



# MAKERERE UNIVERSITY

## A Model for Predicting Transformer Failure Tendencies on the 132 Kilovolts Power Network in Uganda

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# DECLARATION

This study is original and has not been submitted for any other degree award to any other University before.



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# APPROVAL

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# TABLE OF CONTENTS

<b>DECLARATION</b> . . . . .	<b>i</b>
<b>APPROVAL</b> . . . . .	<b>ii</b>
<b>ACKNOWLEDGMENT</b> . . . . .	<b>iii</b>
<b>LIST OF FIGURES</b> . . . . .	<b>xi</b>
<b>LIST OF ACRONYMS</b> . . . . .	<b>xi</b>
<b>ABSTRACT</b> . . . . .	<b>xii</b>
<b>Chapter ONE: INTRODUCTION</b> . . . . .	<b>1</b>
1.1 Background . . . . .	1
1.2 Problem Statement . . . . .	2
1.3 Objectives . . . . .	3
1.3.1 Main Objective . . . . .	3
1.3.2 Specific Objectives . . . . .	3
1.4 Research Questions . . . . .	4
1.5 Significance . . . . .	4
1.6 Justification . . . . .	4
1.7 Contribution of this Research . . . . .	5
1.8 Scope of Study . . . . .	5
1.9 Conceptual Framework . . . . .	6
1.10 Summary . . . . .	7
<b>Chapter TWO: LITERATURE REVIEW</b> . . . . .	<b>8</b>
2.1 Introduction . . . . .	8
2.2 Parameters Influencing Power Transformer Failure . . . . .	8
2.2.1 Diagnostic and Prognostic Methods . . . . .	8
2.2.2 Diagnostic and Prognostic Tools . . . . .	9
2.3 Modelling of Power Transformer Degradation . . . . .	10
2.4 Determining the Most Opportune Time for Power Transformer Replacement . . . . .	14
2.4.1 The Weibull Distribution Model . . . . .	14

2.4.2	Reliability-Centered Maintenance (RCM)	14
2.4.3	Genetic Algorithm (GA)	15
2.4.4	Monte Carlo Simulation	15
2.4.5	Paper Insulation Decomposition and Degradation	15
2.4.6	Fuzzy Logic Rules	15
2.4.7	Gray Incidence Analysis (GIA)	15
2.5	Review of Related Literature and Gaps Identified	16
<b>Chapter THREE: METHODOLOGY</b>		<b>18</b>
3.1	Introduction	18
3.2	Parameters Influencing Failure of 132kV Transformers	18
3.2.1	Research Approach and Design	18
3.2.2	Data Collection Tools and Methods	18
3.2.3	Data Treatment and Justification	19
3.2.4	Transformer Selection Criterion	20
3.2.5	Data Dictionary	21
3.2.6	Basis for Stochastic Processes	21
3.2.7	Parameterization	22
3.3	Development of a Prediction Model for 132 kV Transformer Degradation	25
3.3.1	Modelling and Analysis	25
3.4	Transformer Health Index (HI) Classification	28
3.4.1	PSO-ANFIS Algorithm	33
3.4.2	Model Constraints	35
3.5	Validation of the Developed Predictive Model under Diverse Loading Environments	36
3.5.1	Cross Validation	36
3.5.2	Validity Analysis	37
3.5.3	Internal Validation	38
3.5.4	Data Quality Evaluation	38
3.5.5	Verification of Model Assumptions	39
3.5.6	Summary of Validity	39
3.6	Developing a Cost-effective Replacement Strategy for Degrading 132 kV Transformers	40

3.7	Summary . . . . .	41
<b>Chapter FOUR: PRESENTATION OF RESULTS. . . . .</b>		<b>42</b>
4.1	Introduction . . . . .	42
4.2	Determining Parameters Influencing 132 kV Transformer failure in Selected Substations	42
4.2.1	Results for Health Index . . . . .	58
4.3	Prediction Model for Condition Based Factors Affecting Transformer Performance . .	60
4.3.1	Prediction of 132 kV Transformer Failure using ANFIS . . . . .	62
4.4	Validation of the Predictive Model under Diverse Loading Environments . . . . .	73
4.5	A Cost-Effective Replacement Strategy for Degrading 132 kV Transformers . . . . .	78
4.6	Summary . . . . .	81
<b>Chapter FIVE: DISCUSSION OF RESULTS . . . . .</b>		<b>83</b>
5.1	Introduction . . . . .	83
5.1.1	Goodness-of-Fit Tests . . . . .	83
5.1.2	Hazard Rate in Weibull Analysis . . . . .	83
5.1.3	Reliability in Weibull Analysis . . . . .	84
5.2	Determining Parameters Influencing 132 kV Transformer Failure in Selected Substations	84
5.2.1	Shape and Scale Parameters . . . . .	84
5.2.2	Condition Based Parameters . . . . .	85
5.2.3	Break Down Voltage . . . . .	85
5.2.4	Moisture Content . . . . .	85
5.2.5	Acidity . . . . .	86
5.2.6	Inter-facial Tension . . . . .	86
5.2.7	Color . . . . .	87
5.2.8	2-Furfural Dehyde . . . . .	87
5.2.9	Dissolved Gas Analysis . . . . .	87
5.3	Prediction Model for Condition Based Factors Affecting Power Transformer Performance	88
5.3.1	ANFIS . . . . .	88
5.3.2	PSO-ANFIS . . . . .	89
5.4	Validation of the Prediction Model Under Diverse Loading Environments . . . . .	90
5.5	A Cost-Effective Replacement Strategy for Degrading 132 kV Transformers . . . . .	90

5.6	Practical Applications of the Results Obtained . . . . .	91
5.6.1	Predictive Maintenance Scheduling . . . . .	91
5.6.2	Condition-Based Replacement Planning . . . . .	92
5.6.3	Risk-Based Asset Criticality Assessment . . . . .	92
5.6.4	Decision Support for Operations and Maintenance . . . . .	92
5.6.5	Regulatory and Financial Planning . . . . .	92
5.6.6	Training and Capacity Building . . . . .	93
5.6.7	Policy and Standards Development . . . . .	93
5.7	Risks Arising and Their Mitigation . . . . .	93
5.7.1	Data-Related Risks . . . . .	93
5.7.2	Model Uncertainty and Parameter Estimation Risk . . . . .	93
5.7.3	Technological and Tool Limitations . . . . .	94
5.7.4	Implementation and Operational Risks . . . . .	94
5.7.5	Economic and Resource Risks . . . . .	94
5.7.6	Assumption-Related Risks . . . . .	94
5.7.7	External and Environmental Risks . . . . .	94
5.8	Limitations of the Study . . . . .	95
5.9	Summary . . . . .	95
<b>Chapter SIX: CONCLUSIONS AND RECOMMENDATIONS . . . . .</b>		<b>97</b>
6.1	Introduction . . . . .	97
6.2	Contribution of the Research to UETCL . . . . .	97
6.2.1	Development of a Predictive Reliability Framework . . . . .	97
6.2.2	Establishment of a Transformer Health Index Framework . . . . .	97
6.2.3	Cost-Effective Replacement and Maintenance Decision Support . . . . .	98
6.2.4	Enhancement of Asset Management Policy . . . . .	98
6.2.5	Capacity Building and Knowledge Transfer . . . . .	98
6.3	Conclusions . . . . .	98
6.4	Recommendations . . . . .	99
6.4.1	Recommendations for Further Study . . . . .	99
6.4.2	Recommendations for UETCL . . . . .	101

6.5 Summary . . . . .	103
<b>REFERENCES . . . . .</b>	<b>104</b>
<b>APPENDICES . . . . .</b>	<b>107</b>

# LIST OF FIGURES

1.1	Conceptual Framework . . . . .	7
2.1	Power Transformer System Fault Tree (Innocent, 2019) . . . . .	10
2.2	The Bathtub Curve (Lee, 2020) . . . . .	11
3.1	Process flow for analysis of condition-based factors . . . . .	25
3.2	ANFIS Structural Layout . . . . .	31
3.3	ANFIS flow chart . . . . .	33
3.4	PSO-ANFIS flow chart . . . . .	34
4.1	Time to Failure considering varying year of commission for power transformers . . . . .	43
4.2	Reliability Analysis for Most Critical Transformers . . . . .	44
4.3	Reliability plot for the critical transformers . . . . .	45
4.4	Hazard Rate for Critical Transformers . . . . .	46
4.5	BDV Analysis for Mutundwe 132/33 kV Transformer-1 . . . . .	47
4.6	BDV Analysis for Lugogo 132/33 kV Transformer-2 . . . . .	48
4.7	Moisture content for Mutundwe 132/33 kV Transformer-1 . . . . .	48
4.8	Moisture content for Lugogo 132/33 kV Transformer-2 . . . . .	49
4.9	Acidity for Mutundwe 132/33 kV Transformer-1 . . . . .	50
4.10	Acidity for Lugogo 132/33 kV Transformer-2 . . . . .	50
4.11	Interfacial tension for Mutundwe 132/33 kV Transformer-1 . . . . .	51
4.12	Interfacial tension for Lugogo 132/33 kV Transformer-2 . . . . .	51
4.13	Color of Oil for Mutundwe 132/33 kV Transformer-1 . . . . .	52
4.14	Furfural Dehyde for Mutundwe 132/33 kV Transformer-1 . . . . .	53
4.15	Furfural Dehyde for Lugogo 132/33 kV Transformer-2 . . . . .	53
4.16	Hydrogen concentration for Mutundwe 132/33 kV Transformer-1 . . . . .	54
4.17	Methane concentration for Mutundwe 132/33 kV Transformer-1 . . . . .	54
4.18	Carbon monoxide concentration for Mutundwe 132/33 kV Transformer-1 . . . . .	55

