to find the various states after *n* time-steps in the state-space model of Figure 5-4 (b), numerical values of λ_{F1}, λ_{F2}, μ_{R1}, and μ_{R2} were inserted in equation (5.7). These values are from two selected case studies: transformers aged 25 and 30 years. These transformers are similar to those used to provide the data in Table 5-1, but their failure rates are for annual averages from a 3-year period. Thereafter, equation (5.7) was computed according to equation (5.8), assuming that P (0) = [1 0 0 0], in order to determine the transient probabilities. The MTTFF was computed using equation (5.18).

Table 5-3 presents the repair and failure rate data that was used to analyze the transient probabilities and the MTTFF for the two cases, whereas Table 5-4 presents the MFPT matrix and MTTFF values. In Table 5-4, the MTTFF is in the cell P_1-P_4.

Table 5-3: Average repair and failure rates for 12 MVA transformers

	Case #1: 25-yr. old transformers		Case #2: 30-yr. old transformers	
Repair rate 1	599.999 repairs/yr.	μ_{R1}=0.0685	674.52 repairs/yr.	μ_{R1}=0.077
Repair rate 2	729.997 repairs/yr.	μ_{R2}=0.0833	762.12 repairs/yr.	μ_{R2}=0.087
Failure rate 1	149.998 failures/yr.	λ_{F1}=0.0171	192.72 failures/yr.	λ_{F1}=0.022
Failure rate 2	100.004 failures/yr.	λ_{F2}=0.0114	175.2 failures/yr.	λ_{F2}=0.02

Table 5-4: MTTFF matrix for transition from States *P_1 to P_4*

MTTFF for case #1 (in the cell P_1-P_4)					MTTFF for case #2 (in the cell P_1-P_4)				
	P_1	P_2	P_3	P_4		P_1	P_2	P_3	P_4
P_1	1.42	62.2	99.1	302.34	P_1	1.5813	50.476	57.42	164.51
P_2	15.55	5.69	106.77	271.66	P_2	14.42	5.535	64.17	140.9
P_3	13.58	67.89	10.37	260.76	P_3	13.2	56	6.8786	140.48
P_4	21.25	37.22	65.19	41.5	P_4	19.95	32.39	40.14	24.08

Figure 5-6 presents plots of the transient probabilities, corresponding to the data in Table 5-4, for cases # 1 and 2. For both cases, it was assumed that the system started in State 1. The annotation in Figure 5-6 shows the complements of the uptime state, P_1 (that is, 1-P_1), which represent the risk of system failure. The complement of the uptime state for case # 1 and 2 are, respectively, 0.296 and 0.37.

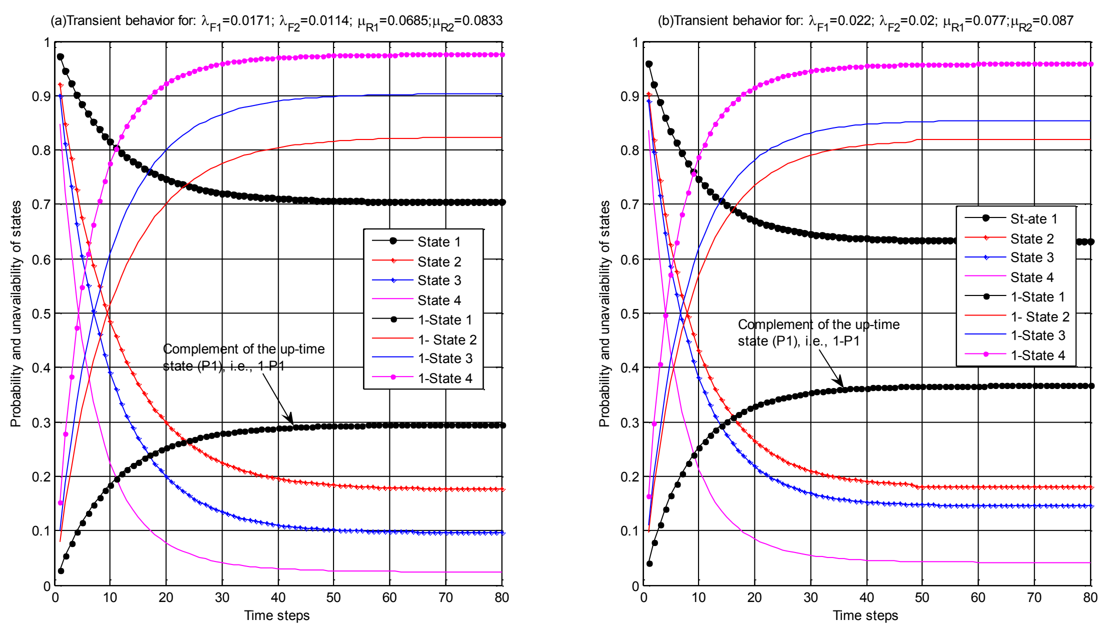


Figure 5-6: Transient probabilities for cases 1 and 2

Tables 5-5 to 5-7 and Figures 5-7 to 5-9 present results that have been simulated for different cases. The two-component model (Figure 5-4) has been applied, assuming that situations can arise when one component is repaired much faster than the other; or one component fails at a much higher rate than the other. Then, the impacts of these scenarios on the MTTFF and costs are evaluated. In practice, the repair and failure rates for all similar equipment are assumed to be constant. This is the major flaw of the application of the Markov processes in industry [81].

Figure 5-7 shows a special case where the combined effects of the failure and repair rates for the system result in State 2 being predominantly the uptime state. Although the system started in State 1, the initial state is short-lived and the system dwells in State 2, where component # 2 has the highest limiting transient state probability at 0.8294 or 82.9%. The MFPT matrix and MTTFF associated with Figure 5-7 are presented in Table 5-5.

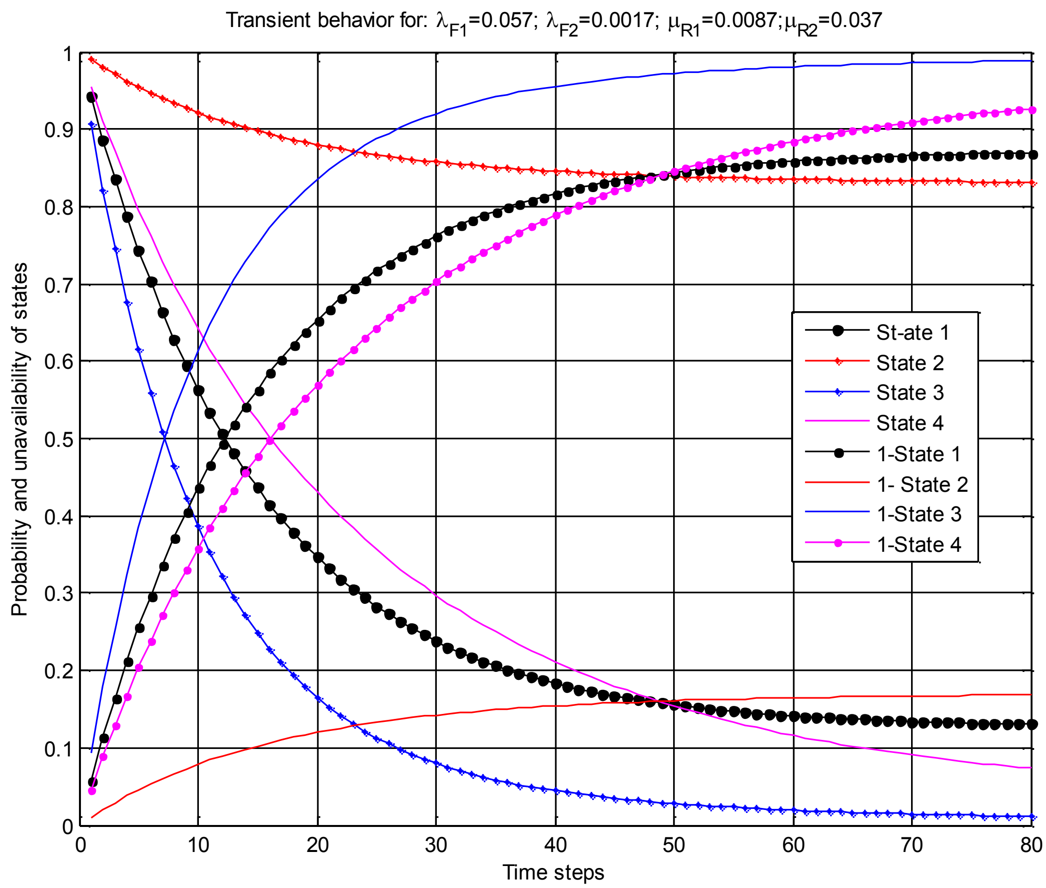


Figure 5-7: Transient probabilities for case #3

Table 5-5: MFPT matrix and MTTFF associated with Figure 5-7

MTTFF [x 10^3] (in the cell P_1-P_4)				
	P_1	P_2	P_3	P_4
P_1	0.009	0.0181	2.0169	0.6280
P_2	0.1183	0.0012	2.0595	0.6215
P_3	0.0927	0.0351	0.1719	0.2578
P_4	0.1353	0.0286	1.6893	0.0262

Figure 5-8 presents plots of case # 4 where component #2 (from the two component model, Figure 5-4) has a lower failure rate and a higher repair rate than component # 1. In this case, State 2 has a higher transient state probability than State 1. Its corresponding MFPT matrix and the MTTFF are presented in Table 5-6. This scenario may occur if component # 2 is newer than component # 1. Hence, it follows that the complement of the transient probability of component # 2 is 0.136 or 13.6%, which presents the lowest failure probability in the system. In terms of best practice asset management, component # 2 is critical to the continued reliability of the system, hence all efforts must be made (by the asset manager) to ensure that it is in the up-state.

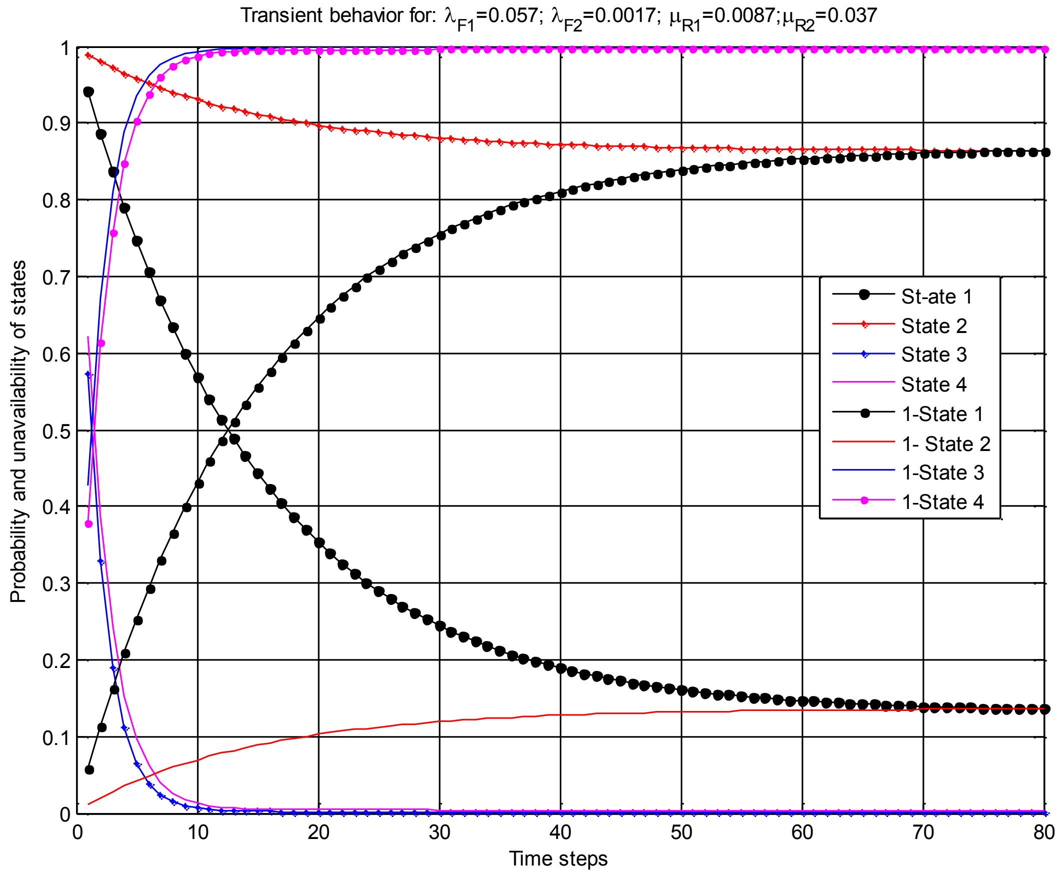


Figure 5-8: Transient probabilities for case #4

Table 5-6: MFPT matrix and MTTFF associated with Figure 5-8

MTTFF [x 10^3] (in the cell P_1-P_4)				
	P_1	P_2	P_3	P_4
P_1	0.0076	0.0176	3.8633	0.6794
P_2	0.1150	0.0012	3.9610	0.6645
P_3	0.0178	0.0180	1.6512	0.5911
P_4	0.1154	0.0031	3.8726	0.2520

Figure 5-9 shows plots of case # 5, which is a scenario where $\lambda_{F1} = \lambda_{F2} = 0.017123$ and $\mu_{R1} = \mu_{R2} = 0.068493$. This scenario leads to the following limiting transient state probabilities: P_1=0.64, P_2=P_3=0.16, and P_4 = 0.04; and the corresponding MTTFF is 204.4. The MFPT matrix and the MTTFF for this case is presented in Table 5-7, whereby the MTTFF is in the cell P_1-P_4. It can be shown that a similar case where $\lambda_{F1} = \lambda_{F2} = 0.011416$ and $\mu_{R1} = \mu_{R2} = 0.08333$ yields better results where $P_1 = 0.77$, $P_2 = P_3 = 0.106$, and $P_4 = 0.02$; and the MTTFF is 451.1.

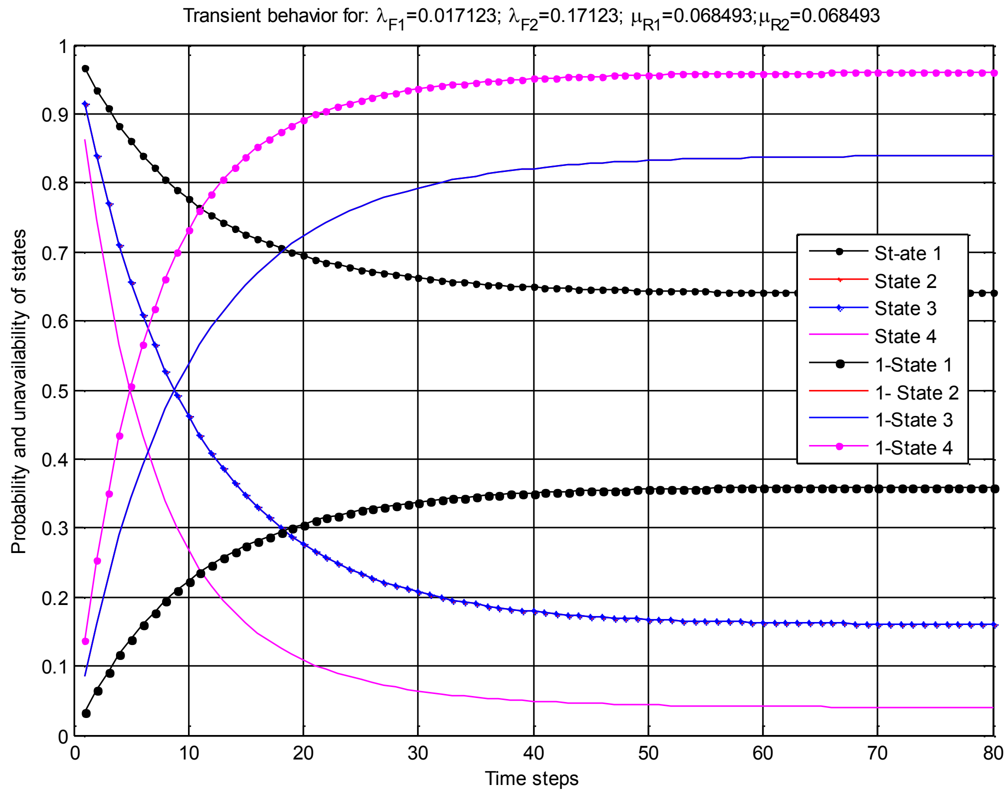


Figure 5-9: Transient probabilities for case #5

Table 5-7: MFPT matrix and MTTFF associated with Figure 5-9.

MTTFF (in the cell P_1-P_4)				
	P_1	P_2	P_3	P_4
P_1	1.5625	65.7010	65.7010	204.4051
P_2	16.4250	6.2501	73.0010	175.2046
P_3	16.4250	73.0010	6.2501	175.2046
P_4	23.7250	43.8005	43.8005	25.0006

5.4.2.2 General discussion of CDF, h (t), PDF and MTTFF plots

In general, Figure 5-5 is a comparative or benchmarking model that applies historical failure data to model risk of component failure, if the asset population has adequate data for statistical analysis. On the other hand, Figures 5-6 to 5-9 model risk of component failure even with a very limited amount of failure data and from as short a time horizon as one year. Figures 5-6 to 5-9 have shown that, depending on the failure and repair rates, it is possible for a two component redundant system to behave like a series system. When the system behaves in this way, it will portray a Poisson (distribution) effect; that is, its failure will be catastrophic or of the binary form (existing as either 1 or 0). In other ways, the uptime state of such a system will basically depend on the uptime state of a single component. This single component, therefore, becomes the most critical one for a sustained system reliability. For example, at a point where $\lambda_1 = \mu_1 = 0.01112$ and $\lambda_2 = \mu_2 = 0.01211$, $P_1 = P_2 = P_3 = P_4 = 0.9768$ at the start of simulation (i.e., at t = 0), and the limiting states are $P_1 = P_2 = P_3 = P_4 = 0.2718$; whereas the MTTFF is 172.5. This is a kind of Poisson distribution, displayed by Figure 5-10, of the following form:

$$P_x(t) = \frac{(\lambda t)^x e^{-\lambda t}}{x!} = e^{-\lambda t} \Big| x = 0 \tag{5.20}$$

where x = times the failures are occurring in the interval (0, t), similar to what is alluded to in [92].

This Poisson distribution analogy or concept is also similar to what was demonstrated in modelling of transformer spares to account for catastrophic failures, as advanced in [65].

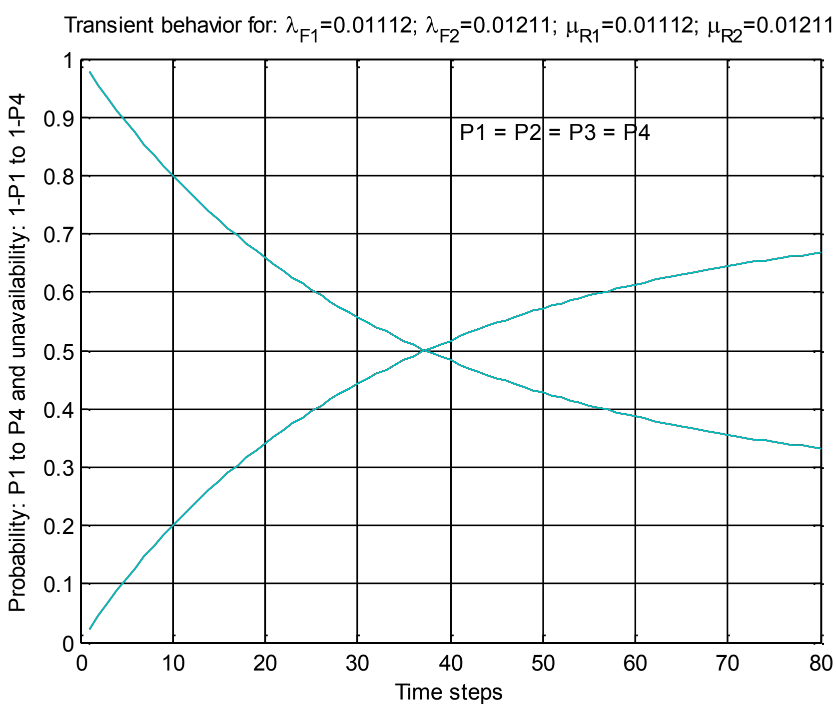


Figure 5-10: Transient behavior for a case acting as a Poisson process

Section 5.4.3 demonstrates how the transient probabilities can be applied in AM modelling within the RCM approach.

5.4.3 Application of transient probability inferences

From Figure 5-6, State 1 has the highest survival probability, hence the most desirable and the one that asset managers would want to sustain. It also represents the least level of risk, in terms of failure, in comparison with other states. Besides, its value can be predicted with certainty. Hence, this thesis advances that the state should be used as the basis for computing the failure probabilities to be used in the FMECA. It is advanced that the risk of system failure is the complement of the steady-state value of the transient probability of the uptime state (as a process that exists in either a an uptime or a failed state, i.e., of binary form), which (assuming that State 1 is the uptime) is 29.6% (0.296) for case # 1 and 36.7% (0.367) for case # 2. In Figure 5-6, these are shown as $1\text{-}P_1$. Therefore, these probabilities are the ones to be used as inputs into the FMECA; for example, see Table 5-3 (b) column F. Alternatively, the complement of the limiting state probability, for example, P_1 obtained from equation (5-14), can be used to obtain the same failure probabilities. For instance, the limiting state $P_1 = 0.7036$ and its complement ($1\text{-}P_1$) is 0.296 for case # 1, whereas $P_1 = 0.632$ and $1\text{-}P_1$ is 0.367 for case # 2. The graphical approach (Figure 5-6) is less tedious than the evaluation of the limiting states from frequency (s) and time (t) domains. From Figure 5-6, the transient probability that approaches the limiting state can simply be determined from the value at which the probability plot approximates a constant value, that is, the portion that is almost parallel to the *x*-axis.

Although the probabilities in Figures 5-5 and 5-6 are derived from similar equipment, they are not the same. This is expected because the operating conditions and the time horizons used to generate the graphs are different. Figure 5-5 is generated from a 43-year historical time to failure data, whereas Figure 5-6 comes from the annual average failure rates. By substituting the MTTFF from cases #1 to #5 (that is, Tables 5-4 to 5-7) into equation (5.19), when the F_C = US$ 123000 and the T_R = 60 hours, the expected failure costs per year are evaluated and the relationship is as outlined in Figure 5-11. In the figure, Point A corresponds to the MTTFF from case #1, whereas point B represents the MTTFF for case # 2.

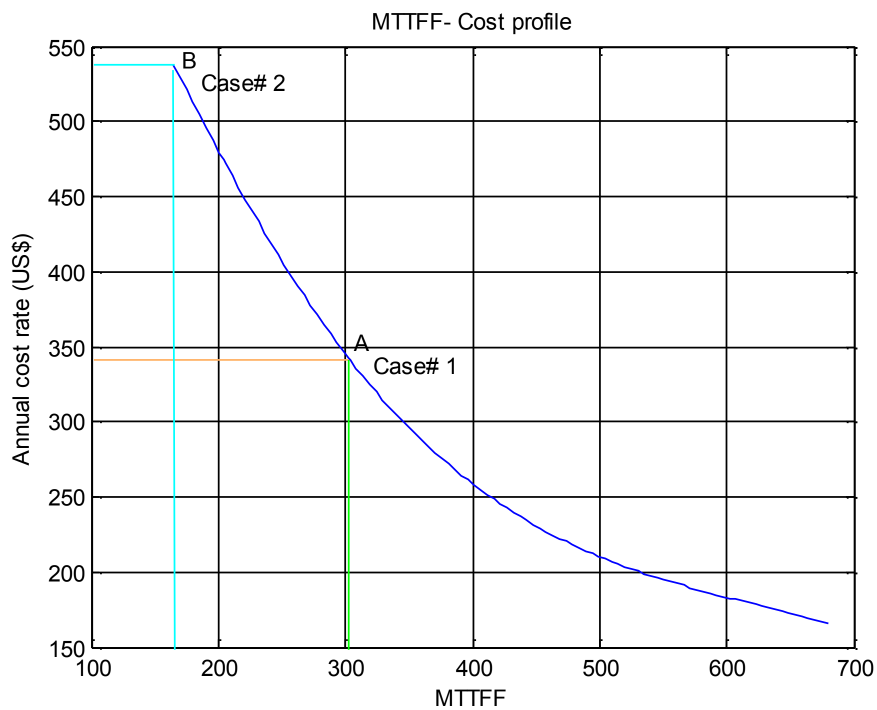


Figure 5-11: Variation of costs with the simulated values of the MTTFF

In Section 5.2.1, it was shown that one of the major concerns about the RCM is its inability to quantify the benefits of maintenance strategies on costs. Figure 5-11 shows that the MTTFF is inversely proportional to maintenance costs, which agrees with what was shown by [5]. This relationship can be used to establish the impact of strategies on costs (the quantitative benefits of maintenance strategies on costs), thereby improving performance measurement in the RCM. Therefore, in order to apply the model, average failure data from assets where the RCM is being implemented should be collected and used to compute the MTTFF. The MTTFF can then be used to track the cost profiles to determine whether the strategies add any financial benefit or not, as demonstrated in Figure 5-11. This approach can be applied to asset groups, as a rule of thumb, to assess the effectiveness of strategies in systems where the RCM or any other philosophy has been implemented.

5.4.4 Comparison of effectiveness of methods used

The application of the Markov approach enables the use of data from very short time periods, for example, one year. In contrast, the MOM uses data collected from longer periods of time as is the case with most statistical models. However, in comparison with other statistical models like the LSM (as shown in Section 5.3.1), the MOM is more desirable as it can utilize very few data sets. In addition, the MOM generates a failure probability distribution comparative model which current approaches to FMECA or root cause analysis do not do. Neither is this possible with the Markov process. However, the strength of the Markov process lies in its ability to generate transient probabilities and the MTTFF that can be used for measurement of the performance of RCM strategies. The Markov can also model derated states, which the MOM cannot do. Despite the differences between the two techniques, the failure probabilities computed compare very well. For example, the Markov yields probabilities of 0.296 and 0.367 for the 25-year old and 30-year old transformers, respectively; whereas the MOM generates probabilities of 0.23 and 0.387, respectively. As expected, the probabilities from the two approaches cannot be exactly the same because they are derived from data from different time horizons, and for different operating conditions. So what is remarkable about the chosen approaches is the capability to generate failure probabilities that can be used in the FMECA and fault root cause analysis. This can strengthen or augment the current approaches which have based the computation of these probabilities only on condition monitoring as alluded to in [4].

5.5 Chapter conclusions

In the chapter, the literature review highlighted major challenges in the current approaches for conducting the RCM and risk assessment. Next, case study data was applied to illustrate the application of the risk assessment model developed. The originality of the study is three-fold. First, the inverse proportional relationship between the MTTFF and costs was trended (profiled) and applied as a KPI of the effectiveness of the RCM strategies. Since average annual costs, and repair and failure rates are used to produce the KPI, the approach is a convenient and cost effective way of providing a broad view of the effectiveness of the strategies on a group of network assets. Second, the MOM is applied to statistical data to generate a failure probability distribution benchmarking model; in addition to the current practices for conducting the FMECA, where failure probabilities are based only on condition monitoring, the notion that is describes as inadequate [4]. Third, Markov techniques generate failure probabilities for use in the FMECA, with data from as short as a one-year time frame, using the complement of the uptime-steady-state transitional probability values. The current approaches rely on data collected over a long time period. This is especially useful in giving a strategic direction when data is inadequate or when a large population of transformers or equipment is involved. The proposed method forms a priority-screening phase; so that any rigorous testing procedures, especially for an aged system, which has a significant impact on the system reliability [21]; can still be carried out but only on the critical assets, thereby reducing operating costs. Finally, the method can be used to contextualize, monitor and trend the risk profiles associated with power transformers and other physical assets. This method has also been presented in [119], where it is envisaged to offer a promising road map for a risk-based power distribution AM in future.

So far, the systems approach has led to the development of a component risk and cost trend monitoring model and an integrated risk management model; where the RCM plays a central role in the selection of appropriate strategies, in risk assessment and prioritization, and in risk characterization. For the systems approach to be all encompassing, it must be able to evaluate the impacts of AM paradigms on sustainable business operation. Thus, Chapter six is dedicated to the determination of the effect of the paradigms on sustainability of power distribution business, by employing a multidimensional (holistic) approach.

CHAPTER SIX

IMPACT OF PARADIGMS ON SUSTAINABLE ENERGY SUPPLY

6.1 Introduction

In view of the Publicly Available Standard (PAS) [1], the purpose of physical asset management (AM) is to optimize the lifecycle business impact of operating firms for sustainability of their businesses. Asset managers undertake (follow) various AM paradigms in pursuit of the optimization of the business impact. The Oxford dictionary defines a paradigm as an illustration, configuration, or epitome of something. It may contain rules and guidance for problem solving, conducting business or perceiving change. The change in paradigm can be referred to as a paradigm shift. Some paradigms are traditional, generally pursued without any justification. Others are based on gut-feel; they may appear to indicate excellent performance in the short term, but could also have hidden-losses (weakness) that are difficult to detect by mechanistic (non-holistic) approaches.

This chapter advances the need for a paradigm shift in the strategies employed in maintenance (management) of electric power and energy distribution systems for sustainable energy supply. It is based on a multi-method approach involving case studies in a vertically integrated power utility with generation, transmission and distribution business units in Southern Africa; statistical inference; and parametric reliability-modelling techniques. It applies systems thinking philosophy, a methodology that enables managers to have a holistic view of the environment in which problems exist [41]. It provides a systems view of run-to-failure strategy as applied to the electric power distribution assets and evaluates the effects of the strategy on the sustainability of business operations. It critically examines the repercussions of the notion that a power utility can implement the run-to-failure strategy on most of the power distribution system components because the items are not as capital intensive as those in the transmission and generation systems (business units). Furthermore, it exposes how metrics that are applied at a power generating station can affect the sustainability of the entire energy supply or distribution system by analyzing generation adequacy indices.

The way the energy infrastructure is managed can greatly affect the sustainability of energy supply. Sustainability leads to sustainable development and it refers to resource endowment, existing energy infrastructure, development needs, favorable environmental quality and energy efficiency [61]. Sustainable development means the development that satisfies the current needs without endangering the ability of upcoming generations to satisfy their own requirements [62]

This chapter also applies statistical and stochastic techniques to time to failure data in order to generate life parameters that are used in reliability and cost models. Failure statistics are very important in modelling reliability and maintenance strategies, but it is very difficult to get sufficient data for the statistical analysis [2], [60]. For this reason, this study has explored a method of modelling with a few data sets using the Weibull distribution [35], [120]. The Weibull distribution can be used to relate changes in component behavior to maintenance operations in electric power systems [120] and in accelerated failure models [121]. The Weibull distribution is applied to statistical data sets to estimate life-modelling parameters using the MOM and MLE (introduced in earlier chapters). The statistical data sets can then be used to predict long term monetary consequences of maintenance strategies as alluded to in [122].

6.2 Methodological approach

This section provides the background that motivated the study, the application of systems thinking philosophy to determine cause and effects, and the probabilistic and statistical approaches undertaken to develop model parameters. Case studies and statistical as well probabilistic inferences are applied.