4.19	Carbon dioxide concentration for Mutundwe 132/33 kV Transformer-1 . . . . .	55
4.20	Ethylene concentration for Mutundwe 132/33 kV Transformer-1 . . . . .	56
4.21	Ethane concentration for Mutundwe 132/33 kV Transformer-1 . . . . .	56
4.22	Acetylene concentration for Mutundwe 132/33 kV Transformer-1 . . . . .	57
4.23	Results of health index for representative transformers . . . . .	60
4.24	Condition Based Factors Influencing 132 kV Mutundwe transformer-1 Reliability . . .	61
4.25	Schematic Diagram for BDV prediction showing inputs and outputs using ANFIS . . .	62
4.26	BDV training process using ANFIS . . . . .	63
4.27	BDV model showing base case scenario . . . . .	64
4.28	BDV prediction model at 80% loading . . . . .	64
4.29	ANFIS-Predicted BDV beyond 23 years of transformer operation . . . . .	65
4.30	PSO-ANFIS Predicted BDV beyond 23 years of transformer operation . . . . .	65
4.31	ANFIS-Moisture content prediction model at 90 and 100% loading . . . . .	67
4.32	PSO-ANFIS Moisture content prediction model at 90 and 100% loading . . . . .	68
4.33	Training of Acidity Data . . . . .	69
4.34	ANFIS Prediction of Acidity beyond 23 Year of Operation . . . . .	70
4.35	PSO-ANFIS Prediction of Acidity beyond 23 Year of Operation . . . . .	70
4.36	Determination of OPT for Fortportal transformer-5 . . . . .	79
4.37	Determination of OPT for Mutundwe transformer-2 . . . . .	80
4.38	Determination of OPT for Mutundwe transformer-1 . . . . .	80
4.39	Determination of OPT for Namanve transformer-3 . . . . .	81

# LIST OF ACRONYMS

ACA	Asset Criticality Assessment
AGAN	As Good as New
ANFIS	Artificial Neural Fuzzy Interface System
BDV	Break Down Voltage
CBM	Condition Based Monitoring
DGA	Dissolved Gas Analysis
ERA	Electrical Regulatory Authority
2-FD	Furfural Dehyde
FTA	Fault Tree Analysis
IFT	Interfacial Tension
MC	Moisture Content
FPCA	Functional Principal Component Analysis
HI	Health Index
kV	Kilo Volts
MCS-CEM	Minimum Cut Set-Cost Estimation
MYT	Multi-Year Tariff
MTTF	Mean Time To Failure
OQA	Oil Quality Analysis
RMSE	Root Mean Square Error
RUL	Remaining Useful Life
PPM	Parts Per Million
PSO	Partical Swarm Optimisation
PSO-ANFIS	Particle Swarm Optimization-Artificial Neural Fuzzy Interface System.
SPSS	Statistical Package of Social Science
SVRM	Support Vector Regression Machines
TSOs	Transmission System Operators
UETCL	Uganda Electricity Transmission Company Limited
WDM	Weibull Distribution Model

# ABSTRACT

Uganda's 132 kV transmission network has experienced increasingly frequent and costly power transformer failures, often occurring without warning and leading to cascaded outages, extended downtime, and significant corrective maintenance expenses. The prevailing asset management framework remains largely reactive, lacking an effective condition-based monitoring and predictive maintenance strategy. This study was thus motivated by the need to develop a robust prediction tool capable of identifying transformers approaching critical degradation, minimizing unexpected failures, and guiding timely replacement decisions based on actual transformer health rather than age alone.

To achieve this, the study set out to: (i) identify key operational parameters influencing 132 kV transformer failure, (ii) develop a predictive model for degradation under diverse stochastic and loading environments, (iii) validate the model's accuracy, and (iv) derive a cost-effective replacement strategy. Using a quantitative research approach, historical condition-based monitoring data for 30 transformers across selected substations was collected over a 23-year period. A hybrid Particle Swarm Optimization–Adaptive Neuro-Fuzzy Inference System (PSO-ANFIS) model was developed to predict transformer degradation trends using key condition variables such as breakdown voltage (BDV), moisture content, acidity, interfacial tension (IFT), and dissolved gas analysis (DGA) parameters. Model performance was evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The PSO-ANFIS model consistently outperformed the traditional ANFIS across all parameters, with average improvements of 25–35% in accuracy. For BDV, the PSO-ANFIS achieved an RMSE of 1.75, MAE of 1.42, and MAPE of 5.4%, compared to ANFIS values of 2.35, 1.89, and 7.2%, respectively. Similar improvements were observed for other indicators—moisture (MAPE 4.7% vs. 6.8%), acidity (5.2% vs. 8.5%), and key DGA gases (average MAPE 5.5% vs. 8.4%).

The results showed that the PSO-ANFIS model significantly improved prediction accuracy, enabling early identification of asymptomatic transformers and supporting a proactive, cost-efficient replacement strategy tailored to the Ugandan grid. The study's findings present an important step toward modernizing transformer asset management using intelligent prediction models.

# CHAPTER ONE: INTRODUCTION

## 1.1 Background

A highly effective asset management framework requires that prior planning is performed to ensure high reliability in a 132 kV network (SHEC, 2019). Asset management frameworks also require that system reliability and power quality are high, coupled with cost effectiveness as well as productivity in network implementation (Suwnansri, 2014). A risk assessment strategy of Asset Criticality Assessment (ACA) has been adopted by transmission companies to ensure the well-being of power transformers (SHET, 2019). The strategy assesses power transformer criticality by identifying power transformers at the highest risk of failure, thus prioritizing maintenance action. The strategy also takes into account future loading projections and the probability of transformer failure based on various failure mechanisms (Khuntia et al., 2015). This creates a list of power transformers that need to be changed, along with an explanation and an estimate of the cost. Thus, it should be noted that poor asset management frameworks result in an escalation of power transformer asset degradation and several other underlying impacts such as loss of productivity and revenue for utilities.

The major challenge of the prevailing asset management frameworks in Uganda, is being more reactive than proactive (Musiimenta et al., 2023). The existing frameworks, manned by the Uganda Electricity Transmission Company Limited (UETCL) maintenance department, are implemented in such a way that replacement and repair are only carried out in the event of maximum 132 kV transformer degradation (UETCL, 2021). Given that the working life of a power transformer is often assumed to be 40 to 50 years (based on the N-1 planning criteria and the loading guide) (Bohatyrewicz and Mrozik, 2021), there are many units that have exceeded this age, yet are kept in service unless there is sufficient business reason to replace them (Martin et al., 2017). The Multi-Year Tariff (MYT) framework (2023-25) established by the Electrical Regulatory Authority (ERA) requires that UETCL performs quarterly servicing of its assets to ensure service quality (ERA, 2019). In addition, the MYT framework is crafted to motivate the utility towards effective planning and substantial investments in superior-quality power transformers (Costello, 2019). Despite the presence of regulatory frameworks and consistent mainte-

nance schedules designed to uphold service quality, the occurrence of high impact power transformer failures on the 132 kV network remains a concern.

Presently, power transformers on the 132 kV network fail abruptly without warnings and related signs of potential failure. When this event happens, on a central substation, it leads to induced and progressive outages in connected substations (UETCL, 2023). This results into cascaded failures. Furthermore, connected substations may be smaller in load capacity, unable to sustain the load previously manned by the central substations. Other effects may include overrun of generators, loss of synchronization for some generating units and increased deemed energy among others (Augustine, 2023). Occurrence of cascaded failures has resulted into events of total blackout and loss of supply to the distribution network (Dai et al., 2022). In Uganda for instance, 80% of the distribution network has encountered loss of supply due to cascaded failures (UETCL, 2023). The most recent 132 kV transformer replacement records indicated a minimum of UGX. 271,044,505 spent on replacement of a single degraded power transformer unit, with an average of 30 monthly transformer related outages recorded in 2022/23 (Hitachi, 2023).

As of 2023, four transformers experienced asymptomatic failure namely; Mutundwe transformer-3, Lugazi transformer-1 and 2 and Namanve transformer-2. To ensure continuity of supply, the temporary solution was to transfer transformers from other regions to replace the affected transformers. As a result of transformer failure, the outage durations took between 1 to 3 months (UETCL, 2023). The challenges identified point to a lack of knowledge regarding the best time to replace damaged power transformers in order to reduce the expense of corrective maintenance and its effects on the reliability of the 132 kV network. Because predictive maintenance more accurately depicts the ageing status of power transformers than reactive based maintenance, it has been chosen as an appropriate replacement approach for the decaying power transformers (Sirvio, 2015).

## **1.2 Problem Statement**

Ensuring timely replacement of power transformers before maximum degradation is crucial to maintain the reliability of the 132 kV network and its operational cost-effectiveness. Ideally, a well-functioning power transformer should handle up to 120% of its rating, operate reliably within its prescribed life,

with minimum asymptomatic failures these are failures occurring without prior warning through standard diagnostic indicators, even in the midst of multiple disturbances. Power transformers with signs and symptoms of degradation are also required to be identified and retired within a known time frame. However, UETCL-operated 132 kV transformers tend to fail abruptly without notice, causing cascaded failures and widespread outages. When such an event occurs on the central substation, it leads to induced and progressive outages in connected substations, resulting in cascaded failures and significant financial burdens. Maintenance records show that 37.5% of UETCL transformers have faced mature failures for the past 5 years, with internal operational factors as the highest expected drivers, exceeding the global 20–30% average (UETCL, 2023). The challenge stems from the lack of an effective condition-based monitoring tool to predict 132 kV transformer degradation and guide reliable replacement strategies. Addressing this issue is paramount to preventing technical and financial impacts on network reliability, necessitating the development of a robust prediction tool based on Remaining Useful Life (RUL) capability.