6.2.1 Problem background

A systems thinking approach is employed to determine root causes of AM related energy supply problems and their impacts. Case studies from Southern African power utility set-up are used. Systems thinking helps to establish root causes so that analytical techniques can be employed to solve the specific problems that have been identified [26]. The systems approach does so by using causal loop diagrams [2], [28]. The application of systems thinking concept showed how the energy supply problems cascaded from the generation down to the distribution business unit in a vertically integrated power utility firm. At the generation business unit, the systems approach indicated how the use of availability as a metric, as opposed to Energy-Not-Supplied (ENS), had put the utility off-balance. In addition, it showed that outsourcing of refurbishment and maintenance works led to a decline in the firm's technical-skills-base as demonstrated in Figure 6-1. In the causal loop diagrams (Figures 6-1 and 6-3), independent variables are at the beginning of arrows, whereas the dependent variables are at the arrow heads. An "s" means: when the independent variable changes, the value of the dependent variable will be above what it was before the input from the independent variable, whereas an "o" means it will be below what it was before the input from the independent variable. Other symbols and notations used in causal diagrams are as described beneath Figure 6-1.

Figure 6-1 shows that outsourcing enables the firm to focus on core activities, but leads to loss of its technical-skills-base in the long run. In addition, it increases the outsourced contractor's financial returns and technical capabilities, which in turn increases the host institution's asset performance. Besides, increase in the contractor's skill base reduces the host institution's technical skills, but the effect is delayed (i.e., it is not immediately evident).

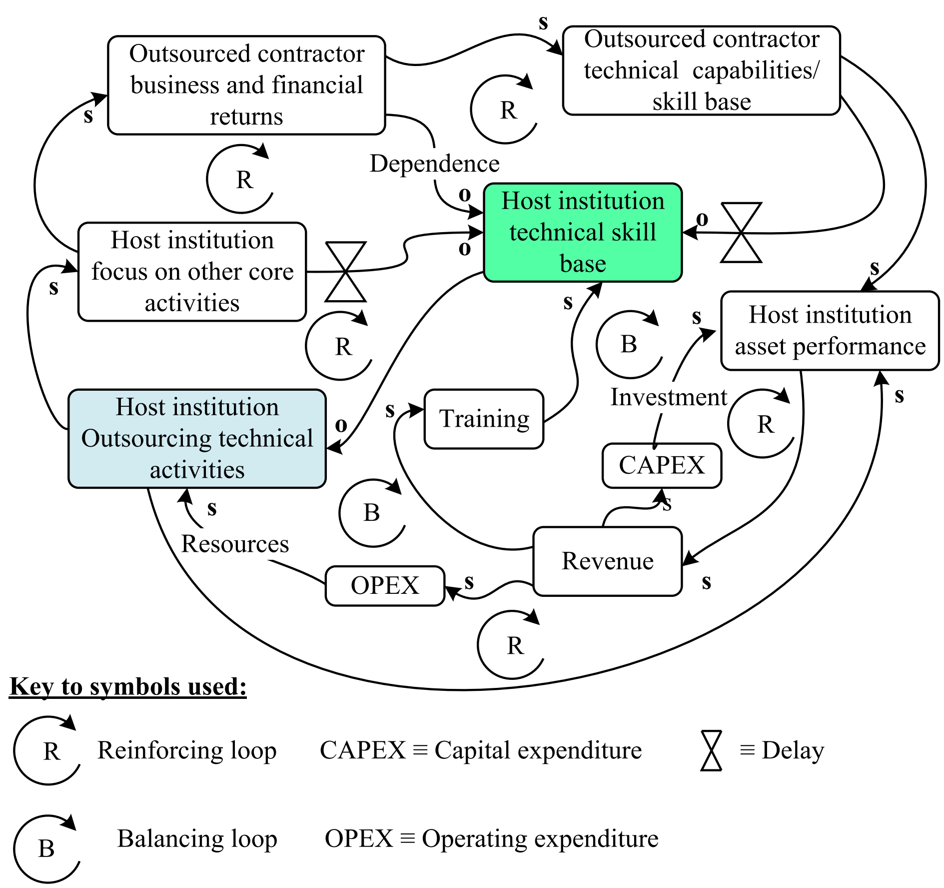


Figure 6-1: Systems view of outsourcing technical skill

Figure 6-1 further shows that outsourcing of the host institution's technical activities enhances its focus on core competencies (activities), but eventually diminishes its technical skills. Finally, as the outsourced contractor increases the host institution's asset performance, it increases revenue and resources for OPEX and leads to more outsourcing activities. It also increases revenue for CAPEX in investment activities, thereby further increasing asset performance; and enhancing training of the host institution's staff to advance their technical skills.

The systems view was also applied to evaluate how equipment management paradigms are affecting the operating business risk or the sustainability of power distribution in the industry. Since the Second World War, the equipment management paradigms have evolved from a reactive strategy to preventive, condition-based and proactive strategies, as well as those that incorporate probabilistic models [105]. These paradigms have been distinguished by different characteristics, strategies and rationales (motivations) [26]. Figure 6-2 outlines the evolution of the paradigms. Each paradigm has a measure of impact on the sustainability of business operations or on the risk profile of the asset base.

Figure 6-2: Evolution of equipment management paradigms

Figure 6-2 shows that the physical AM has gone through four strategic paradigms from 1940 to the present time. Each of these paradigms can be viewed as a technological generation with unique characteristics that distinguishes it from other generations [25], [105]. The first paradigm is the reactive strategy [25], [26]. It was more predominant from the time of the Second World War to around 1954 than it is today. It aims at fixing the assets after failing; hence it subjects the firms to surprises. Its basic rationale is to realize quick wins or short term cost savings. After that, the preventive paradigm emerged, predominantly spanning from around 1955 to 1977. This is implemented through time-based maintenance schedules. The motivation behind this is to reduce costs, thereby raising profit margins; and in so doing to eliminate surprises. The period between 1978 and 2000 was marked by a shift to predominantly condition-based paradigm, where maintenance and renewal regimes or tasks were determined by parameters indicative of the condition or state of the equipment. The rationale for this was to take advantage of every opportunity to lengthen the life of equipment by carrying out maintenance when it is necessary, unlike in the preventive regime where 50% of tasks might be unnecessary and wasteful [25]. Its main characteristic is that the equipment is maintained so that there is no breakdown. Finally, proactive strategies with probabilistic models have mainly been applied in the period between 2000 and the present. This paradigm is predominantly based on pre-emptive tasks that are aimed at optimizing reliability and avoiding failure. Like the condition-based, this is also opportunity driven, but it is characterized by continuous improvement in order to gain competitive advantage over other firms [25].

In practice, industries tend to incorporate a mix of these strategic paradigms. Therefore, even in the paradigm that is predominantly condition-based or proactive, some reactive strategies may still be employed. There are many reasons for such a mix. For example, in this research a case study of the run-to-failure strategy (which is one of the reactive strategies), has been applied and it shows that, traditionally, power utilities view that the strategy is suitable for the less capital-intensive assets. Figure 6-3 outlines a systems view of the strategy. It shows that short term strategies aimed at quick wins lead to the run-to-failure strategy and they negatively affect the AM planning process and asset condition. The case study showed that failure rates in the distribution business unit were very high and that asset managers implemented the run-to-failure strategy as the default strategy.

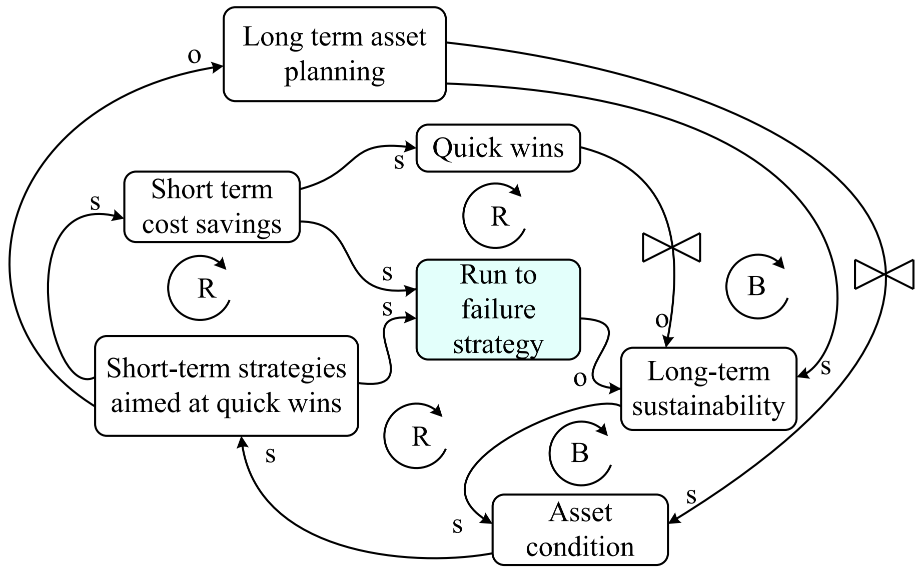


Figure 6-3: Systems view of run-to-failure strategy

The case study showed that there was no incentive for instituting radical changes in the distribution business unit as the value of the individual power transformers, relative to their transmission counterparts, was perceived to be very low. This is a reductionist thinking. A holistic, systems approach is required to change that mechanistic thinking in the power sector.

The case study further showed that, unlike the transmission system which in most cases has SCADA technology, most of the MV distribution assets are not connected to the SCADA. That makes control and fault location difficult. For this sub-Saharan Africa scenario, distribution losses have been recorded at as high as 22% (see, for example, Appendix I), which for a small power utility, translate to annual losses due to the ENS to the magnitude of US$ 1.0 million; against annual sales averaging at US$ 3.6 million (i.e., the ENS is 27.7% of annual sales). For this typical case, the capital outlay for extending the SCADA to the distribution (MV) is around US$ 20 million. The context highlighted above sheds some light as to why it is so difficult to have a technological advancement in the distribution sector in the region. Hence, sustainable energy supply cannot be achieved unless there is a paradigm shift in the way energy or power distribution assets are managed. This background reinforces earlier publications that revealed that the distribution system takes 30 to 40% of total investment in the electrical sector, but the industry has not received the technological impact in the same manner as the generation and transmission systems [23].

6.2.2 Mathematical formulation

This section adapts some statistical inference models from Chapter four, Section 4.2.2; and power generation data from case studies (from Appendix H) to show how AM paradigms affect the sustainability of energy supply. The data applied in the study is detailed in Section 6.3, whereas the results of the analysis are presented in Section 6.4.

6.2.2.1 Overview of statistical parameter estimation

In Chapter four, Section 4.2.2, it was demonstrated that the Weibull distribution parameters can be used in the component life-time modelling. The Weibull distribution is one of the most widely used distributions for analyzing failure data. The reason is that it can be used to model failure for various distributions including those where non-constant hazard conditions apply, and that its shape parameter (β) directly relates to the bathtub curve [35]. The bathtub curve represents life patterns of maintainable engineering systems based on the hazard rate, *h (t)*. Figure 6-4 outlines the bathtub curve hazard rates and the shape parameter.

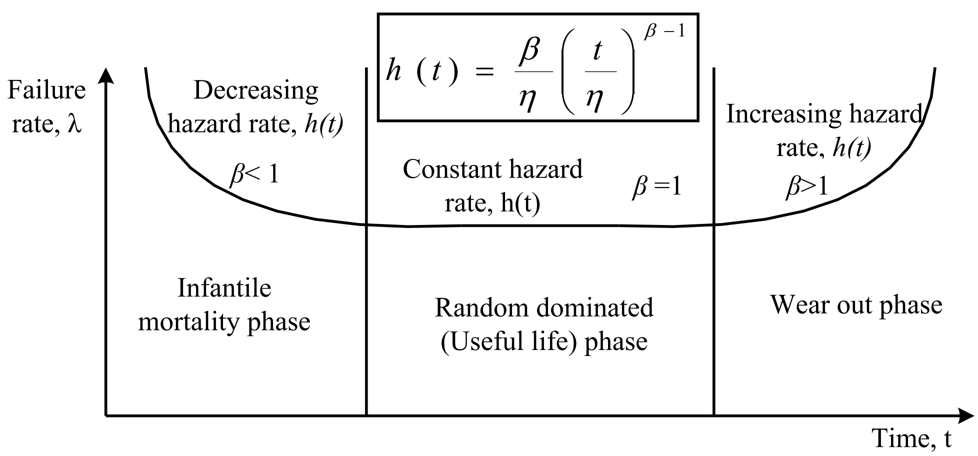


Figure 6-4: Weibull shape parameter and the bathtub curve

In the preceding chapters, it was shown that methods for processing data in order to determine the Weibull parameter estimates are the LSM, the MLE and the MOM [35], [82]. The LSM gives accurate results for large sizes of failure data and when the data is non-censored or un-truncated (complete). The MLE provides accurate results for both censored and non-censored data [35], but when the sample size is large, it simply reduces to the LSM [82]. The MOM may be used instead of, or to validate the results of the MLE [102]. In this thesis, the MOM and the MLE have been applied as a means of handling a few data sets (small sample sizes) as well as both censored and non-censored data. This section adapts these methods in processing the failure data that is presented in Section 6.3. Cost models that were presented in Chapter four are revisited because they are applied in some of the analyses.

6.2.2.2 Overview of cost models

In Chapter four, two forms of cost models were considered. One of them was based on the renewal theory as propounded by [59]. The other one was founded on Weibull-based survival likelihoods [35]. The one that is based on the Weibull survival likelihoods can easily model failure data even where small sample sizes are available, which is in contrast to the renewal-theory-based model and it was adopted with modifications as follows [98]:

$$C_T = £_u \cdot \left\{1 - e^{\left(-\frac{t}{\eta}\right)^{\beta}}\right\} + £_p \cdot R(t) \tag{6.1}$$

where C_T is the cost, $£_u$ and $£_p$ are unplanned and planned preventive maintenance costs, respectively, $R(t)$ is the reliability function; t is the time to failure; β and η are shape and scale parameters, respectively.

6.2.2.3 Generation adequacy models

This section outlines a case study of a power utility in the sub-Saharan Africa to examine how AM paradigms impact on sustainable energy supply by carrying out a mathematical analysis of the metrics (performance measures) that are employed by the utility. The case study shows how problems cascade from the generation business unit through the transmission to the distribution systems. The utility that is considered used availability to measure the performance of its generating power stations. Availability can be expressed in terms of the mean time between failure (MTBF) and mean time to repair (MTTR) as follows:

$$\text{Availability, } A = \frac{MTBF}{MTBF + MTTR} = \frac{1}{1 + \lambda_F\, t} = \frac{Uptime}{Uptime + downtime} \tag{6.2}$$

where, λ_F is failure rate and

$$MTBF = \frac{1}{\lambda_F} = \frac{Total\ \ operating\ \ \ time}{Number\ \ of\ \ failures} \tag{6.3}$$

$$\text{MTTR} = \tau = \frac{Total\ outage\ \ \ time}{Number\ \ of\ \ failures} = \frac{1}{\mu_R} \tag{6.4}$$

where μ_R is repair rate.

In general, availability of ≥ 97% is rated as World Class performance [25]. In the case study, the utility gets the satisfaction when the target world class availability level is achieved. This chapter critically examines this proposition with respect to two generation indices, namely: loss of load expectation (LOLE) and loss of energy expected (LOEE) or Expected Unsupplied Energy (EUE).

The LOLE is the average number of days where the daily peak demand is expected to exceed the available generation capacity. The LOEE or EUE is the expected energy not supplied by the generation system when the load demand exceeds the available generation capacity. These indices are expressed as follows [22]:

$$LOLE = \sum_{i=1}^{n} P(C_i - L_i)[day/year] \tag{6.5}$$

$$LOEE = \sum_{i=1}^{n} E_k p_k \; [MW] \tag{6.6}$$

where C_i = the available capacity on day i; L_i = forecast peak on day i; $P(C_i - L_i)$ = probability of loss of load on day i as obtained from capacity outage cumulative probability table; subscript k represents magnitude of capacity outage, O_k; p_k = probability of capacity outage corresponding to O_k; E_k = energy curtailed by a capacity of magnitude O_k. $p_k = P(x,p,n)$ and is computed by applying the binomial distribution given as follows:

$$P(x,p,n) = \binom{n}{x} p^x (1-p)^{n-x} \tag{6.7}$$

$$\therefore \; P(x,p,n) = p^n + np^{n-1}q + \frac{n(n-1)}{2!}p^{n-2}q^2 + \frac{n(n-1)\ldots(n-r+1)}{}p^{n-r}q^r + \ldots q^n \tag{6.8}$$

where x is the number of successes, p is the probability of success and n is the number of trials (in this case, it is the number of power generating station units).

In Section 6.3, the data that is used for the critical analysis is presented. The results and discussion follow in Section 6.4.

6.3 Modelling data

This section presents primary data, from a power utility, used to compute the results that are presented in Section 6.4.

Table 6-1 outlines times to failure for distribution transformers under the run-to-failure strategy (paradigm) and for transmission transformers under planned preventive maintenance paradigm. These data sets are processed to obtain life modelling parameters according to the mathematical formulation that was presented in Chapter four, Section 4.2.2. The average annual maintenance costs corresponding to the two types of transformers are presented in Table 6-2 (extracted from Appendix B, Table B4).

Table 6-1: Times to failure data for transformers

	Time to failure (x 10^3 hrs.)			
Distribution (200 kVA)	0.07488	0.07488	0.01123	0.03182
	0.06739	0.07301	0.0805	0.8237
	0.09173	1.554	2.771	4.512
	Time to failure (x 10^5 hrs.)			
Transmission (12 MVA)	1.892	1.971	1.971	2.182
	2.31	2.418	2.365	3.715
	3.925	4.03	4.188	4.366

Table 6-2: Costs of planned and unplanned maintenance

Type of transformer	Average maintenance costs in US $	
	Planned ($£_p$)	Unplanned ($£_u$)
Transmission	17 466.7	30 000
Distribution	748.3	1300

Computation of generation adequacy indices was based on three power stations (from Appendix G) with 5 x 20 MW, 2 x 25 MW and 2 x 32 MW units at 83.7%, 97.7% and 97.3% availability, respectively.

6.4 Results and discussion

This section presents and discusses the results of the Weibull parameter estimates, generation adequacy analysis and simulation of reliability functions as well as trends of preventive maintenance costs. Data from Table 6-1 is used to compute the parameters using the MLE and MOM models that were elaborated in Section 4.2.2, whereas Table 6-2 is used to evaluate costs using the cost model, that is, equation (6.1).

6.4.1 Computed life parameters

Table 6-3 shows the Weibull parameters that have been computed using the mathematical models that were presented in Section 4.2.2.

Table 6-3: Life modelling parameter estimates

Method used	Parameter (standard error, se, shown in parenthesis)			
	Transmission		Distribution	
	$\hat{\beta}$	$\hat{\eta}$ [10^5] hrs.	$\hat{\beta}$	$\hat{\eta}$ [10^3] hrs.
MLE	3.434 (se: 0.788)	3.29 (se: 0.293)	0.5257 (se: 0.111)	0.3846 (se: 0.225)
MOM	3.499 (se: 0.669)	3.279 (se: 0.303)	0.6904 (se: 0.551)	0.5556 (se: 0.397)

The parameter estimates obtained using the MLE and MOM are so close to each other (almost the same) that it can be suggested (inferred) that the two methods can be used interchangeably. However, the parameters from the MLE have been applied in the further analysis, because it gives better standard deviations when the number of hours to failure is small as is the case for the distribution transformers on the run-to-failure strategy. The further analysis of the parameters includes generation of reliability plots. Furthermore, generation adequacy indices are calculated. The results of generation adequacy analysis are presented in Section 6.4.2, whereas the application of the parameters to generate the plots of probability functions and trends of costs associated with the two maintenance regimes (paradigms) are demonstrated in Section 6.4.3.

6.4.2 Generation adequacy analysis

Equations (6.5) − (6.7) were applied to compute the results of LOLE and LOEE for the three power generating stations that are listed in Section 6.3. These are presented in Tables 6-4 to 6-6. The full analysis of percentage (%) of time the load is curtailed is presented in Appendix G, whereas the raw data used for the analysis is presented in Appendix H.

Table 6-4: LOLE/LOEE at 83.7% availability (Station I)

Units out	Capacity out (MW)	Capacity Available (MW)	Load loss (MW)	Expected Load loss (MW)	Probability	Probability of load loss	% time	LOLE (Days/yr.)	LOEE (MW
0	0	57.66	0	0.0000	0.4123	0.0000	0.0000	0.0000	0.0000
1	20	37.66	0	0.0000	0.3997	0.3997	0.0000	0.0000	0.0000
2	40	17.66	0	0.0000	0.1550	0.1550	0.0000	0.0000	0.0000
3	60	-2.34	3.18	0.0955	0.0300	0.0300	0.3705	1.1134	0.0354
4	80	-22.34	23.18	0.0675	0.0029	0.0029	0.7902	0.2302	0.0534
5	100	-42.34	43.18	0.0049	0.0001	0.0001	1.0000	0.0113	0.0049
				0.1679	1.0000	0.5877		1.3549	0.0936

Table 6-5: LOLE/LOEE at 97.7% availability (Station II)

Units out	Capacity out (MW)	Capacity Available (MW)	Load loss (Curtailed) (MW)	Expected Load loss (MW)	Probability	Probability of load loss	% time	LOLE (Days/yr.)	LOEE (MW)
0	0	50	0	0.000	0.955	0.000	0.000	0.000	0.000
1	25	25	0	0.000	0.045	0.045	0.332	1.485	0.000
2	50	0	7.45	0.004	0.001	0.001	1.000	0.052	0.004
				0.004	1.000	0.045		1.538	0.004

Table 6-6: LOLE/LOEE at 97.3% availability (Station III)

Units out	Capacity out (MW)	Capacity Available (MW)	Load loss (Curtailed) (MW)	Expected Load loss (MW)	Probability	Probability of load loss	% time	LOLE (Days/yr.)	LOEE (MW)
0	0	64	0	0.000	0.947	0.000	0.000	0.000	0.000
1	32	32	14.04	0.738	0.053	0.053	0.390	2.047	0.287
2	64	0	46.04	0.034	0.001	0.001	1.000	0.073	0.034
				0.034	1.000	0.001		2.120	0.321

The results show that the LOLE and LOEE are better metrics for power utility AM performance evaluation than availability. It is possible to see the magnitude of loss margin (risk level) with the LOLE and LOEE, but not so with the availability. For example, the 97.3% and 83.7% availability yield LOLE of 2.12 (from Table 6-6) and 1.35 (from Table 6-4) days/yr., respectively. Availability of ≥ 97% is rated as world class [25]. Thus, it is evident that the high (world class) availability (97.3%) leads to poorer LOEE than that from the low availability (83.7%). Most often power utilities use availability, an adjunct of the MTBF, and Effective Forced Outage Rate (EFOR) instead of the loss margin (LM). Neither the MTBF nor the EFOR can show the ability to operate when required, but the LM (e.g., LOEE) can do that [25].

Section 6.4.3 compares trends of reliability and costs associated with the two AM paradigms, namely: the run-to-failure and planned preventive maintenance in order to demonstrate how a systems thinking approach can help in ensuring sustainable energy supply.

6.4.3 Reliability and cost analysis

In the Chapters three to five, it was shown that the CDF, PDF and hazard rate are important in modelling the technical life of components; so that the impact of strategies on costs can be evaluated. Time horizons considered for cost models must be based on the CDF and PDF because of the following reasons: the CDF gives a projection of the life span or the probability of having a life span of at most x, whereas the PDF indicates the chance of a unit failing at the age of x. These functions play an important role in mitigating the risk in the process of energy supply. The CDFs, PDFs and plots of costs were generated using parameters that were derived by the MLE, listed in Table 6-3. The detailed analysis and discussion is provided in Section 6.4.3.1.

6.4.3.1 Survival probabilities and hazard rates

Figures 6-5 and 6-6 are hazard rates for the distribution transformers and transmission transformers, respectively. The hazard rate, *h (t)*, is the probability that a component that has survived up to a given time will fail. It represents the risk associated with the component. For the distribution transformers, the *h (t)* at time zero is 0.023 and it decreases asymptotically. For the transmission transformers, the *h (t)* increases gradually from zero at t = 0 and it takes about 25 years to reach the value of its distribution counterparts at time zero. This shows that the risk of failure for the distribution transformers under the run-to-failure strategy is very high.

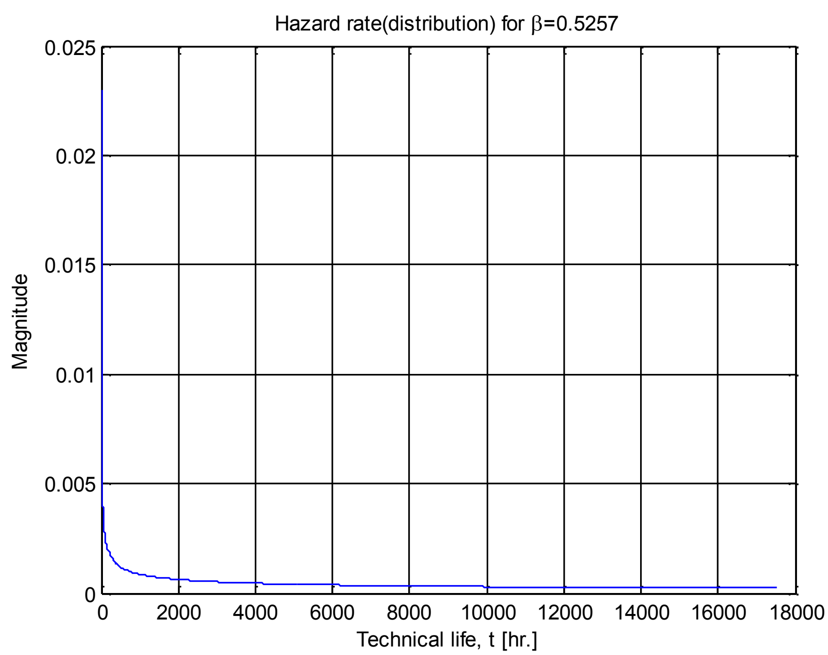


Figure 6-5: Hazard rates (distribution transformers)

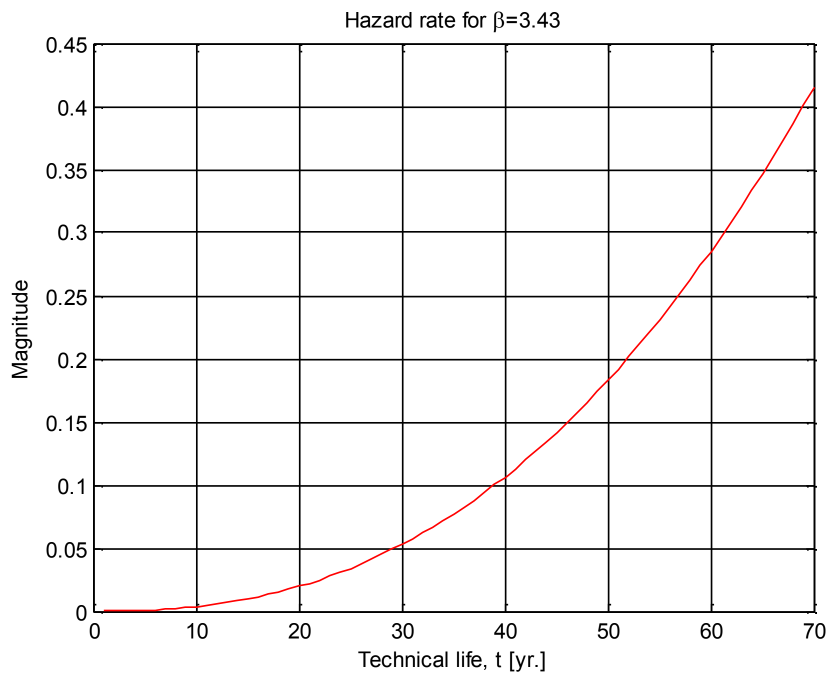


Figure 6-6: Hazard rates (transmission transformers)

Figures 6-7 and 6-8 display the PDFs for the distribution and transmission transformers, respectively. The PDF for the distribution is very low, ranging from 0 to 4 x 10^{-3} within a year; whereas that for the transmission is relatively high, ranging from 0 to 0.035 within 70 years.

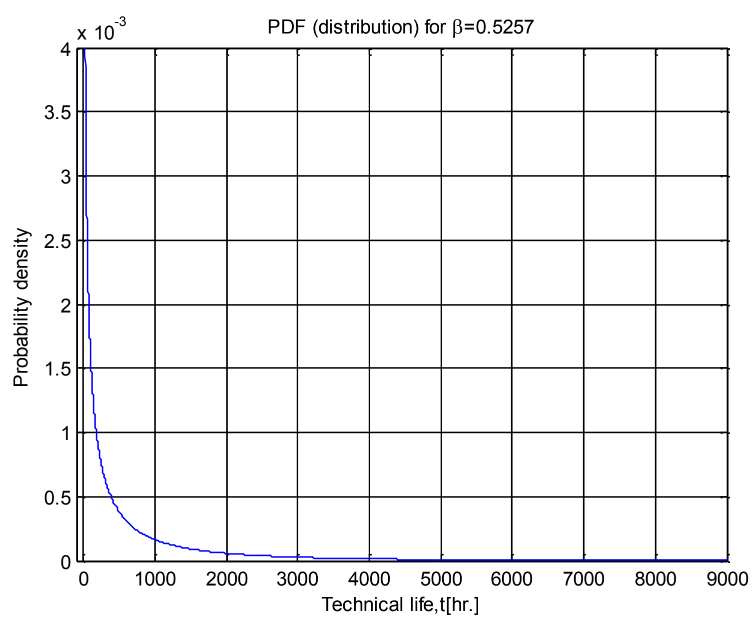


Figure 6-7: PDF (distribution)

A critical examination of the distribution asset history showed that the poor asset performance was partly caused by the run-to-failure strategy and partly by poor pre-installation planning. For example, failure analysis showed that 50% of causes of failure were related to improper earth impedance, fuse rating and surge diverter rating. On the other hand, the situation for the transmission transformers was different as they went through a thorough planning phase prior to the installation stage.

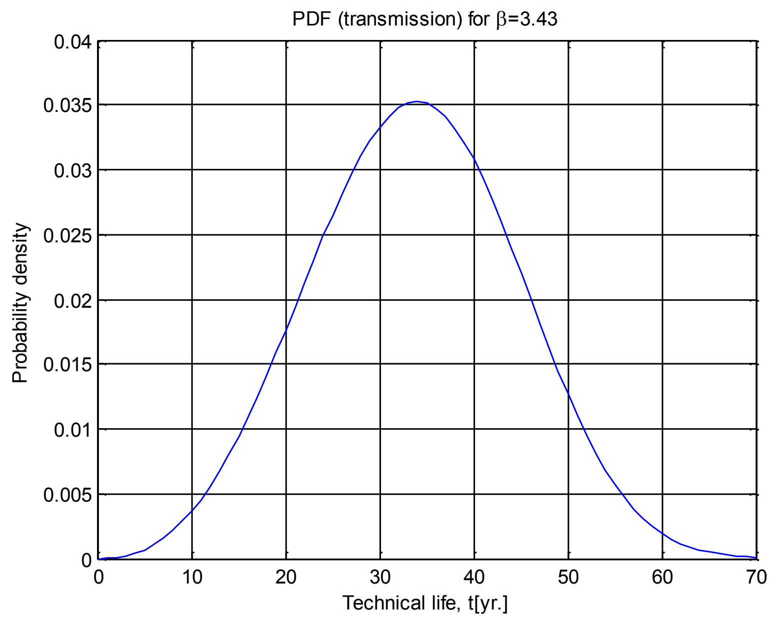


Figure 6-8: PDF (transmission)

Figure 6-9 portrays the CDF for the distribution transformers, which rises from 0 to 1 in about 1.2 years. Figure 6-10 is the CDF for the transmission transformers. It rises from 0 to 1 in about 70 years (actually, 67years).