## **1.3 Objectives**

### **1.3.1 Main Objective**

The main objective of this study was to develop a statistical predictive model for 132 kV transformer failure and related fault drivers in Uganda as a tool to enhance optimal replacement strategies.

### **1.3.2 Specific Objectives**

- i. To identify and quantify key condition-based parameters that influence 132 kV transformer degradation using statistical and Weibull reliability analysis.
- ii. To develop and implement a PSO-ANFIS hybrid predictive model for accurate estimation of transformer degradation indicators.
- iii. To validate the predictive performance of the developed PSO-ANFIS model under diverse loading and degradation conditions using error-based metrics.
- iv. To formulate a cost-effective transformer replacement strategy based on Weibull cost modelling and reliability-centred decision analysis.

## 1.4 Research Questions

The following research questions guided this research;

- i. What are the most critical parameters that influence the performance of 132 kV transformers in the selected substations on the 132 kV network?
- ii. What is the relationship between 132 kV transformer failure and the expected time of maximum degradation?
- iii. How accurate is the developed model towards predicting 132 kV transformer degradation under diverse loading and stochastic environments?
- iv. What is the most appropriate cost-effective solution for 132 kV transformer replacement?

## 1.5 Significance

According to [Ihendinihu et al. \(2023\)](#), there is a notable absence of robust risk assessment frameworks aimed at optimizing the performance of 132 kV transformers. Specifically, there is a lack of clear strategies addressing both cost-effectiveness and the reduction of operation and maintenance expenses during the deployment of power transformers. This deficiency has led to significant degradation and increased costs associated with the deployed transformers. Therefore, the significance of this study is it formulated a prognostic risk-based framework that guide the efficient planning, deployment and retirement of power transformers within the 132 kV network. The goal is to mitigate the existing issues of high-impact failure events and their corresponding negative consequences. The formulation of suitable replacement strategies is essential not only for minimizing catastrophic events caused by power transformer failures and reducing associated maintenance expenses but also for prolonging the operational lifespan of deployed transformers. This approach benefits asset managers and Transmission System Operators (TSOs) by enhancing overall system reliability and efficiency ([Christina et al., 2018](#)).

## 1.6 Justification

The rationale of this study was to develop a transformer replacement strategy, based on the present failure drivers. This study was motivated by the fact that on-load UETCL power transformers experience frequent long duration failures, thus resulting into prolonged network outages. Despite the fact

that planned maintenance and occasional replacements on power transformers have been done, there has not been any explicit strategy to retire symptomatic transformers. Power transformer failure often occurs without warning and thus replacements are carried out on a post mortem basis after a large fault impact, which results into overwhelming corrective maintenance costs. This research thus aimed at scaling down the high costs involved in corrective maintenance by developing a predictive tool for identification of asymptomatic transformers based on diverse failure modes. In addition, the study was based on 132 kV transformers since they have existed for quite some time, where it is possible to have a large data size compared to 220 kV transformers which have been recently installed.

## **1.7 Contribution of this Research**

The contribution of this research lies in advancing the understanding of internal and often unobserved health conditions of transformers across Uganda's diverse regional transmission contexts, an area that has not previously been explored in the country. At present, no frameworks exist to determine the asymptomatic state of power transformers. let alone, globally reviewed approaches fall short by overlooking the resolution needed for accurate transformer prediction. This gap directly affects the precision of forecasting transformer health status and consequently, undermines decisions on the appropriate timing for retirement and replacement.

This study thus uniquely contributes to the field of power systems reliability by developing and validating a PSO-ANFIS hybrid model for 132 kV transformer degradation prediction using multiparameter CBM data. This model has not been explicitly used in previous studies and has yet been instrumental in optimal tuning the conventional ANFIS. This has promoted achievement of more accurate predictions. Unlike prior work, this study also integrates failure trend modeling with a cost-optimized replacement strategy tailored to Uganda's national grid conditions, thus bridging a practical gap between transformer monitoring, failure prediction, and asset management decision making.

## **1.8 Scope of Study**

This study focused on large power transformers in operation on the 132 kV network, manned by UETCL. The reason for selection of 132 kV transformers is that they are the most affected units, experiencing frequent long duration failures, thus resulting into prolonged network outages, compared to

other voltage levels such as 400 kV, 220 kV and 66 kV. It should be noted that when power transformers fail, a lot of adverse impacts are likely to occur namely; disconnection of 80% of the distribution network, cumulative generator tripping and occasional shutdowns amongst others. The study focused on determining when power transformers are likely to fail and allow for early replacement. Selection of power transformers considered power transformers in both healthy and degraded states, considering those which have not yet undergone retirement.

The study specifically focused on power transformers with a minimum of 23 years of operation. A sample of 30 power transformers out of a total population of 76 unretired power transformers on the transmission network were considered from selected substations for reliability assessment (UETCL, 2023). The study utilized quantitative data of power transformer operation for a period of 23 years. This research is anticipated to span a duration of 10 months.

## **1.9 Conceptual Framework**

The conceptual framework as illustrated in Figure 1.1 shows the different study variables and their close interactions. The independent variables comprise the parameterisation of 132 kV transformer reliability, failure tendencies and replacement model parameters. On the other hand, the failure impacts on network reliability and replacement strategies and frameworks constitute the dependent variables.

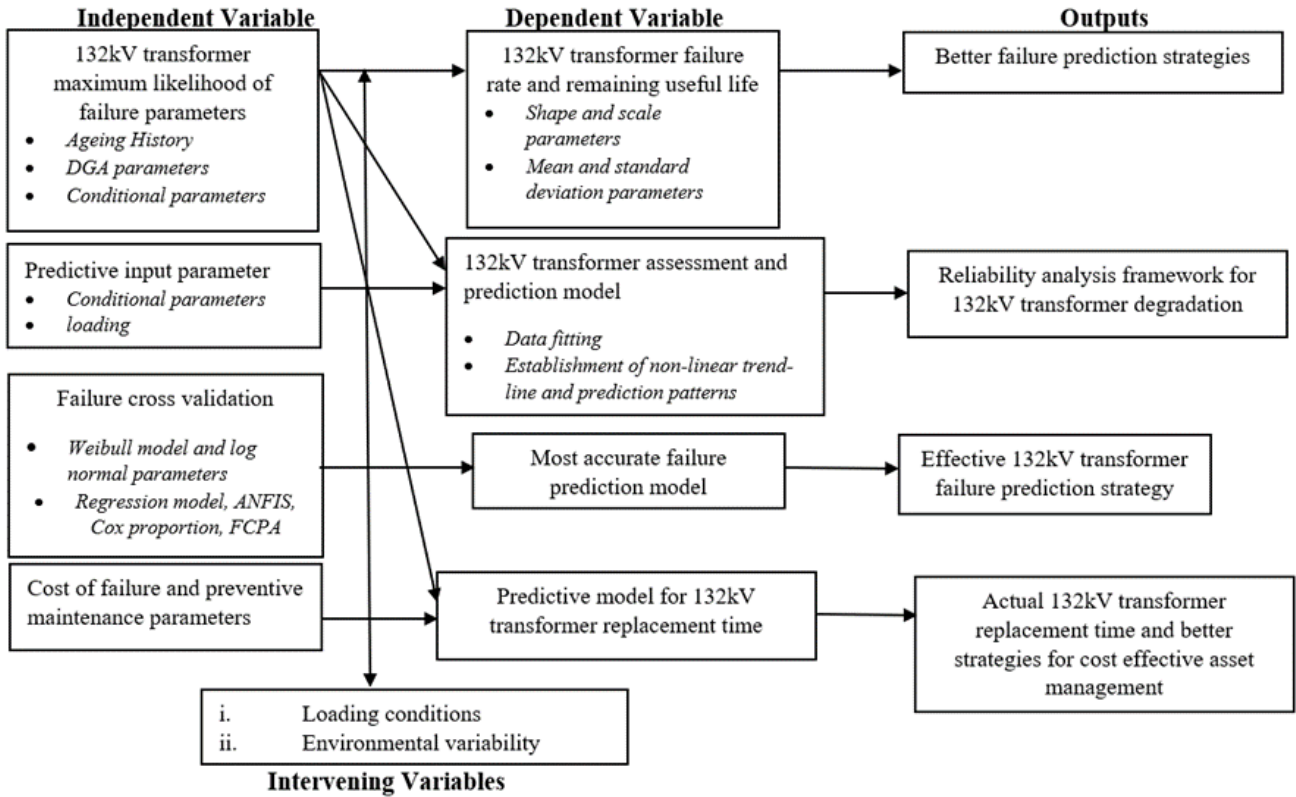


Figure 1.1: Conceptual Framework

## 1.10 Summary

Chapter one: Describes the background of the problem, the problem statement, objectives that were followed to achieve results in my research, the significance, scope of my study and conceptual framework. Chapter two: Offers a detailed review from various sources namely textbooks, journals, conference proceedings, technical reports, etc. It provides a preliminary review of desired asset management frameworks, a comparative analysis of different prediction models that have been developed as replacement strategies and points out the gap necessitating the model developed. Chapter three: Constitutes of the various methods which were considered to achieve results of the empirical research. These methods were aligned according to the objectives developed. Chapter four: Presents the results based on the objectives developed. Chapter five: Offers a discussion of results of the study based on a comparative analysis between different scholars' findings and findings, which were achieved in my research work. Chapter six: Offers a detailed conclusion of findings based on the objectives developed and clearly highlighting the contribution of my research.