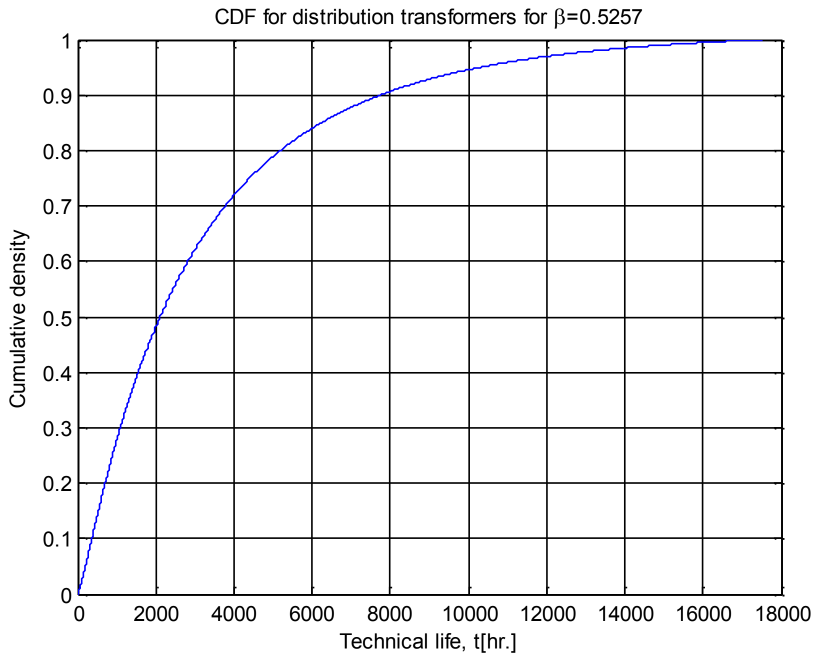


Figure 6-9: CDF (distribution transformers)

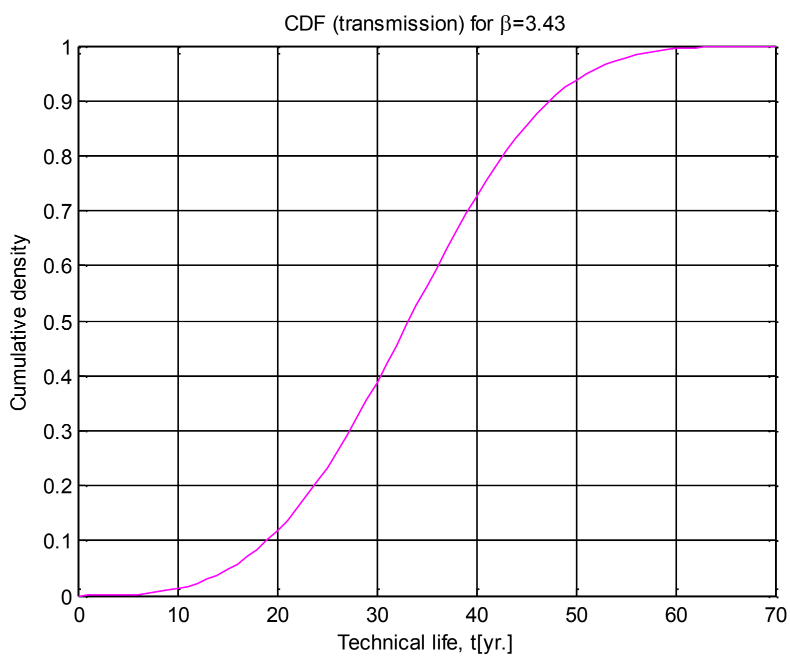


Figure 6-10: CDF (transmission transformers)

The CDF shows the ultimate lifespan that each of the two asset groups can attain, which is very poor for the distribution assets that are managed on the run-to-failure strategy.

The next section concludes the presentation and analysis of results, but focusing on the impact of the strategies on maintenance costs.

6.4.3.2 Simulation and modelling of costs

Figure 6-11 compares costs for distribution and transmission transformers under the run-to-failure regime and planned preventive maintenance, respectively. Point A on Figure 6-11 is a point in time when planned costs equal unplanned costs for the distribution transformers, which happens just at about a month of operation. This point corresponds to point B for the transmission transformers, which occurs at about 30 years of age.

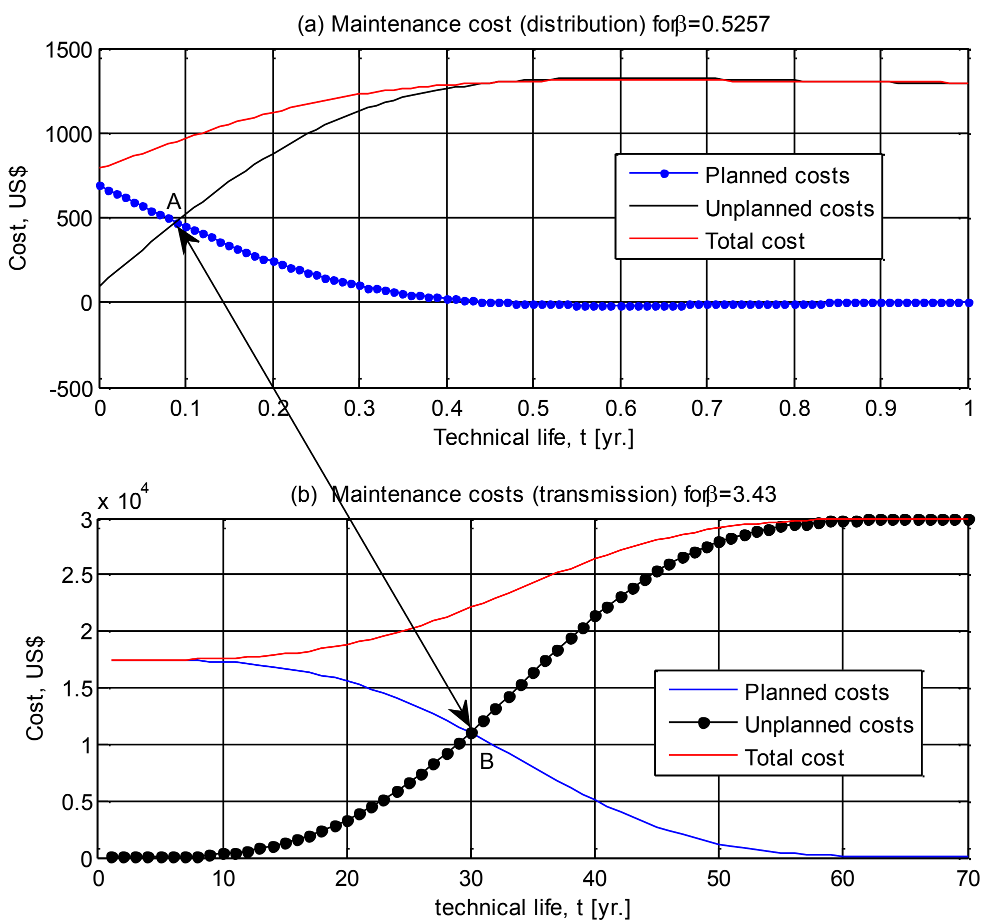


Figure 6-11: Comparison of costs: (a) distribution and (b) transmission transformers

In terms of AM, points A and B are decision criteria for either refurbishment or other end-of-lifecycle strategies so as to ensure that downtime costs do not exceed planned maintenance costs. It can be seen that point A (Figure 6-11) is reached too early in the distribution items (that are run-to-failure) to make the strategy sustainable. The frequency of failure means that high operating costs are incurred in an effort to rectify the problems.

Point B represents 44.8% of the lifespan of the transmission transformers. It can be inferred that the refurbishment can be timed at, say, 42-44% of the lifespan, that is, 28 to 30 years of age. Thus the model presented can be a useful tool for the life cycle management planning by power utilities.

Comparison of costs in Figure 6-11 shows that costs incurred on the distribution transformers per year account for 5.2% of costs incurred in a 30-year period of their transmission counterparts. Therefore, although the run-to-failure strategy is viewed to provide quick wins in the short term, it is too expensive and unsustainable in the long run. This result is similar to what another researcher indicated by stating that the run-to-failure strategy is not the least cost option for aging infrastructure assets, as most utilities think, because it leads to high customer interruption costs [13]. It has been possible to see this (holistic picture) because of the systems approach that was applied in this chapter. This result is similar to what [25] showed by stating that industries tend to lose out when they focus on short term gains at the expense of long term sustainability.

6.5 Chapter conclusions

The chapter employed a multi-method technique comprising a longitudinal case study, statistical inferences from the MLE and MOM as well as parametric reliability modelling using the Weibull distribution. The study showed that a holistic view, provided by systems thinking approach, helped to narrow down to root causes of unsustainable power utility AM practices. The study further showed that reliability modelling is a crucial part of the risk management planning and analysis (simulation) processes, but it is usually hard to get sufficient data needed for the analysis. Hence, modelling reliability and drawing statistical inferences with a few data sets was achieved by the application of the Weibull distribution. The statistical parameters were estimated using the MOM and MLE. In terms of the standard errors, the MLE provided more accurate results than the MOM when the number of hours to failure was small. This was particularly the case for the distribution transformers which were on the run-to-failure strategy. Hence, the MLE results were adopted for simulation and modelling. Moreover, literature review also confirmed that the MLE was the best for the censored data and for such small sample sizes as the ones encountered in the study. Furthermore, the study demonstrated that asset managers can get a revelation of some hidden losses by applying metrics that show the magnitude of the loss margin such as the LOLE and LOEE, as opposed to relying solely on availability (as a metric used by default). It was also shown that assets with world class level of availability (i.e., 97%) had poorer LOLE than those with relatively low availability (i.e., 83%). Furthermore, the study showed that unbalanced (uncontrolled) outsourcing can lead to irreversible loss of technical skills. The systems approach as well as the reliability and cost analyses applied in the study showed that the adoption of the run-to-failure strategy is not as good as asset managers may think. It provides quick wins, but at the expense of security of energy supply as it drains financial resources that would otherwise be re-invested in the energy or power infrastructure. The analysis showed that planned and unplanned maintenance costs for distribution transformers under the run-to-failure strategy in the first year of operation can reach up to 5% of costs incurred in a 30-year period of their transmission counterparts. The power distribution industry can offer great financial returns if rigorous attention is paid during the planning phase as is the case with the transmission system. A systems view of distribution AM must be implemented for long term sustainability of energy supply. The distribution system accounts for 40% of total assets in the power utility and may encounter system losses of up to 22% of the load dispatched with ENS as high as 27.7% of energy sales, but it does not receive the attention it deserves. Conclusively, in order to optimize returns on assets for sustainable energy supply, a paradigm shift, from reductionist or mechanistic view to systems thinking, must take place. The shift can help in eliminating the strategies that do not lead to a sustainable energy supply in a resource constrained, developing world. This approach should form part of an integrated risk management modelling process. Although the model provided in Chapter six views AM with respect to a small power utility, the results are relevant to large industrial and commercial users of energy as well [123]. The model can be used during the AM planning processes by the utilities. Appendix C contains comments from peer reviewers regarding the importance of the approach presented in this chapter. Risk modelling can be viewed as the best way of forecasting risk scenarios so that contingency plans can be made well in advance to avoid operational bottlenecks. The chapter that follows presents conclusions and suggestions for future research.

CHAPTER SEVEN

CONCLUSIONS AND SUGGESTIONS FOR FUTURE WORK

This chapter gives a brief summary of research findings and presents suggestions for further work.

7.1 Conclusions

In this research, the objectives and hypothesis have been fulfilled. A component risk trending model has been developed and its application demonstrated. It is capable of trending the failure risk and the associated cost benefits. This can be used in the risk management of physical assets. The model could enable asset managers to forecast when to implement asset management (AM) renewal strategies to best mitigate the risk and achieve financial returns that are required for long term sustainability of their business operations. The model showed that the impact of major end-of-life renewal on the risk is great, but the intended financial benefits (savings in O & M costs) come too late in the lifespan. On the other hand, the major mid-life renewal yields steady financial (cost) benefits which come in good time for reinvestment into the business. The risk trending model can be applied to any type of physical asset provided the expression representing its failure function over its lifespan is established or known.

The study incorporated analytical techniques in the systems thinking approach, thereby enhancing the quantitative capabilities of the approach. This was possible by developing and utilizing a dynamic hypothesis, that is, a theory (or expression) defining how the problem evolves. In the context of the current study, the problem that was dealt with by focusing on how to model the application of renewal strategies to alter the risk profile of physical assets. However, it is worth mentioning that the application of systems thinking to establish causation on its own does not optimize AM systems, but the tools that are used to solve the specific problems that have been identified through the systems approach should be used to optimize the systems or processes. In this thesis, the Weibull distribution parameters were the ones that were optimized through the application of parameter optimization methods, that is, the MLE and MOM. Other methods that could be used for optimization of the actual maintenance or inspection strategies are the SMDP and MDP models, but these are beyond the scope of this thesis.

The risk trending model also showed that, through sensitivity analysis of the risk factor with respect to the O & M costs, it can be used to predict the appropriate timing of refurbishment. This is shown to be at a point just before the cost of unplanned maintenance exceeds the cost of planned maintenance. For the 12 MVA transformers that have been used as an illustrative case, this happens at 44.6% of the technical life. This means, allowing for logistical delays in the execution of the renewal (refurbishment) work, the best time for starting the work should be at about 40% of the lifespan.

The model tackles one of the key challenges in power utility AM, that is, the data unavailability problem. This is done by utilizing only a few sets of data (sample sizes). The data unavailability problem arises because most utilities have problems putting their asset registers up to date. They tend to lose track of the records because of the long lifespan of the assets. The problem becomes more complicated when the number of assets in the network is large. In the current study, it was possible to get up to date failure statistics (singly censored data, for transformers from the same manufacturer) from a small electric grid in which the number of equipment was small enough to easily track their records.

Since the RCM is a very important philosophy in the establishment of appropriate maintenance strategies and in risk assessment, the study incorporated the RCM in an integrated risk-based AM approach. The study revealed that the RCM does not have a robust probabilistic capabilities, it is heuristic and requires extensive expert consultations during its decision algorithm process, especially during the implementation of the FMECA. Two models have been developed and proposed to augment the RCM and to simplify the risk assessment and characterization process, namely: a comparative failure probability model, where the CDF and hazard rates are generated and plotted to represent the risk; and a Markov transient probability model, where probabilities and MTTFF are generated. These generated probabilities can be used for benchmarking against similar equipment and as inputs into the FMECA. Furthermore, the MTTFF is inversely proportional to annual cost rates; hence this property was applied to quantify the benefits of maintenance strategies that are implemented within the RCM philosophy. This capability has been lacking in the current approaches for conducting the RCM philosophy, and it has been one of the major criticisms about the RCM. In general, the RCM model that has been developed can be used for risk-priority screening when a large population of transformers or equipment is involved in the risk assessment; so that any rigorous testing procedures can still be carried out but only on the critical assets, thereby reducing operating costs and time.