# CHAPTER TWO: LITERATURE REVIEW

## 2.1 Introduction

This chapter expounds upon important performance indicators and metrics that impact reliability of power transformers, based on different scholarly articles and books. In addition, a thorough analysis of various academic publications highlighting the gaps found was conducted, along with a discussion of the various models employed in evaluating power transformer degradation.

## 2.2 Parameters Influencing Power Transformer Failure

### 2.2.1 Diagnostic and Prognostic Methods

Diagnostic and prognostic techniques play a crucial role in evaluating the failure of power transformers. Diagnostic methods are employed to identify and characterize faults, providing insights into the root causes of failure. During the diagnostic process, the entire system is dissected into its constituent components, and an evaluation of failure for each individual component is conducted (Li et al., 2017). In contrast, prognostic techniques are utilized to anticipate the probable progression and outcome of failure in a power transformer (Gopakumar and Sree Renga Raja, 2023). Understanding the lifespan of a power transformer is essential when utilizing diagnostic and prognostic methods to evaluate potential failures. This understanding facilitates the formulation of strategic interventions based on the remaining operational life of the power transformer. According to research by Hillary et al. (2017), power transformers are typically designed to last between 20 and 40 years.

Nevertheless, through effective maintenance practices, the operational life of a power transformer can be extended up to 60 years, as highlighted by (Innocent, 2019). It is noteworthy that the degradation of power transformers tends to escalate with age, posing an increased risk of potential failures. Recognizing this, prognostic techniques become imperative for pinpointing optimal times for maintenance, thereby prolonging the operational life of the power transformer. During the diagnostic process of a power transformer, the root causes of failure are identified and evaluated. For example, occurrences like

short circuits, transient switching, lightning strikes, and sabotage are recognized as primary contributors to transformer failures (Singh and Singh, 2016). Initially, a newly installed transformer is in an "As Good as New" (AGAN) state, exhibiting sufficient mechanical, chemical, and electrical strength. However, exposure to the aforementioned disruptive factors leads to a gradual decline in the transformer's reliability, ultimately impacting its functionality (Ochella et al., 2022).

The reliability of a power transformer is described by the degree of functionality of its system components. Power transformer core problems have been attributed to core insulation fault, an open ground strap, or shorted laminations. Other miscellaneous faults have been caused by current power transformers, oil leakage owing to inadequate cistern welds, oil contamination from metal particles, overloads and over voltage (Innocent, 2019). According to Christina et al. (2018), the failure of bushing is generally considered the primary source of power transformer failure. Typically, a single type of fault can result from multiple causes. For instance, the occurrence of arcing and overheating in solid insulation may be attributed to coil turn-to-turn short-circuits (Innocent, 2019). Similarly, arcing and corona discharges can be caused by factors such as the presence of free water or excessive moisture in the oil. This complexity adds intricacy to the process of pinpointing the exact location of faults. Despite this, fault diagnosis remains sufficiently effective in developing information for a maintenance program. It forms the groundwork for implementing preventive maintenance strategies and serves as a basis for prognostic initiatives (Fernandes et al., 2022);(Martin et al., 2018)

### **2.2.2 Diagnostic and Prognostic Tools**

An article by Wang proposes the method of Fault Tree Analysis (FTA) for probabilistic assessment of the power transformer failure drivers. This tool determines the direction of failure of the power transformer from the smallest system component (Wang and Lei, 2018). Each event of failure is characterized by sub-events behind it, which collectively influence occurrence of the main failure event. All sub-events are represented as logical events. The logic data includes using instructions such as "OR", "AND", "NOR", "EXCLUSIVE-OR" and "EXCLUSIVE-NOR" on low-level events. The Fault Tree Analysis (FTA) technique plays a crucial role in developing a risk management plan or alleviating the impacts of a scientific problem. The minimum cut-set, representing the smallest number of sub-events influencing the occurrence of the top event, is a key concept in FTA (Wang and Lei, 2018). The

probability of the top event is then calculated as the sum of all cut-sets. However, FTA alone does not precisely ascertain the extent and severity of failure over time; it primarily serves as a tool for diagnosing the impact of faults. To address this limitation, the Statistical Package of Social Science (SPSS) tool has been integrated with FTA. This combined approach aims to comprehensively establish the relationship between various transformer performance factors and time (Mago et al., 2012). The incorporation of SPSS enhances accuracy, providing a more precise technique for determining when specific failures exert the highest impact on transformer performance. This information becomes instrumental in devising proactive action strategies. Figure 2.1 shows the implementation of FTA in diagnosing power transformer failure.

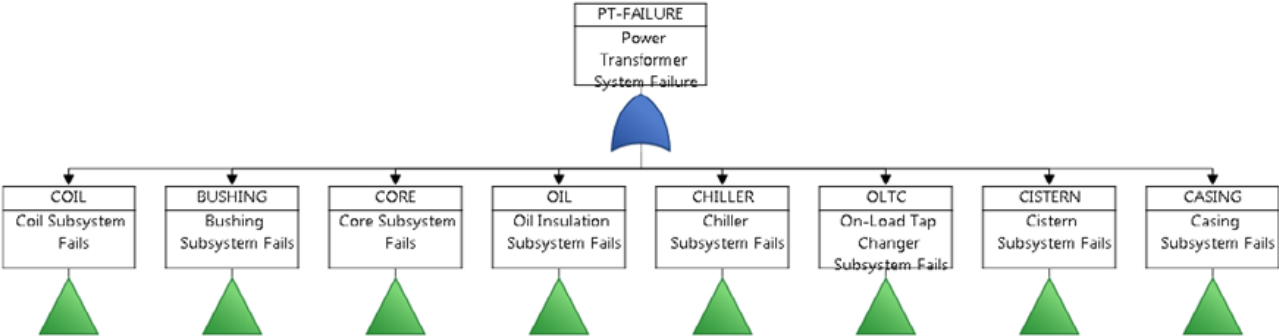


Figure 2.1: Power Transformer System Fault Tree (Innocent, 2019)

### 2.3 Modelling of Power Transformer Degradation

Modelling the degradation of power transformers is crucial for identifying the optimal timing for maintenance interventions. As a power transformer ages, the likelihood of failure steadily rises. Hence, it becomes imperative to undertake refurbishment or replacement before reaching the point of maximum degradation, as highlighted by (Martin et al., 2018). Modelling of power transformer degradation is mainly categorized into two methods namely; parametric methods and non-parametric methods. Parametric methods assume that the data follows a specific distribution (e.g., normal distribution) with a fixed number of parameters (Turner et al., 2020). Common parametric tests include t-tests, analysis of variance (ANOVA), linear regression and reliability centred models such as Weibull and Log-Normal among others. On the contrary, non-parametric methods make fewer assumptions about the distribution of the data. They are used when the data does not meet the assumptions of parametric tests or when dealing with ordinal or non-normally distributed data (Turner et al., 2020) Parametric methods

such as the Weibull model have been considered to determine the distribution of failure of a power transformer based on key performance parameters such as the shape parameter; for determining failure rate and the scale parameter; for remaining useful life. Picher carried out a reliability study on 2,000 power transformers owned by Canadian utility; Hydro-Québec (Picher et al., 2014). More than 50% of their transformers were over 30 years old, with this utility considering the technical end of life as being between 40 and 50 years old. The group used a Weibull distribution to model failure, comparing it to a non-parametric method (Kaplan-Meier). They found a good match using these two methods, concluding the Weibull distribution is appropriate for use.

The Weibull model is preferred for providing the exact parameter estimates that describe a given failure distribution, as opposed to non-parametric methods. However, non-parametric methods are more suitable in cases where accounting for censored data is required, as opposed to parametric methods (Johansen et al., 2021). The failure distribution of the power transformers is divided into three main stages namely; the infant mortality stage, when the power transformer has just been commissioned and is in AGAN state, the stage of constant random failure and the wear out stage, where the power transformer failure increases with time (Lee, 2020). This is shown in Figure 2.2.

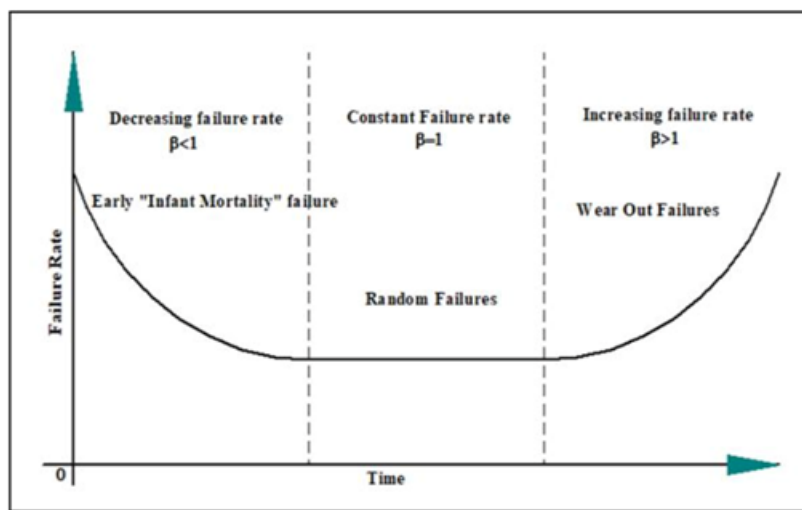


Figure 2.2: The Bathtub Curve (Lee, 2020)

Shan proposed an early warning criterion for determining power transformer degradation (Shan et al., 2023). The model considered diverse historical and observed patterns of power transformer degradation over time, whilst measuring changes in performance, frequency maintenance, failure rates and

signs of ageing amongst others. Understanding power transformer degradation patterns enables timely maintenance, prolonging transformer life and enhancing cost savings in would be adverse transformer failure. Yuehan utilized a technique for prediction of oil-paper insulation, based on Functional Principal Component Analysis (FPCA), where data on oil-paper insulation degradation was developed and analysed as a continuous function (Qu et al., 2022). In FPCA, the correlation of power transformer performance variables is analysed and the most critical patterns of failure are achieved. Based on the observed critical patterns, a projection of the power transformer failure trend is implemented.