Furthermore, the systems view of AM paradigms revealed hidden opportunities for improvement of AM performance by showing how some most commonly used metrics can be misleading when viewed in isolation. This was demonstrated by applying mathematical expectation theory to power generating station data to derive a measure of loss margin which was compared with the availability. It was demonstrated that availability is just like MTBF in that it is neither able to show the degree of loss margin incurred by a firm, nor the ability of the equipment to operate when needed; whereas metrics like LOLE, ENS and LOEE are able to show that. Hence, firms need to apply multiple performance measures so that the hidden risks and loss margins can be revealed. This is a systemic (holistic) application of metrics (performance measures). Similarly, the systems approach was able to show that some strategies that appear to reap economic returns in the short term may not be good for the long-term sustainability of the firm. This was demonstrated by contrasting cost trends and reliability functions for distribution transformers under the run-to-failure strategy with those under the planned maintenance. The run-to-failure strategy subjects assets to high hazard rates and high maintenance costs. The analysis showed that planned and unplanned maintenance costs for the distribution transformers under the run-to-failure strategy in the first year of their operation can reach up to 5% of costs incurred in a 30-year period of their transmission counterparts.

In summary, the systems thinking approach that was applied in the development of models in this study has fulfilled the objectives of the study in three ways. First, it has integrated system dynamics concepts with stochastic and probabilistic inferences to develop risk trending models. Second, it has augmented the probabilistic capabilities of the RCM so that it better fulfils its role in the integrated risk management process and in quantifying the cost benefits of the selected maintenance strategies. Third, it has holistically evaluated the impacts of AM paradigms on the risk profile so as to expose the unsustainable practices or performance measures. In addition, it has shown how risks can cascade from the generation business unit down to the distribution system. The study has fulfilled the hypothesis and the objectives, but there are still some windows of opportunity for further research. These are outlined in Section 7.2.

7.2 Suggestions for future work

In order to develop the risk trending model in Chapters three and four, the power grid AM was presented as consisting of several subsystems in state-space transition. Only one subsystem, consisting of components under high-operating intensity, was considered for further model development. In future, more subsystems should be modelled as more data becomes available. For example, the operations and performance subsystems are potential candidates for future model development.

Besides, the risk trending model was developed based on the number of components renewed. It was assumed that all components have equal impact on the risk level. In practice, some components will have greater impacts than others. Future research should therefore incorporate weighting factors to distinguish components that have greater impact on the risk profile from those that have lower impact.

In addition, the current work only utilized failure statistics. Further work should consider both failed and surviving components in the network. Utilization of surviving items requires a lot of data, which will pose a great challenge in the initial stages of the data analysis, but it will eventually be feasible as more data is acquired.

Furthermore, the type of cost models considered in the cost benefit analysis in Chapter four utilized planned preventive and unplanned (breakdown) costs only. These models are simpler than the MDP or SMDP models that are normally used for optimizing inspection rates and maintenance strategies or policies. The simple maintenance cost models were chosen to illustrate the application of the cost benefit analysis in the risk trending model. Since the purpose of the risk trending is to show how the risk profile varies with time (and not necessarily to optimize maintenance or inspection strategies), the application of the simple cost models sufficed for the analysis. Moreover, these models could prove to be user friendly to most asset managers in industry. This leaves more avenues to explore in future, such as incorporating imperfect repair costs and applying the MDP and SMDP models in the optimization of maintenance policies and strategies.

Finally, the present research mainly considered power transformers and some reactors. Further research should, therefore, expand the analysis to other types of assets like switch gears, contact breakers and load interrupters.

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APPENDICES

Appendix A: Robot type of risk matrix

Table A-1: Risk matrix model showing the probabilities and impact scales [10]

RISK MATRIX (RISK LEVELS)								Financial	Safety	Community	Environmental	Govt. relation
		3	1			1		>500m m = million	more than 10 fatalities	more than one fatality	Irreversible impact pristine environment	Breakdown in relations with Govt.
		3	2			1		100 - 500m	more than 1 fatalities	one fatality	Serious national environmental impact	Breakdown in relations with MEC
		4	3			2		10 - 100m	one fatality	hospital or multiple press	Very serious long term environment regional	Breakdown in relations with people in Govt. dept.
		5	3			3		1m - 10m	hospital	Press article wrt. complaint	Serious long term impact regional environment	Breakdown in relations, local Govt.
		6	5			4		100 000 - 1 m	LWDC	Complaint against e.g. smell	Serious but reversible impact regional level	None
		6	6			5		10 000 - 100 000	Medical treatment / Light duty	None	Moderate reversible impact local	None
		6	6			6		10 000 - 100 000	Medical treatment / Light duty	None	Moderate reversible impact local	None
		3	4			7		<10 000	First aid / no injury	None	Limited effect within plant boundaries	None
Remote	highly unlikely	Not during lifetime of operation	Once in lifetime of operation	Once in ten years	Once per year	More than once per year						
0.0005%	0.005%	0.05%	0.05 - 10%	10 - 68%	69 - 90%	91 - 100%						
Probability								**Impact scales**				

Appendix B: Transformer life-data and average annual O & M costs

Source: Electricity Supply Corporation of Malawi (ESCOM)

Table B-1: Life data of 12 MVA, 66/11 kV transformers

No	In-service yr.	Retirement yr.	Max. yrs.	Service hrs.	Service hrs. at 92% availability factor	DP at retirement
1	1969.0	1993.0	24.0	210200.0	189200.0	150
2	1969.0	1994.0	25.0	219000.0	197100.0	200
3	1969.0	1997.0	27.7	242400.0	197100.0	200
4	1969.0	1998.0	29.0	254000.0	218200.0	180
5	1969.0	1998.3	29.3	256668.0	231001.2	200
6	1969.0	1999.7	30.7	268669.2	241802.3	180
7	1969.0	1999.0	30.0	262800.0	236520.0	150
8	1969.0	2005.0	36.0	403797.8	371494.0	150
9	1969.0	2007.7	38.7	426678.6	392544.3	180
10	1969.0	2009.0	40.0	447811.1	403030.0	200
11	1969.0	2011.0	42.0	465331.1	418798.0	200
12	1969.7	2013.0	43.3	485148.2	436633.4	200

Note: Data in Table B1 is Single vintage, singly censored and from same manufacturer

Table B-2: Times to failure for 200 kVA, 33/0.4 kV transformers on a run-to-failure strategy

No.	Substation code	In-service time	Service hrs. at failure
1	A-Ndodo	14/05/2011	74.88
2	B-Jenala	18/01/2013	74.88
3	C-Malika	23/03/2012	11.23
4	D-Patrick	07/09/2012	31.82
5	E-Chika	23/03/2012	67.39
6	F-LL	18/02/2012	73.01
7	G-Silicon	17/03/2013	80.50
8	H-Masanja	28/02/2012	82.37
9	I-Admark	18/12/2012	91.73
10	J-Njuli	13/05/2012	1554.0
11	K-Chika	16/05/2012	2771.0
12	L-Didi	03/02/2013	4512.0

Table B-3: Average HV transformer operations and maintenance (O & M) costs

Transformer description	Average annual O & M costs (US$)	
	Planned	**Unplanned**
TRFR, 11kV/240V, 16kVA, ONAN, 31mm/kV	40.96	69.58
TRFR, 22kV/240V, 16kVA, ONAN, 31mm/kV	47.57	80.80
TRFR, 10MVA, 132/11-kV, YNd1, OLTC, 31mm/kV	12314.83	20920.37
TRFR, 12MVA, 66/11-kV, YNd1, OLTC, 31mm/kV*	17466.01	29671.17
TRFR 40MVA, 132/11-kV, YNd1, OLTC, 31mm/kV (High Imp)	24404.37	41458.02
TRFR 10MVA, 132/22-kV, YNd1, OLTC, 31mm/kV	12845.39	21821.68
TRFR 20MVA, 132/22-kV, YNd1, OLTC, 31mm/kV	17022.28	28917.36
TRFR 40MVA, 132/22-kV, YNd1, OLTC, 31mm/kV	21416.94	36382.99
TRFR 20MVA, 132/33-kV, YNd1, OLTC, 31mm/kV	18365.80	31199.73
TRFR 40MVA, 132/33-kV, YNd1, OLTC, 31mm/kV	23618.26	40122.59
TRFR 80MVA, 132/33-kV, YNd1, OLTC, 31mm/kV (Arc Furnace use)	30806.43	52333.81
TRFR 10MVA, 88/11-kV, YNd1, OLTC, 31mm/kV	11001.14	18688.68
TRFR 20MVA, 88/11-kV, YNd1, OLTC, 31mm/kV	15372.40	26114.55
TRFR 10MVA, 88/22-kV, YNd1, OLTC, 31mm/kV	10933.01	18572.95
TRFR 20MVA, 88/22-kV, YNd1, OLTC, 31mm/kV	15140.24	25720.16
TRFR 20MVA, 88/33-kV, YNd1, OLTC, 31mm/kV	16900.87	28711.12
TRFR 40MVA, 88/33-kV, YNd1, OLTC, 31mm/kV	26082.78	44309.30
TRFR 80MVA, 88/33-kV, YNd1, OLTC, 31mm/kV (Arc Furnace use)	29163.42	49542.68

*This data is applied for the computation of costs in Chapters four and six.

Table B-4: Average MV/LV transformer annual O & M costs

Transformer description	**Average O & M costs (US$)**	
	Planned	**Unplanned**
TFR 1000kVA 11kV/415V W/CBL BOX	4686.32	8141.39
TFR 1000kVA 22kV/415V W/CBL BOX	4342.81	7544.61
TFR 200kVA 11kV/415V *	748	1300.00
TFR 100kVA 22kV/415V	764.49	1328.13
TFR 16kVA 11kV/240V	234.00	406.53
TFR 16kVA 22kV/240V	257.65	447.60
TFR 200kVA 11kV/415V	1224.00	2126.42
TFR 200kVA 11kV/415V W/CBL	1242.78	2159.03
TFR 200kVA 22kV/3.3kV	1578.51	2742.29
TFR 200kVA 22kV/415V	1324.20	2300.48
TFR 200kVA 22kV/415V W/CBL BOX	1231.30	2139.10
TFR 25kVA 11kV/415V	374.05	649.83
TFR 25kVA 22kV/415V	403.59	701.14
TFR 315kVA 11kV/415V	1601.40	2782.07

Note: * This data set has been applied in Chapter Six

Appendix C: Excerpts of peer reviewers' comments

C1: International Conference on Industrial and Commercial Use of Energy (ICUE, 2014)

Comments from two peer reviewers state that the paper is excellent. While the paper approaches the problem of asset management from the perspective of the utility, the results are of importance for all large industrial and commercial users of electricity that maintain a sizeable electrical infrastructure.

The paper is well written and well structured. The paper is grammatically and typographically sound. Graphic presentations are readable, correctly annotated and of good quality.

The mathematical modelling is detailed and correct. An extensive simulation study is conducted to produce the results.

A set of relevant results, focusing on distribution transformers, are presented. The results are well interpreted and highly relevant to the local utility and large consumers with electrical infrastructure. The authors identify the practical issues that can impact on the validity of the results, e.g. sample size, data availability, etc.

C2 Component risk trending model — IEEE Systems Journal

Comments from four reviewers indicate that the journal article presents an interesting and innovative way of trending the component risk profile by applying the MLE of Weibull parameters to systems thinking in an innovative way. The paper is highly relevant to the IEEE Systems Journal.

C3: Transformer risk modelling (Part of Chapter 5) — EPSR Journal

Comments from three peer reviewers state that the paper presents new ideas with promising results in the way the RCM should be conducted in future, and that the paper is well organized.

Appendix D: Asset management technologies and techniques

This appendix provides a brief description of asset management technologies and techniques, extending what was discussed in Chapter two, Section 2.5.1. The excerpts are mainly sourced from [25]. Specific areas that have been obtained from elsewhere have been clearly shown, for example, excerpts from [2], [68], [124], [125], [126].

D1.1 Hardware type of technologies

The review of asset management (AM) technologies begins with a brief description of the hardware type of technologies. First, resistance to ground (RTG) is mostly performed off-line to measure direct current (DC) leakage flowing to and through insulation system to ground under pressure of a controlled DC voltage to monitor the integrity of the insulation system isolating the power conductors from the ground. A variation of the RTG is the polarization index (PI): the ratio of the RTG after 10 minutes to the RTG after 1 minute of continuously applied constant voltage [25], [124]); and dielectric absorption ratio: the RTG value taken at 1 minute divided by the TRG value taken after 30 seconds of continuously applied, constant voltage. A profile of the PI called polarization index profile (PIP) can be made by plotting the RTG using a 500 or 1000 volt DC every five seconds, for up to 10 minutes. Through the PIP, weak systems or presence of water in the system exhibit dips on the profile [25].

Second, surge comparison or surge testing involves off-line insertion of controlled electrical pulses into a motor or generator from capacitor or capacitor like circuits; then, monitoring return-pulses which have been damped and may exhibit instability caused by change in inductive reactances of the motor coils or resistance in the circuit. These are evaluated to assess the condition of winding coil turn-to-turn and insulation, or to reveal phase-to-phase insulation and coil orientation [25].

Third, high potential (Hi Pot) testing involves off-line application of AC or DC voltage, higher in value than that for which an electrical circuit is rated, to evaluate the integrity or margin of the ground insulation system (against its breakdown under the electromotive force) by measuring leakage current through and over the ground insulation system [25].

Fourth, motor current balance analysis (MCBA) involves taking a set of two or three current measurements in poly-phase electrical circuits and mathematically comparing them to determine their percentage unbalance resulting from impedance mismatch between circuit phases, faults in power generation, transmission and distribution systems.

Fifth, partial discharge monitoring (PDM) refers to detection of partial (corona) discharges (small electrical sparks occurring in void spaces in and around conductor insulation) by a corona detector when voltage differential is strong enough to initiate and sustain them. They are most prevalent inside and at exits of stator winding slots and between end-turns.

Sixth, motor circuit analysis (MCrA) or motor circuit evaluation (MCE) is an off-line measurement of the following naturally occurring electrical parameters: resistance in the conductor path; inductance; capacitance to ground; and resistance to ground. Analysis involves development of trends, pattern recognition, correlation of combination of parameters, statistical comparison, calculation of unbalance, and graphical presentation for diagnosis of defects.

Seventh, motor current signature analysis (MCSA) mostly involves analysis of two AC motor line current spectra, the first one analyzed after Fast Fourier Transformation (FFT) in the frequency domain around the power supply frequency (60 or 50 Hz) whereas the second in the frequency domain around the center frequency. Frequency spikes (side bands) in the spectrum around the line frequency spikes indicate the presence and influence of various motors faults on current amplitude, as well as the dominant mechanical characteristics of both the motor and devices driven by it. The severity of faults is indicated by comparing current amplitudes of spikes at the line frequency and sideband frequency.

Eighth, motor power (electrical signature) analysis (MPA) involves measuring, conditioning and instantaneously recording and further processing for time and frequency domains of all phase currents and voltages associated with a motor, while on-line and carrying some amount of load. It detects degraded conditions at very early stages of their development through calculations of power losses and measurement of waveform to detect output voltage spikes and harmonics.

Ninth, motor flux or leakage flux analysis (MFA) as the name infers, refers to detection of leakage flux. Leakage flux, as opposed to flux concentrated inside the shell or enclosure, refers to magnetic flux detected in the space near the outside of motors while in operation (on-line). The analysis involves comparing conditioned output signals from the flux coil presented on a FFT frequency spectrum that typically runs from 0 Hz to 10 or 20 Hz above two times the line frequency. Specific frequency lines in the spectrum flux amplitudes can be related to particular types of defects and as the defects increase, the amplitudes also increase.

Finally, time domain reflectrometry (TDR) involves inserting a voltage pulse into an electrical circuit to let it travel to the end of the circuit unless it encounters a defect such as a high resistance connection. The defect will reflect a portion of the energy of the inserted pulse back to the origin. The time it takes for the reflected voltage signal to make the round trip and return to the insertion point is a measure (one half time converted to distance) of location of a defect in a fashion similar to pulse-echo sonar or radar.

On critical examination of the above technologies, it is evident that they generally fall into either the on-line or the off-line categories. The exception is PDM which can either be on-line or off-line. The on-line ones include MCSA and MFA. The off-line ones consist of RTG, Hi-Pot, MCBA, MCrA, MPA and TDR. The merit of the on-line technologies and methods over the off-line ones is that they are not invasive hence they can be applied without interrupting power supply thereby minimizing operational risk on the power utility. However, in contrast, initial costs of the off-line technologies are less than those of the on-line technologies.

D1.2 IT based technologies

This sub-section provides a review of the IT based asset management technologies. First, artificial intelligence (AI), rule-based expert systems and inferential engines have three facets. AI programs are intended to mimic human behavior through rule-based expert systems where rules represent heuristics (rules of thumb). These rules are a set of patterns that specify how the rules should be activated. The expert system provides a mechanism called inference engine which automatically matches facts against patterns and determines which rules are applicable. An example is the "C" Language Integration Production that has been in use in NASA and the US Department of Defense (DoD) [25]. The advantage of expert systems is that they do not require real data but a knowledgeable expert to invoke the rules. The disadvantage is that since the rules tend to follow the structure of the rule development environment, some potential non-linear and correlated relationships may be lost.

Second, fuzzy logic (FL) systems stem from fuzzy sets that were introduced in 1965. Fuzzy sets were initially invented as a means of generating conventional set theory to model the realities of everyday life by assigning membership classes to situations. For example, "hot" or "cold" could be two membership classes that overlap and in which a specific temperature "T" lies as illustrated in Figure C1-1. The figure shows "T" lying on 0.3 on membership class cold and 0.8 on membership class hot [25]

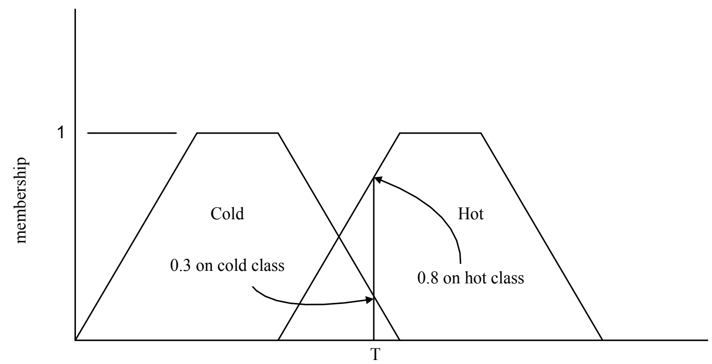


Figure D-1: Illustration of fuzzy logic membership temperature class [25]

Development of fuzzy members to form fuzzy rules can be through the application of standard software packages or by a developer assigning fuzzy membership functions by hand using intuition or expertise in applying the shape of functions [25]. Alternatively, the functions can be estimated from training data with the developer specifying the function parametric shape as trapezoidal or Gaussian, and estimating the parameters from the data. Fuzzy logic has proven to work successfully for a variety of control problems involving a small number of inputs and outputs, but as the system becomes more complex, the success requires training of the system with example data (see also, for example, the models in [69], [125]. Despite the shortfall, fuzzy rules are advantageous over those (rules) developed with an expert system in that the degree of membership is carried throughout the computation and a "hard" decision is only generated at the very last step.

Third, model-based approaches use mathematical (physical or statistical) model for the machine being monitored. Physical models account for all operating conditions but their accuracy depends on the availability of data on all modes of operation and fault condition. Statistics are developed on collected input/output data hence they may not account for conditions that are not recorded unless the data is good enough. Figure D1-2 is a schematic outline of the model-based fault detection system [25].

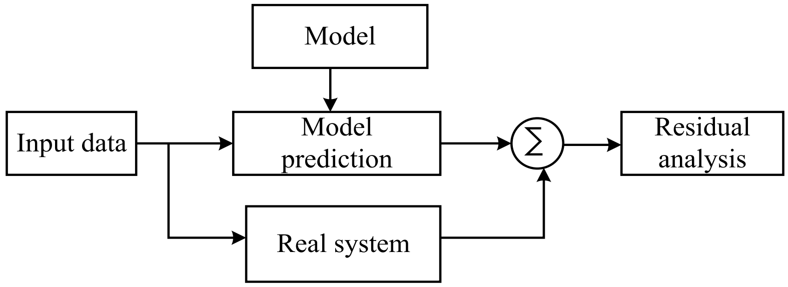


Figure D-2: Model-Based Fault Detection [25 p. 245]

Fourth, neural networks include artificial neural networks (ANN) or neural nets (NNs). ANN or NNs attempt to model the brain with many densely interconnected simple processing elements (PE). Two most popular examples of NNs are the multi-layer perceptron (MLP) consisting of layers of PE and radial basis function (RBF) NNs [25]. They are ideal for developing non-linear transformation to map the input data to outputs, henceforth they can be used for classification as well as prediction. Both the MLP and RBF NNs require real data that represents known fault classes to be trained, thus their accuracy improves with time of usage when more known fault classes are available.

Finally, data mining or automated rule extraction is a software based tool originated from the financial community for processing data to target customers for marketing. In rule extraction, rules are extracted from input data by brute force examination (as binary trees, i.e., true or false algorithm) of the data which must consist of fault class labelled samples. Advantages of rule extraction over NNs are as follows: comprehensibility, as it be can be easily understood by humans; explanation, as it can tell the user as to why the system did what it did; validation, as it allows the user to explore all possible sets of inputs to ensure that the system operates as expected under all conditions; and discovery, as it may find something new in the features of data that was not previously known.

Data mining is an effective method for developing classifiers, but real data illustrative of all of the conditions under consideration must be collected before applying the technique [25]. One of the developments in data mining focuses on combining rule extractors with models called oracles, whereby the rule extractor queries the oracle with inputs and analyzes the oracle outputs to develop rules. The oracle model can be physical, statistical, NN based, or any combination which achieves higher performance than NNs and be able to fill in gaps in collected data for unrecorded fault conditions. However, as a precautionary measure, the new rules must be traced back to reality. Data mining tools and techniques come in different forms. For instance, [126] used a Support Vector Machine (SVD) method to descriptively and predictively carry out on-line monitoring of partial discharges (PD). The predictive phase was used for classification, whereas the descriptive one was applied for rule extraction to describe the different classes. The SVD was used to extract rules from the PD and then presented classes of three discharge types, namely: corona in air, surface discharge at cable termination and internal discharge in void as class 1, class 2 and class 3, respectively [125]. In that way, on-line monitoring of PD, involving capturing of an enormous amount of data was possible. The superiority of FL, NNs and data mining technologies rests in their non-intrusive nature during the implementation of fault diagnosis. This represents a means of ensuring that a low risk profile is sustained by the power utilities that apply these technologies. However, they require highly specialized expert knowledge to implement.

On the other hand, SCADA and GIS are generally viewed as part of telecommunication plant as well as AM technologies. They have the capability to minimize fault location time and to improve the availability of the power systems' assets and maintenance efforts. A surveyed breakdown strategy is a typical application of the SCADA and GIS which has been described in detail in [2, p. 649].

Appendix E: Transformer condition quality analysis

Condition-based programs outlined in this appendix were reformulated from US Army Corps of Engineers (USACE) [127] to provide generic principles for transformers by [10]. They are applicable to equipment rated above 6.9 kV. These kinds of programs should be used to augment the risk-based systems approach in power distribution asset management.

Table E-1: Computation of transformer condition quality index (TCQI) [10], [127]

A	B	C	D	E	
Condition indicator (CI) category	**Indicator value**	**Exceptions**	**Condition indicator**	**Weighting factor**	**Score = (D x E)**
Oil analysis: Total Dissolved Combustible Gas (TDCG) Ref IEEE C57-104, IEC 60599 & Delta X Research Transformer Oil Analysis (TOA) software	Gas generation rate <30ppm/month	CO generation <70ppm/month & Acetylene(C_2H_2) Generation rate =0ppm	3		
	≥30 & <50ppm/month or 2FAL Furans ≥150 & <200ppb for thermally upgraded paper otherwise divide by 3 since non-thermally upgraded paper generates 3 times more gas before problems appear	CO generation rate <150ppm/month & C_2H_2=0 ppm/month (ppm=parts/million)	2	1.143	
	≥50 & <80ppm/month & all individual combustible gas generation rate <250ppm/month 2FAL Furans≥200 & <250ppb (i.e. Parts per billion)	CO generation rate ≥350ppm/month and C_2H_2<10ppm/month	1		

	≥80ppm/month & any combustible gas generation rate >50ppm/month Or 2FAL Furans ≥ 250ppb	CO generation rate ≥350ppm/month & C_2H_2<10ppm/month	0		
Power factor & excitation current	Normal (Good) & compares to previous patterns/tests	-	3	0.952	
	Minor degradation (degradation-D) or minor deviation	-	2		
	Significant deviation or as compared to previous	-	1		
	Severe degradation (Bad-B) or severe compared to others	-	0		
O & M Historical data e.g. overloading, abnormal temperature, corona, deteriorated protection & control, previous failures etc.	O & M normal	-	3	0.762	
	Some abnormality in operating conditions and or additional maintenance above normal one	-	2		
	Significant operation outside normal &/or significant additional maintenance required, or forced outage occurs/extended outages to carry out maintenance	-	1		
	Repeated forced outages ; maintenance not cost effective or severe/major leaks or mechanical problems or failure of similar machines	-	0		
Age	<30 years		3	0.476	
	≥30 & 45 years		2		
	≥45 years		1		
Total of category 1 (tier 1) test: Gross Transformer Condition Index (TCI) (Sum of column F)					∑ tier 1

Note: Tests in Table E1 are referred to as tier 1 (category 1) tests. They are base-case results from which other tests results should either be deducted or added to get a net TCQI.

Appendix F: Extract of reactor life parameters (Referred to in Ch. 3)

Table F-1: Mean life and its standard deviation (Sd) for 20 retired reactors [77]

Parameter	Normal	Weibull	Sample mean
Mean life (years)	30.191	29.727	29
Sd (years)	3.65	3.909	
Shape parameter		9.407	
Scale parameter		31.361	

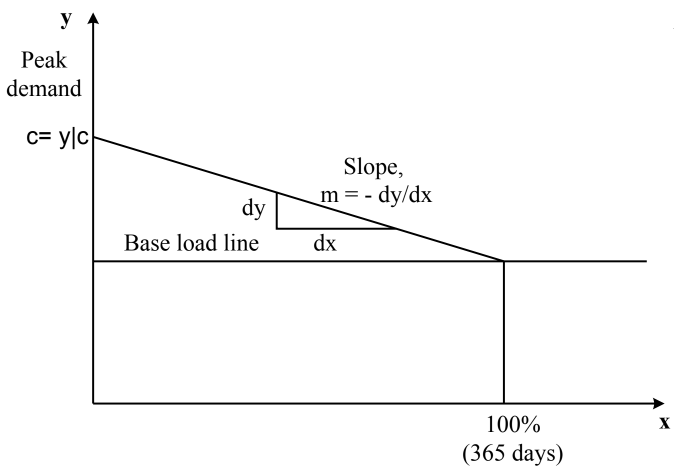
Table F-2: Reactor failure data [years]

8.3574	22.9241	26.3832	31.0241	33.7392
16.0002	23.5561	27.1043	31.4091	34.3701
21.3252	24.1437	29.3927	32.073	36.0493
22.4335	26.0759	30.8809	33.5665	41.9918

Note: The failure data in Table F-2 has been generated from the Weibull parameters listed in Table F-1, by some programming implemented by MATLAB software.

Appendix G: Capacity outage cumulative tables for LOEE and LOLE for Chapter 6

Calculation of time percentages, LOLE and LOEE, assuming a linear distribution of peak demand, is as outlined in Figure G-1. A base load of 10 MW is used. Appendix H provides the raw data that is used in this appendix. The LOLE and LOEE are calculated from expressions G1.1 to G1.3 [22].



$$LOLE = \sum_{i=1}^{n} P(C_i - L_i)[day/year] \quad \ldots\ldots\ G1.1$$

$$LOEE = \sum_{i=1}^{n} E_k p_k \, [MW] \quad \ldots\ldots\ G1.2$$

$$P(x,p,n) = \binom{n}{x} p^x (1-p)^{n-x} \quad \ldots\ldots\ G1.3$$

Where C_i= the available capacity on day i; L_i= forecast peak on day i; $P(C_i$-$L_i)$= probability of loss of load on day I obtained from capacity cumulative probability table; subscript k represents the magnitude of capacity outage, O_k; pk= $P(x,p,n)$, the probability of capacity outage corresponding to O_k; E_k=energy curtailed by a capacity of magnitude O_k.

Figure G-1: Time percentage, LOEE and LOLE calculation model

Table G-1: Time percentage of load curtailment for Station I

y = mx + c = capacity available		Capacity Available	x	% Time
x = (y - c)/m		100	-88.84	0.0000
m = (y2-y1)/(x2-x1) =	-0.4766	80	-46.87	0.0000
c = y-mx = y|x = 0	57.66	60	-4.91	0.0000
		40	37.05	37.0541
		20	79.02	79.0180
		0	120.98	100.0000

Table G-2: LOLE and LOEE for Station I at 83.7% Availability

Units out	Capacity out (MW)	Capacity Available (MW)	Load loss (MW)	Expected Load loss (MW)	Probability	Probability of load loss	% time	LOLE (Days/yr.)	LOEE (MW
0	0	57.66	0	0.0000	0.4123	0.0000	0.00	0.0000	0.0000
1	20	37.66	0	0.0000	0.3997	0.3997	0.00	0.0000	0.0000
2	40	17.66	0	0.0000	0.1550	0.1550	0.00	0.0000	0.0000
3	60	-2.34	3.18	0.0955	0.0300	0.0300	37.05	1.1134	0.0354
4	80	-22.34	23.18	0.0675	0.0029	0.0029	79.02	0.2302	0.0534
5	100	-42.34	43.18	0.0049	0.0001	0.0001	100.00	0.0113	0.0049
				0.1679	1.0000	0.5877		1.3549	0.0936

Note: For station I, the value of p to be fitted in equation G1.3 is 0.837.

Table G-3: Time percentage of load curtailment for Station II

y = mx + c = capacity available		**Capacity Available**	**x**	**% Time**
x = (y - c)/m		50	-78.17	0.0000
m= (y2-y1)/(x2-x1) =	-0.2245	25	33.18	33.1849
c = y-mx = y|x = 0	32.45	0	144.54	100.000

Table G-4: LOLE and LOEE for Station II at 97.7% Availability

Units out	Capacity out (MW)	Capacity Available (MW)	Load loss (Curtailed) (MW)	Expected Load loss (MW)	Probability	Probability of load loss	% time	LOLE (Days/yr.)	LOEE (MW)
0	0	50	0	0.000	0.955	0.000	0.00	0.000	0.000
1	25	25	0	0.000	0.045	0.045	33.2	1.485	0.000
2	50	0	7.45	0.004	0.001	0.001	100.0	0.052	0.004
				0.004	1.000	0.045		1.538	0.004

Note: For station II, the value of p to be fitted in equation G1.3 is 0.977.