Yu et al proposed an approach to oil temperature prediction of power transformer based on modified Support Vector Regression (SVR) machines, where the non-linear relationship of oil temperature with time, subject to diverse load conditions, was analysed and the margin of tolerance established (Qu et al., 2022). This was the basis for formulation of a prediction pattern with most data points within the established accuracy threshold margin, with assistance of boundary support vectors. However, SVR having several hyperparameters that influence model performance, selection of the parameters that yield the most accurate prediction might be challenging. This journal article thus proposed Particle Swarm Optimization (PSO) as an approach for optimizing SVR parameter sets, in effort to achieve the parameters that yield the most accurate prediction patterns.

Selva et al carried out a study on comparison of the effectiveness for different statistical distribution models that predict Health Index (HI) of Condition Based Monitoring (CBM) power transformers (Mohd Selva et al., 2021). The statistical distribution models namely; Weibull and normal distribution were selected in order to predict the HI of the transformer population given a limited size of historical condition data. This study involved establishment of the conditional parameters, fitting them into probability plots and extrapolation so as to predict the distribution parameters for the next 10 years. This study however pointed a gap observed in previous scholarly articles, indicating the wide focus on individual conditional parameter data of transformers, but less on multiple conditional assessment for power transformers based on a universal HI. There is thus lack of a comprehensive data plan to track various performance factors of power transformer degradation, thus making it difficult to develop comprehensive prediction models. This research study seeks to address the aforementioned gap.

The prediction of transformer remnant life is crucial for improving asset management and ensuring system reliability. Adaptive Neuro-Fuzzy Inference Systems (ANFIS) have been widely explored in this context due to their capability to handle nonlinear, uncertain, and sparse data effectively (Nezami et al., 2021). ANFIS combines the human-like reasoning style of fuzzy logic with the learning and connectionist structure of neural networks, enabling the system to model complex relationships between transformer condition parameters and remaining useful life (RUL). In typical applications, key condition monitoring factors such as breakdown voltage (BDV), moisture content, dissolved gas analysis (DGA) indicators, oil acidity, and color index are fed as inputs to the ANFIS model (Pandey et al., 2014). Through a hybrid learning process, involving forward pass (least squares estimation) and backward pass (error backpropagation), ANFIS tunes its membership functions and rule base to minimize prediction errors. As shown in studies like Pandey et al. (2014), the model successfully learns patterns from historical degradation data, thus offering reliable estimations of transformer health status and providing early warnings of potential failures.

While conventional ANFIS models are effective in predicting transformer degradation, their performance can be limited by issues such as poor initialization of membership function parameters and convergence to local minima (Li et al., 2023). To address these challenges, researchers have proposed hybrid models combining Particle Swarm Optimization (PSO) with ANFIS (PSO-ANFIS). PSO, inspired by the social behavior of bird flocking, is a global optimization technique that efficiently explores the parameter space to find near-optimal solutions (Li et al., 2023). In PSO-ANFIS, the PSO algorithm is utilized to optimize the initial membership function parameters and/or fuzzy rules before training, ensuring better starting conditions and improved generalization ability. Applied to transformer degradation prediction, PSO-ANFIS models take critical condition indicators (such as DGA gases, BDV, moisture, and acidity) as inputs and predict the remnant life or degradation level of the asset. This hybrid approach enhances the model's robustness, reduces prediction error, and ensures faster convergence compared to conventional methods, as demonstrated in recent studies (Li et al., 2023). As a result, PSO-ANFIS is increasingly recognized as a powerful tool for transformer life cycle management in modern power systems.

## **2.4 Determining the Most Opportune Time for Power Transformer Replacement**

### **2.4.1 The Weibull Distribution Model**

By creating a prediction model to calculate the precise replacement period of power transformers, an optimal replacement strategy can be quantitatively identified. An optimal replacement strategy is achieved at a point in time when the costs of preventive maintenance and failure are at minimum. The replacement cost functions are essential for calculating accurate replacement time values. This is in line with research by [Lin and Miyauchi \(2017\)](#). Due to the WDM's precision, it is considered the most accurate model in determining optimal replacement time of assets. Due to their discrete character, other approaches such as Markov Analytical Model and Cut Set-Cost Estimation do not produce accurate replacement time estimates. They have the potential to either overestimate or underestimate in agreement with [\(Teng and Ho, 1996\)](#). Furthermore, because cost values are just projected or approximated deterministically, approaches such as the Minimum Cut Set-Cost Estimation (MCS-CEM) technique does not reliably foresee the future costs of asset failure and accompanying replacement time. Machine learning, a commonly used approach in prognostic studies also faces challenges of large data sets required, complexity of decision-making processes during straining and challenges to constantly evolving parameters [\(Zhou et al., 2017\)](#). Thus, the WDM has been considered the most suitable model that guided into determination of most opportune time for power transformer replacement.

### **2.4.2 Reliability-Centered Maintenance (RCM)**

RCM focuses on ensuring system reliability by identifying critical components and defining maintenance strategies based on failure modes. For power transformers, RCM schedules inspections, replacements, or overhauls based on the risk and consequence of failure. It considers transformer load, oil condition, and age. However, RCM can be data-intensive and relies heavily on expert input; it may not adapt well to rapidly changing operating environments or new failure patterns without continuous updates [\(Aldhubaib, 2013\)](#).

### **2.4.3 Genetic Algorithm (GA)**

GA optimizes transformer maintenance schedules by simulating the process of natural selection. It searches for the best time to perform maintenance or replacement that minimizes cost and maximizes reliability by evolving a population of candidate solutions. However, GA may converge to local optima and is sensitive to parameter settings. It doesn't inherently account for uncertain degradation paths unless hybridized with probabilistic models ([Balanta et al., 2023](#)).

### **2.4.4 Monte Carlo Simulation**

Monte Carlo Simulation evaluates the probability of transformer failure over time by simulating thousands of random degradation scenarios based on historical data and probabilistic models. This helps estimate the most likely replacement period under uncertainty. However, the accuracy of this model heavily depends on the quality and completeness of input data (e.g., failure rates, degradation patterns). It lacks deterministic precision and may require significant computation ([Zhang et al., 2018](#)).

### **2.4.5 Paper Insulation Decomposition and Degradation**

This method involves chemical analysis of transformer insulation (e.g., Degree of Polymerization, furfural content in oil) to estimate the remaining life of the paper and hence the transformer. It provides direct evidence of internal ageing. However, this approach may require oil sampling and lab analysis, which is intrusive and can't be done too frequently. Results can also be affected by external factors like oil contamination or loading variability ([Balanta et al., 2023](#)).

### **2.4.6 Fuzzy Logic Rules**

Fuzzy logic models expert knowledge using linguistic rules (e.g., "If oil moisture is high and temperature is moderate, then ageing is medium") to estimate transformer health and replacement needs. It handles imprecise inputs well. However, rule creation is subjective and dependent on expert opinions. Without learning mechanisms, fuzzy systems may not adapt to new patterns or unseen conditions unless constantly revised ([Malik et al., 2023](#)).

### **2.4.7 Gray Incidence Analysis (GIA)**

GIA quantifies the degree of influence between different condition parameters (e.g., load, temperature, gas content) and transformer health. It ranks which indicators most strongly correlate with failure, helping prioritize maintenance or replacement timing. However, GIA does not model time-based progression well and lacks predictive power for degradation trends. It's better for short-term condition

correlation than long-term lifespan estimation ([Ingle and Ingle, 2014](#)).

## 2.5 Review of Related Literature and Gaps Identified

[Innocent \(2019\)](#), conducted a thorough evaluation of power transformer reliability within the Nigerian Electrical Supply Industry . The analysis involved a qualitative examination of power transformer component failures using FTA and quantitative analysis utilizing SPSS. However, the study overlooked the influence of age on power transformer degradation, leading to a lack of precision in estimating the severity of failure rates for individual system components. Additionally, the research was not sufficiently explicit regarding actual component failures, creating a discrepancy between bushing and coils as the primary contributors to failures. This discrepancy stemmed from the absence of a model to precisely quantify the extent of these failures over time. In contrast, [Martin et al. \(2018\)](#) investigated the modelling of Australian power transformer failure and retirement. The study validated failure patterns by comparing parametric and non-parametric methods but focused solely on the interdependency between failure rates and time for various failure modes. It did not, however, consider the specific times of maximum degradation to develop an effective replacement initiative. [Amran et al](#) established predictive models to determine the health index of condition-based transformers ([Mohd Selva et al., 2021](#)). However, the predictions did not accurately demonstrate the anticipated failure patterns, since the model only focused on data fitting and only extrapolated the trend line for all conditional parameters.

A gap has also been identified in present scholarly articles of power transformer degradation predictive modelling, being that there is lack of long-term statistical analysis on multi-dimensional degradation data of power transformers. In otherwords, the lack of comprehensive data to track patterns of various performance factors influencing power transformer degradation has been noticed, thus making it difficult to develop a comprehensive statistical prediction model for time based degradation ([Mohd Selva et al., 2021](#)), ([Shan et al., 2023](#)), ([Qu et al., 2022](#)) and ([Zhou et al., 2017](#)). In Uganda, no frameworks exist to monitor and predict failure trends for key power transformer conditional factors.

While several studies have explored transformer failure prediction using soft computing techniques such as ANFIS, most have not addressed the limitations related to convergence accuracy or incorporated multiple condition-based parameters in a single predictive framework. Additionally, few studies have contextualized these models to the operational realities of Uganda's 132 kV transmission net-

work. Notably, absent is a cost-optimized failure prediction approach that combines advanced hybrid algorithms with practical asset management strategies. This study addresses this gap by developing a PSO-ANFIS-based model tailored to Uganda's grid, using real transformer condition data and incorporating cost-based replacement planning.

# CHAPTER THREE: METHODOLOGY

## 3.1 Introduction

This chapter describes the data collection tools and methods, steps that were taken to analyze operational parameter data, procedures for development of the prediction model and the criterion for developing the replacement strategy for potentially degraded power transformers.

## 3.2 Parameters Influencing Failure of 132kV Transformers

### 3.2.1 Research Approach and Design

Given the nature of data required, this research study adopted a quantitative research approach. Quasi experimental research design enabled establishment of the relationship between the data collected and failure impact. The data collected included inventories on transformer time of installation for a 23-year duration, including all operational parameters that influence transformer reliability. These include: moisture, acidity, interfacial tension, colour and gas concentration, among others. This served as the key failure modes for analysis of asymptomatic transformer failure.

### 3.2.2 Data Collection Tools and Methods

Quantitative data was collected by observation of the records for the condition-based parameters affecting power transformer performance for a 23-year period, stored by the UETCL network operation and maintenance department inventories. This data was split into two sub-sets namely; the measured region, where the operational parameters were analysed for the first ten years and the second region is the validation region, where the data for the next set of 10 years was tested for consistency with the first dataset. The indication of consistency meant that the data for operational performance of the transformer for the last 23 years had high precision. In addition, consistency in data enabled achievement of accurate appropriate curve fits and projections.

The data acquisition process involved retrieving historical Condition-Based Monitoring (CBM) records from the UETCL Maintenance Management Information System (MMIS) and laboratory test reports

spanning a 23-year period (2000–2023). The dataset covered 30 power transformers located at strategic substations including Mutundwe, Namanve, Fort Portal, Lugogo, and Kawanda. The parameters acquired included Breakdown Voltage (BDV), Moisture Content (MC), Acidity, Interfacial Tension (IFT), Colour, and Dissolved Gas Analysis (DGA) gases ( $H_2$ ,  $CH_4$ ,  $CO$ ,  $CO_2$ ,  $C_2H_2$ ,  $C_2H_4$ ,  $C_2H_6$ ). Data were primarily obtained from quarterly oil diagnostic reports generated by the UETCL central laboratory in Lugogo and supplementary SCADA logs maintained by the Transmission Operations Department. All test procedures conformed to IEC 60422, IEC 60599, and ASTM D877 standards for transformer oil assessment.

Field engineers and laboratory technologists recorded values using calibrated instruments such as BDV testers, Karl Fischer moisture analyzers, acid value titrators, and IFT tensiometers. For each transformer, sampling points were taken from the main tank and on-load tap changer compartments. The collected data were manually entered into Excel spreadsheets and later exported to MATLAB for pre-processing and model training. Each record was time-stamped and cross-validated with transformer maintenance logs to confirm consistency between laboratory readings and operational events such as overloads, trippings, and oil filtration.

The 30 selected transformers were chosen to represent both healthy and degrading units, ensuring coverage of different climatic zones and load environments across Uganda's 132 kV grid. Consistency checks were performed to ensure measurement frequency, data completeness, and accuracy before statistical analysis. Missing or inconsistent records were verified against physical logbooks and asset registers. The resulting cleaned dataset provided a reliable foundation for the subsequent modeling and reliability analysis stages.

### **3.2.3 Data Treatment and Justification**

The raw data obtained from UETCL's transformer condition monitoring database contained inconsistencies, missing entries, and occasional measurement errors due to variations in test frequency and human input. To address this;

- Outliers were identified using the plus or minus three sigma statistical limit and were verified against maintenance records to confirm whether they represented actual anomalies or data entry errors.

- Missing values were treated using linear interpolation and expert estimation based on the trend of adjacent readings.
- Invalid records (e.g., repeated or incomplete data) were excluded from further analysis.

Justification: Data cleaning ensured that the dataset was complete and representative of the true operational condition of transformers. This improved the accuracy of subsequent modelling and statistical estimation by reducing uncertainty and bias.

### **3.2.4 Transformer Selection Criterion**

The study began with a population of more than sixty-six transformers installed on Uganda’s 132 kV transmission network between 1936 and the present. Since the objective was to focus on units approaching the end of useful life, the first step was to filter out recently commissioned transformers that had operated for less than half of their expected lifespan, typically 20 years. Such younger units are generally in the “as good as new” state and exhibit minimal degradation, meaning their inclusion would bias the model toward healthy operating conditions rather than reveal patterns of failure.

The second stage of filtering targeted transformers that had surpassed 50 % of their designed life and displayed increasing rates of deterioration. This was done by applying the Weibull distribution model, where units with a shape parameter  $\beta \leq 1$  were flagged as being in the wear-out phase. This statistical criterion ensured that only those transformers with a rising probability of failure were considered for deeper analysis, reflecting the phase of operation where predictive modelling is most meaningful and where asset managers face critical replacement decisions.

From this process, five transformers were selected: Namanve-3, Mutundwe-1, Mutundwe-2, Fort Portal-5, and Kawanda-1. These were not only identified as technically at risk but also as strategically critical assets within the transmission network. The Mutundwe units serve Kampala’s metropolitan load, while Namanve-3 supplies major industrial customers, making their failures particularly disruptive. Fort Portal-5 represents an isolated node with limited redundancy, and Kawanda-1 sits on the central corridor, where previous breakdowns have proved costly. Their selection therefore balanced statistical evidence of degradation with operational criticality, ensuring that the predictive model was applied to transformers where early replacement decisions carry the greatest reliability and economic

benefits. The determination of the Weibull shape parameter ( $\beta$ ) was based on a combination of empirical data fitting and reliability–engineering interpretation. The Maximum Likelihood Estimation (MLE) method was applied to the 23-year transformer failure and condition-based dataset to obtain statistically consistent estimates of  $\beta$  and the corresponding scale parameter ( $\eta$ ). The resulting  $\beta$  values were interpreted using standard reliability criteria, where  $\beta < 1$  indicates a decreasing failure rate (infant mortality),  $\beta = 1$  a constant failure rate (random failures), and  $\beta > 1$  an increasing failure rate (wear-out failures). The estimated  $\beta = 5.2$  therefore reflects a pronounced wear-out phase, consistent with aging and cumulative stress mechanisms observed in 132 kV transformers that have operated for over two decades. The use of MLE ensured unbiased parameter estimation even with censored data, while cross-validation against historical outage records confirmed that the fitted shape parameter realistically represented the observed degradation trend in the UETCL fleet.

### **3.2.5 Data Dictionary**

#### **Data Dictionary**

Table 3.1 provides a summary of all key variables used in the analysis and model development. It defines each variable, specifies its measurement unit, describes its meaning in the context of transformer condition assessment, identifies its data source, and indicates whether it served as an input or output in the developed PSO–ANFIS model. This structured dictionary ensures consistency and clarity in data interpretation throughout the study.

### **3.2.6 Basis for Stochastic Processes**

The degradation and failure behavior of high-voltage transformers was modeled as a stochastic process to capture the inherent randomness and uncertainty associated with operational and environmental conditions. Transformer deterioration does not follow a fixed deterministic path due to variations in loading, ambient temperature, oil contamination, moisture ingress, and maintenance practices, all of which introduce probabilistic fluctuations in aging rates. Modeling these variations stochastically allows the failure rate  $\lambda(t)$  and reliability function  $R(t)$  to be expressed as random variables rather than fixed constants, thereby providing a more realistic representation of field behavior. The use of the Weibull distribution within this stochastic framework enables flexibility in characterizing different life phases (infant mortality, constant failure, and wear-out), while accommodating censored and incomplete data common in utility records. This probabilistic formulation forms the foundation for the subsequent

Monte Carlo-based and PSO-ANFIS predictive analyses, ensuring that both parameter estimation and reliability forecasting reflect the uncertain and dynamic nature of transformer degradation under real operating conditions.

Table 3.1: Data Dictionary for 132 kV Transformer Condition Parameters

Variable	Unit	Description	Data Source	Role
Breakdown Voltage (BDV)	kV	Minimum voltage at which dielectric failure occurs in oil; indicates insulation strength.	UETCL Laboratory Tests (IEC 60156)	Input
Moisture Content (MC)	ppm	Water content in oil; high values accelerate insulation aging.	UETCL Laboratory Tests (IEC 60814)	Input
Acidity	mgKOH/g	Amount of acid in oil; represents oxidation and degradation of insulation.	UETCL Laboratory Tests (IEC 62021)	Input
Interfacial Tension (IFT)	mN/m	Force per unit length between oil and water; decreases with oil contamination.	UETCL Laboratory Tests (ASTM D971)	Input
Colour	–	Visual indicator of oil aging and contamination, rated on ASTM D1500 scale.	UETCL Laboratory Reports	Input
Dissolved Gas Analysis (DGA)	ppm	Concentrations of key gases (H <sub>2</sub> , CH <sub>4</sub> , CO, CO <sub>2</sub> , C <sub>2</sub> H <sub>2</sub> , C <sub>2</sub> H <sub>4</sub> , C <sub>2</sub> H <sub>6</sub> ) used to diagnose incipient faults.	UETCL DGA Laboratory	Input
Health Index (HI)	%	Composite index quantifying overall transformer condition from multiple parameters.	Derived via Weighted Scoring Model	Intermediate
Operational Age	years	Transformer's total service duration since commissioning.	UETCL Asset Register	Input
Failure Occurrence	Binary (0/1)	Indicates whether a failure event occurred within observation period.	UETCL Maintenance Records	Output
Predicted BDV / RUL	kV / years	Predicted dielectric strength or remaining useful life from PSO-ANFIS model.	Model Output	Output

### 3.2.7 Parameterization

A Goodness-of-Fit test was conducted to verify whether the data collected suites a failure distribution. The results are shown in Table 3.1. All the parameters in each distribution were specified and tested against p-value and AD statistics.