Table G-5: Time percentage of load curtailment for Station III

y=mx + c= capacity available		**Cap. Available**	**x**	**% Time**
x=(y - c)/m		64	-49.833518	0
m= $(y_2-y_1)/(x_2-x_1)$=	-0.3604	32	38.9567	38.9567
c = y-mx = y|x = 0	46.04	0	127.7469	100

Table G-6: LOLE and LOEE for Station III at 97.3% Availability

Units out	Capacity out (MW)	Capacity Available (MW)	Load loss (Curtailed) (MW)	Expected Load loss (MW)	Probability	Probability of load loss	% time	LOLE (Days/yr.)	LOEE (MW)
0	0	64	0	0.000	0.947	0.000	0.00	0.000	0.000
1	32	32	14.04	0.738	0.053	0.053	39.0	2.047	0.287
2	64	0	46.04	0.034	0.001	0.001	100.0	0.073	0.034
				0.034	1.000	0.001		2.120	0.321

Note: For station III, the value of p to be fitted in equation G1.3 is 0.973

Appendix H: Power generating station data applied to Chapter six

Table H-1: Detailed performance data for station I (5x20 MW units) at 83.7% Availability

	AVERAGE MONTHLY PERFORMANCE											
	Jul-12	**Aug-12**	**Sep-12**	**Oct-12**	**Nov-12**	**Dec-12**	**Jan-13**	**Feb-13**	**Mar-13**	**Apr-13**	**May-13**	**Jun-13**
Station II												
Availability (%)	99.05	80.65	79.53	79.778	79.00	78.11	79.36	78.32	78.85	78.45	98.24	95.818
Forced Outage (%)	0.07	1.23	0.47	0.222	1.93	1.66	0.55	1.68	0.00	0.15	0.07	0.052
Planned Outage (%)	0.88	18.12	20.00	20	19.07	20.23	20.09	20	21.15	21.39	1.69	4.128
UAGS/7000 hrs.	7.40	5.60	5.60	4.2	4.2	3.4	1.8	2.6	2.2	2.2	1.8	2
Units Generated (GWh)	52.0142	45.9592	44.7795	48.4509	45.6821	45.8083	42.5865	38.6744	44.6588	44.3083	55.1993	51.7898
Unit Transformer-Own use (KWh)	117583	100113	121107	102915	92503	91456	17924.2	99454	104957	103793	132021	131389.2
Hours Run	3452.77	2975.11	2853.86	2966.81	2843.91	2898.02	2914.55	2678.34	2922.36	2824.30	3620.10	3425.06
Number of Faults	3	1	3	2	0	0	4.00	3	0	4	1	2
Mean time to repair (MTTR)	0.50	0.30	2.38	1.65	0.00	0.00	2.452	9.72	0.00	1.10	0.50	0.88
Mean time between failure (MTBF)	520.59	669.45	478.44	594.38	720.00	744.00	494.61	442.88	744.00	647.45	669.35	575.56
Number of Planned Outages	0.00	1.00	2.00	1.00	2.00	1.00	2.00	1.00	4.00	4.00	5.00	10.00
Number of Unit Request	51.00	12.00	7.00	4.00	16.00	8.00	18.00	30.00	15.00	13.00	35.00	12.00
Number of Abortive Starts	0.00	1.00	0.00	0.00	0.00	0.00	4.00	0.00	0.00	0.00	0.00	0.00
Number of Internal Trips	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Number of External Trips	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Available hrs.	736.93	600.07	572.62	593.55	568.80	581.12	590.47	526.31	586.67	564.85	730.94	689.89
Forced Outage hrs.	0.49	9.12	3.38	1.65	13.90	12.35	4.06	11.29	0.00	1.11	0.51	0.37
Planned Outage hrs.	6.58	134.81	144.00	148.80	137.30	150.53	149.47	134.40	157.33	154.04	12.56	29.72
	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Table H-2: Detailed performance data for station II (2x26 MW Units) at 97.7% Availability

	AVERAGE MONTHLY PERFORMANCE											
	Jul-12	**Aug-12**	**Sep-12**	**Oct-12**	**Nov-12**	**Dec-12**	**Jan-13**	**Feb-13**	**Mar-13**	**Apr-13**	**May-13**	**Jun-13**
Station III												
Availability (%)	98.15	99.645	100	100	99.46	99.18	99.42	99.91	97.02	100	100	98.56
Forced Outage (%)	0	0.355	0	0	0.54	0.00	0.58	0.10	0.03	0	0	0.06
Planned Outage (%)	1.85	0	0	0	0	0.83	0	0	2.96	0	0	1.38
UAGS/7000 hrs.	0.5	0.5	0.5	1	1	0.5	0.5	0.5	2	2	2	1.5
Units Generated (GWh)	33.841	26.96	26.606	31.003	28.785	26.375	23.8	22.912	24.162	26.673	24.252	23.838
Unit Transformer-Own use (KWh)	28974	28371	27723	32400	30329	28684	26099	24843	26105	28252	25146	24890
Hours Run	1390.43	1268.05	1074.5	1259.18	1176.47	1112.67	1023.8	956.05	1031.24	1112.87	1014.52	986.7
Number of Faults	2	0	0	1	2	0	3	0	0	0	0	0
Mean time to repair (MTTR)	1.25	0.00	0.00	0.15	1.45	0.00	2.15	0.00	0.00	0.00	0.00	0.00
Mean time between failure (MTBF)	371.05	744.00	720.00	557.93	359.28	744.00	308.72	672.00	744.00	720.00	744.00	720.00
Number of Planned Outages	1	0	0	0	0	0	0	0	2	0	0	1
Number of Unit Request	49	63	65	44	56	66	80	63	73	60	72	70
Number of Abortive Starts	0	0	0	0	0	0	0	0	0	0	0	0
Number of Internal Trips												
Number of External Trips												
Available hrs.	730.24	741.36	720.00	744.00	716.11	737.86	739.68	671.36	721.79	720.00	744.00	709.63
Forced Outage hrs.	0.00	2.64	0.00	0.00	3.89	0.00	4.32	0.64	0.19	0.00	0.00	0.43
Planned Outage hrs.	13.76	0.00	0.00	0.00	0.00	6.14	0.00	0.00	22.02	0.00	0.00	9.94
	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Table H-3: Detailed performance data for station III (2x32 MW units) at 97.3% Availability

	AVERAGE MONTHLY PERFORMANCE											
	Jul-12	**Aug-12**	**Sep-12**	**Oct-12**	**Nov-12**	**Dec-12**	**Jan-13**	**Feb-13**	**Mar-13**	**Apr-13**	**May-13**	**Jun-13**
Station IV												
Availability (%)	97.29	100	100	98.35	88.755	97.86	97.70	87.90	99.85	99.87	99.98	100
Forced Outage (%)	0	0	0	0	5.625	0.31	2.31	1.15	0.15	0.13	0.02	0
Planned Outage (%)	2.71	0	0	1.65	5.62	1.84	0	10.96	0	0	0	0
UAGS/7000 hrs.	20	17	13	13	12.5	5.5	6.5	8.5	9	8.5	8	8
Units Generated (GWh)	36.319	38.301	36.92	36.42	30.021	35.225	34.962	28.868	38.074	37.74	37.429	36.391
Unit Transformer-Own use (KWh)	44184	45556	43657	44110	38108	44671	43846	35453	45464	43605	45253	44396
Hours Run	1446	1488	1440	1463.42	1266.63	1455.86	1431.49	1181.2	1485.8	1438.13	1480.92	1440
Number of Faults	1	0	0	1	4	4	6	10	1	1	1	0
Mean time to repair (MTTR)	0.28	0.00	0.00	0.42	4.93	0.26	0.69	0.41	1.10	0.74	0.14	0.00
Mean time between failure(MTBF)	557.87	744.00	720.00	557.80	428.06	445.99	185.49	114.86	557.45	539.64	557.93	720.00
Number of Planned Outages	1	0	0	2	10	0	0	8	0	0	0	0
Number of Unit Request	1	0	0	2	14	7	13	21	1	1	2	0
Number of Abortive Starts	0	0	0	0	0	0	0	0	0	0	0	0
Number of Internal Trips												
Number of External Trips												
Available hrs.	723.84	744.00	720.00	731.72	639.04	728.08	726.85	590.65	742.88	719.06	743.85	720.00
Forced Outage hrs.	0.00	0.00	0.00	0.00	40.50	2.27	17.15	7.69	1.12	0.94	0.15	0.00
Planned Outage hrs.	20.16	0.00	0.00	12.28	40.46	13.65	0.00	73.65	0.00	0.00	0.00	0.00
	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Table H-4: Detailed performance data for station IV (4x10 MW units) at 97.7% Availability

	AVERAGE MONTHLY PERFORMANCE											
	Jul-12	**Aug-12**	**Sep-12**	**Oct-12**	**Nov-12**	**Dec-12**	**Jan-13**	**Feb-13**	**Mar-13**	**Apr-13**	**May-13**	**Jun-13**
Station I												
Availability (%)	99.695	99.2275	100	99.895	99.18	89.60	98.97	98.63	94.44	97.88	96.09	98.8875
Forced Outage (%)	0.305	0.7725	0	0.105	0.82	10.09	1.03	0.08	0.04	0.61	0.84	1.1125
Planned Outage (%)	0	0	0	0	0	0.31	0.00	1.29	5.53	1.51	3.07	0
UAGS/7000 hrs.	3.25	3	3	3	1.75	2.25	1.75	2	1.5	1.5	3.25	3.25
Units Generated (GWh)	29.1113	29.2467	28.6972	29.6328	28.1764	26.1995	28.8033	25.9185	26.8175	28.8746	27.6214	27.9078
Unit Transformer-Own use (KWh)	38602	45395	34855	38681	37951	35309	38242	35718	37699	37973	37083	38368
Hours Run	2963.11	2948.61	2880	2972.3	2856.37	2655.09	2945.26	2651.27	2808.4	2818.82	2859.73	2847.96
Number of Faults	3	7	0	1	6	10	3	1	0	2	0	2
Mean time to repair (MTTR)	0.83	1.61	0.00	0.78	3.26	36.47	1.78	0.41	0.00	181.83	0.00	1.30
Mean time between failure (MTBF)	603.88	315.24	720.00	650.61	394.04	192.59	525.89	587.80	744.00	538.81	744.00	599.13
Number of Planned Outages	0	0	0	0	0	0	0	1	4	1	3	1
Number of Unit Request	3	15	0	1	9	25	28	3	6	6	6	6
Number of Abortive Starts	0	3	0	1	2	7	0	0	1	0	1	0
Number of Internal Trips												
Number of External Trips												
Available hrs.	741.73	738.25	720.00	743.22	714.10	666.62	736.32	662.81	702.60	704.72	714.93	711.99
Forced Outage hrs.	2.27	5.75	0.00	0.78	5.90	75.07	7.68	0.55	0.30	4.39	6.25	8.01
Planned Outage hrs.	0.00	0.00	0.00	0.00	0.00	2.31	0.00	8.64	41.11	10.89	22.82	0.00
	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Appendix I: Sub-Saharan Africa transmission and distribution energy loss case study (Ref. Ch. 6)

Table I-1: Typical system losses and their impact on energy sales

Energy Sales in KWh based on Operation at 23% Losses					
Year	2013	2014	2015	2016	2017
Domestic customer	546,027,663	611,550,982	718,040,169	837,163,681	959,042,758
General customer	249,478,712	279,416,158	324,180,641	373,480,733	422,780,825
Power LV customer	249,074,954	278,963,948	323,655,984	377,350,804	432,287,692
Power MV customer	452,453,537	506,747,962	587,932,639	677,343,077	766,753,515
Total with 22% losses	1,497,034,866	1,676,679,050	1,953,809,434	2,265,338,294	2,580,864,790
Growth		12%	17%	16%	14%
Energy Sales with reduced targets on Losses					
Year	2013	2014	2015	2016	2017
Losses	22.0%	20.5%	19.0%	17.5%	16.0%
Units Generated	1,919,275,469.27	2,109,030,251.51	2,412,110,412.54	2,745,864,599.20	3,072,458,083.58
Sales with Losses	1,497,034,866	1,676,679,050	1,953,809,434	2,265,338,294	2,580,864,790
Revised	422,240,603	432,351,202	458,300,978	480,526,305	491,593,293
Loss at 22%	1,497,034,866.03	1,645,043,596.18	1,881,446,121.78	2,141,774,387.37	2,396,517,305.19
MK cost to produce (1MK= US$ 400)					
Losses	22%	22%	22%	22%	22%
Generated (MWh)					

Year	Units Generated	Units Sales at 22% Losses	% Losses	Unit Sales - Revised losses	Additional Unit Sales
2014	2,109,030,251.51	1,645,043,596.18	20.5%	1,676,679,050	31,635,453.77
2015	2,412,110,412.54	1,881,446,121.78	19.0%	1,953,809,434	72,363,312.38
2016	2,745,864,599.20	2,141,774,387.37	17.5%	2,265,338,294	123,563,906.96
2017	3,072,458,083.58	2,396,517,305.19	16.0%	2,580,864,790	184,347,485.01
Total	10,339,463,346.83	8,064,781,410.53	18.02%	8,476,691,568.66	411,910,158.13

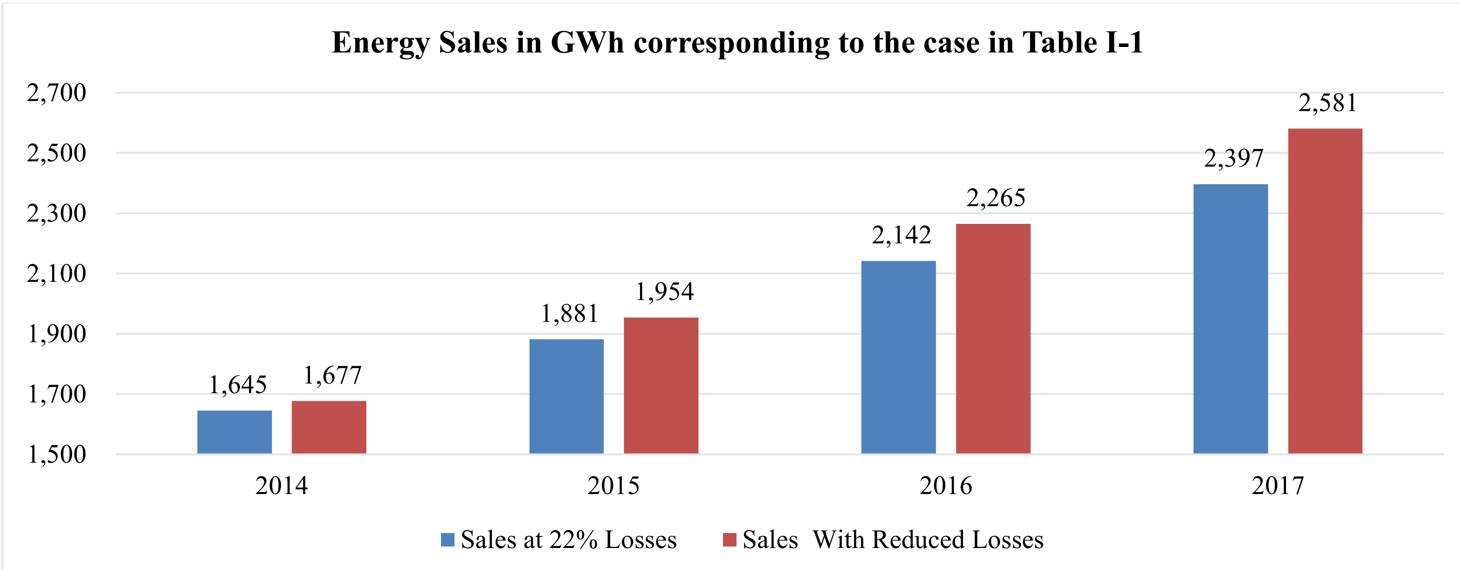


Figure I-1: Impact of 1.5% of system loss reduction on energy sales

Note: Figure I-1 shows that additional 396 GWh sales worth over K11 billion [$36.6 million] can be realized in 4 years through loss reduction