Table 3.2: Goodness-of-Fit Test Results for Time-to-Failure Data of Power Transformers

Distribution	Parameter	Anderson-Darling (AD) Statistic	P-Value	Fit Decision
Normal	$\mu=18.7, \sigma=5.3$	0.915	0.043	Rejected
Weibull	$\beta=5.2, \eta=28.6W$	0.232	0.713	Accepted
Gamma	$\alpha=12.8, \theta=1.4$	0.587	0.087	Marginal
Log-Normal	$\mu = 2.86, \sigma=0.35$ (log-space )	0.765	0.066	Rejected
Beta	$\alpha=2.1, \beta=3.4$ (bounded to [0,50])	1.122	0.028	Rejected

It is thus observed that the Weibull distribution fits the failure data, since it has the lowest Anderson-Darling and highest p-value. The values close to  $p \geq 0.05$  show a marginal fit, whilst all values below 0.05 show a weak/unfit distribution. The common thresholds for the AD-test fit success are minimum values of 0.752, 0.637, 0.708, 0.870 and 0.922, which pertain to normal, Weibull, log-normal, gamma and exponential distribution respectively as defined by (Berlinger et al., 2021). From Table 3.1, the Weibull distribution records an AD-statistic value of 0.232, which is below the minimum threshold (0.637) and it also records a p-value of 0.713, which is above the threshold of 0.05 and thus fit for a failure distribution. The shape parameter  $\beta$  and scale parameter  $\alpha$  for Weibull model, as well as the mean  $\mu$  and standard deviation  $\sigma$  for normal distribution was achieved by Maximum Likelihood Estimation and determined by the likelihood functions shown in (3.1) and (3.2). The shape parameter represents the failure rate, while the scale parameter represents the characteristic life (in years), where 63.2% failures were expected to occur (Sangwongwanich and Blaabjerg, 2022). These parameters enhanced the ranking of transformer operational factors mentioned in Section 3.2.1 based on their severity.

$$L(\alpha, \beta) = \alpha^n \beta^n \left( \prod_{i=1}^n \right) \exp \left( -\alpha \sum_{i=1}^n (x_i^\beta) \right); \quad (3.1)$$

$$L(\mu, \sigma) = \prod_{i=1}^n \frac{1}{\sigma \sqrt{2\pi}} \exp \left( -\frac{1}{2} \left[ \frac{x_i - \mu}{\sigma} \right]^2 \right), \quad (3.2)$$

where  $x$  is the time of power transformer operation in regard to  $n$  condition-based factors for  $m$  trans-

formers. Data fitting was carried out for two distributions namely; the Weibull and normal distribution, in an effort to ascertain models or functions that fit the set of data points collected. Data analysis involved the effect of the factors in Section 3.2.1 on the Weibull and normal distribution parameters. The description of the condition based factors affecting power transformer reliability is shown in Appendix I. Figure 3.1 shows the ranking of weibull reliability parameters for each key transformer operational factor affecting Lugogo transformer-1 reliability. Equations 3.3 and 3.4 define the shape and scale parameters.

$$\eta_i \subset \eta \ni; \eta_i = \left[ \frac{1}{\eta_i} \left( \sum_{i=1}^n x_i^\beta + \sum_{j=n+1}^n y_j^\beta \right) \right]^{\frac{1}{\beta_i}}, \quad (3.3)$$

$$\beta_i \subset \beta \ni; \beta^{-1} = \frac{\sum_{i=1}^n x_i y_i - \frac{(\sum_{i=1}^n X_i)(\sum_{i=1}^n Y_i)}{n}}{\sum_{i=1}^n x_i^2 - \frac{(\sum_{i=1}^n X_i)^2}{n}}, \quad (3.4)$$

where  $\beta$  represents the shape parameter,  $\eta$  the scale parameter for  $n$  operational factors and  $x$  and  $y$  represent the variables measuring time or operational life. The Mean Time-to-Failure (MTTF) was also a parameter used to estimate the operational life span of the power transformers, with an assumption that the degraded transformers are non-repairable, leading to results in Figure 3.1. The MTTF was determined by the Equation 3.5.

$$MTTF = \eta \Gamma \left( 1 + \frac{1}{\beta} \right), \quad (3.5)$$

where  $\Gamma(x)$  is the gamma function which generalizes factorial calculations.

Condition-based analysis was then conducted on each transformer operational parameter such as BDV, moisture content, acidity, color (change of color based on transformer age) and DGA-based factors. The purpose of conducting condition based analysis was to establish and analyze the predictors that largely influence the asymptomatic-ness of the transformer health and consequently degradation. The process of analysis of predictors is shown in Figure 3.2.

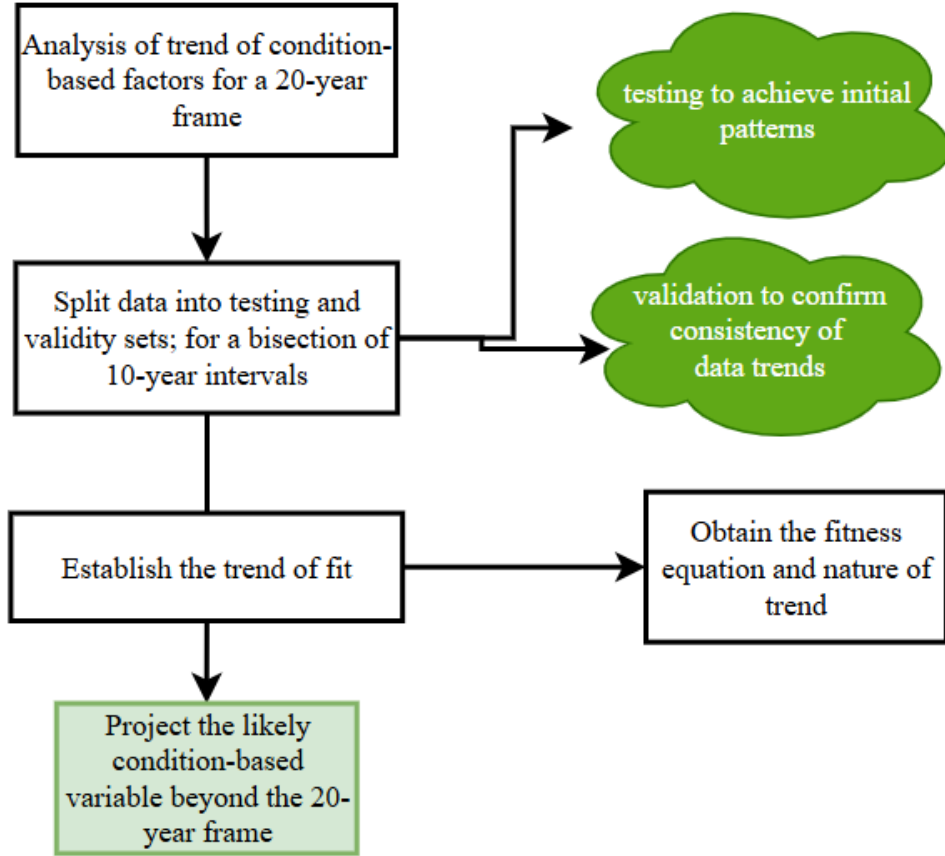


Figure 3.1: Process flow for analysis of condition-based factors

### 3.3 Development of a Prediction Model for 132 kV Transformer Degradation

#### 3.3.1 Modelling and Analysis

The prediction process was initiated by Condition based analysis, which was as a basis for failure assessment, described by reliability functions within the Weibull distribution set namely; the Probability Density Function (PDF), Cumulative Distribution Function (CDF), hazard function and Health Index (HI). The aforementioned continuous functions are shown in Equations (3.6) and (3.7).

$$f(x) = \frac{\beta}{\alpha} \left(\frac{\beta}{\alpha}\right)^{\beta-1} \exp\left[-\left(\frac{x}{\beta}\right)^{\beta}\right] x \geq 0; \beta, \alpha \geq 0, \quad (3.6)$$

$$F(t) = p\{x \leq t\} = 1 - \exp \left[ - \left( \frac{x}{\beta} \right)^\beta \right] \quad x \geq 0; \beta, \alpha \geq 0, \quad (3.7)$$

Prediction of the power transformer health was then carried out using the metric of health index. In this study, the Health Index (HI) was developed as a composite measure to quantify the overall condition of each transformer by integrating multiple condition-based parameters into a single score. Since relying on a single diagnostic factor such as Breakdown Voltage (BDV) or Moisture Content may not adequately capture the holistic ageing behavior of a transformer, the HI provided a more robust indicator of its operational state. Parameters including BDV, moisture, acidity, interfacial tension, dissolved gas analysis (DGA), color index, and 2-Furfuraldehyde concentration were normalized and weighted according to their relative influence on transformer degradation, as established in earlier condition-based monitoring frameworks. The normalized values were then aggregated to generate a health score on a scale from 0–100, where 100 represents a transformer in “as good as new” (AGAN) condition and 0 represents end-of-life or failure.

The computation of the HI was guided by reliability functions within the Weibull distribution model and subsequently validated using the PSO-ANFIS predictive framework. The Weibull model offered shape and scale parameters that quantified the probability of failure across the ageing cycle, while the PSO-ANFIS approach ensured accurate prediction of the degradation trajectory of each conditional parameter. By combining these methods, the HI was not only a static reflection of past condition but also a dynamic predictor of future deterioration trends under varying loading and stochastic environments. This allowed the HI to serve as a central index linking condition monitoring data with predictive modeling outcomes, thereby making it possible to project Remaining Useful Life (RUL) and optimal replacement times.

In practical terms, the HI curves generated for transformers such as Fort Portal-5, Mutundwe-1, Mutundwe-2, and Namanve-3 showed how condition-based data evolved from training to validation and prediction regions. The slight differences in degradation patterns among these units highlighted the role of local operational stress factors and historical loading profiles. Thus, the HI provided both a diagnostic snapshot and a prognostic trajectory, making it a critical component in the development of a cost-effective, condition-based replacement strategy tailored to Uganda’s 132 kV transmission network.

$$s_k = {}_k(x_k), \quad s_k \in [0, 4], \quad k = 1, \dots, m. \quad (3.8)$$

$$\tilde{s}_k = \frac{s_k}{4} \in [0, 1]. \quad (3.9)$$

$$\text{HI}_{\text{comp}} = 100 \times \frac{\sum_{k=1}^m K_k \tilde{s}_k}{\sum_{k=1}^m K_k} = 100 \times \frac{\sum_{k=1}^m K_k s_k}{4 \sum_{k=1}^m K_k} \in [0, 100]. \quad (3.10)$$

$$\text{HI}_{\text{comp}} = \frac{100}{4(K_{\text{DGA}} + K_{\text{OQA}} + K_{\text{FCA}})} \left( K_{\text{DGA}} s_{\text{DGA}} + K_{\text{OQA}} s_{\text{OQA}} + K_{\text{FCA}} s_{\text{FCA}} \right), \quad \begin{aligned} K_{\text{DGA}} &= 10, \\ K_{\text{OQA}} &= 8, \\ K_{\text{FCA}} &= 6. \end{aligned} \quad (3.11)$$

$$\hat{s}_k(t) = {}_k(\hat{x}_k(t)), \quad \hat{x}_k(t) = \mathcal{M}_k(\text{Age} = t, \text{Load}(t), \text{Temp}(t), \dots).$$

$$\text{HI}_{\text{pred}}(t) = 100 \times \frac{\sum_{k=1}^m K_k \hat{s}_k(t)}{4 \sum_{k=1}^m K_k} \in [0, 100]. \quad (3.12)$$

$$\text{HI class} = \begin{cases} \text{Very Good,} & 80 \leq \text{HI} \leq 100, \\ \text{Good,} & 60 \leq \text{HI} < 80, \\ \text{Fair,} & 40 \leq \text{HI} < 60, \\ \text{Poor,} & 20 \leq \text{HI} < 40, \\ \text{Very Poor,} & 0 \leq \text{HI} < 20. \end{cases} \quad (3.13)$$

### 3.4 Transformer Health Index (HI) Classification

The Health Index (HI) is a composite indicator used to assess the overall condition of power transformers by integrating results from multiple diagnostic parameters such as Breakdown Voltage (BDV), moisture content, acidity level, dissolved gas analysis (DGA), and insulation resistance. The HI provides a single quantitative measure representing the relative health status of the transformer insulation system.

To interpret the condition of each transformer, the computed HI values are classified into standard categories that reflect the degree of insulation degradation and the urgency of corrective action. Table 3.3 presents the acceptable HI ranges and their corresponding condition assessments.

Table 3.3: Transformer Health Index (HI) Classification and Interpretation

HI Range	Condition Category	Condition Index (%)	Interpretation
4.1 – 5.0	Excellent	81 – 100	Transformer is in excellent condition
3.1 – 4.0	Good	61 – 80	Good operating condition. scheduled routine.
2.1 – 3.0	Fair	41 – 60	Closer monitoring and diagnostic testing.
1.1 – 2.0	Poor	21 – 40	Significant degradation, refurbish required.
0.0 – 1.0	Very Poor / Critical	0 – 20	Critical, Replacement or are strongly advised.

The above classification aligns with widely accepted industry standards and transformer asset management guidelines (IEEE Std C57.140–2019; CIGRÉ Technical Brochure No. 761). These ranges provide a practical framework for condition-based maintenance (CBM) and prioritization of transformer replacement or refurbishment activities. In this study, the computed HI values for each transformer were mapped to the corresponding condition categories shown in Table 3.3. This facilitated a clear comparison between the predicted failure tendencies and the physical condition of the transformers, thus supporting data-driven decision-making in asset management.

#### Health Index (HI) Formulation

The Health Index (HI) was computed as a weighted aggregate of several condition-based monitoring (CBM) parameters, each reflecting a different aspect of transformer ageing. Formally, the HI at time  $t$  is defined as:

$$HI(t) = 100 \times \frac{\sum_{k=1}^m K_k \tilde{s}_k(t)}{\sum_{k=1}^m K_k} \in [0, 100],$$

where: -  $HI(t)$  = Health Index of the transformer at age  $t$ , expressed as a percentage between 0 (end of life) and 100 (as good as new). -  $m$  = number of condition parameters considered. -  $K_k$  = weighting factor (importance coefficient) assigned to the  $k^{th}$  parameter, reflecting its criticality to transformer degradation. -  $\tilde{s}_k(t)$  = normalized score of the  $k^{th}$  parameter at time  $t$ , scaled to the interval  $[0, 1]$ . Each raw measurement  $x_k(t)$  (e.g., Breakdown Voltage, Moisture, Acidity, Interfacial Tension, Dissolved Gas Analysis, 2-Furfuraldehyde, Oil Color Index) was first converted into a grade  $s_k(t)$  on a scale of 0 to 4 using pre-defined diagnostic thresholds:

$$s_k(t) = \mathcal{S}_k(x_k(t)), \quad s_k(t) \in \{0, 1, 2, 3, 4\},$$

where  $\mathcal{S}_k(\cdot)$  is the grading function for parameter  $k$ . The scores were then normalized as:

$$\tilde{s}_k(t) = \frac{s_k(t)}{4} \in [0, 1].$$

The predicted Health Index, obtained from the PSO–ANFIS model, was computed in a similar way but using predicted parameter values  $\hat{x}_k(t)$  in place of measured values:

$$HI_{\text{pred}}(t) = 100 \times \frac{\sum_{k=1}^m K_k \hat{\tilde{s}}_k(t)}{\sum_{k=1}^m K_k},$$

with

$$\hat{\tilde{s}}_k(t) = \frac{1}{4} \mathcal{S}_k(\hat{x}_k(t)).$$

Thus, the Health Index combines multiple degradation indicators into a single metric that reflects both the current state and the predicted trajectory of transformer condition.

The prediction process was also implemented using the Artificial Neural Fuzzy Interference System (ANFIS) model, shown in Figure 3.3, which is implemented in six stages namely; defining inputs and outputs, fuzzification, rules, normalization, de-fuzzification, aggregation and Output also know as

“layers”. The inputs included the operational status ( $x_1$ ), age ( $x_2$ ), temperature ( $x_3$ ), loading ( $x_4$ ) among others, while the outputs included the failure indicators ( $y_i$ ). Membership functions (e.g., Gaussian or trapezoidal) were used to map each input into fuzzy values. This layer establishes linguistic labels for each input, such as “Low,” “Medium,” and “High” loading. Mathematically, each input  $x_i$  was mapped to a fuzzy set  $B_i$ . Thus

$$y = \mu_{B_i}(x_i) \quad (3.14)$$

is mapped to a fuzzy set. The fuzzified values for loading ( $x_i$ ) might have membership functions  $\mu_{B_i}(x_i)$  to indicate low, medium, and high loading levels. The rule layer is the second stage, where this stage involved combining the input membership values using fuzzy logic rules. Each rule evaluates conditions on the fuzzified inputs to predict transformer failure factors. Let  $\Pi$  represent the firing strength of each rule. For two rules, their firing strengths are denoted as

$$W_1 = \prod \mu_{B_i}(x_i); \quad (3.15)$$

$$W_2 = \prod \mu_{C_i}(x_i), \quad (3.16)$$

where  $W_1$  and  $W_2$  are the rule strengths. The third layer involved normalizing the rule strengths  $W_1$  and  $W_2$  to create a weighted rule activation, expressed as

$$\bar{W}_i = \frac{W_i}{W_1 + W_2}. \quad (3.17)$$

The fourth layer, known as de-fuzzification, involved mapping the normalized weights to functions,  $f_1$  and  $f_2$  which represent the output of the two fuzzy rules. Each function  $f_i$  is a linear equation based on input values. i.e.,

$$f_1 = p_1x + q_1y + r_1; \quad (3.18)$$

$$f_2 = p_2x + q_2y + r_2, \quad (3.19)$$

Where  $p_1, q_1, r_1, p_2, q_2$  and  $r_2$  are linear coefficients of the consequent functions (parameters to be optimized during training). The results of the defuzzified values were aggregated to obtain the final

output  $f$  representing the transformer failure risk score, as follows.

$$f = \sum_{i=1}^n \bar{W}_i f_i. \quad (3.20)$$

This score was then used to predict the likelihood of failure over time  $t$  based on the historical data input into the model. Figure 3.3 shows the ANFIS structural layout.

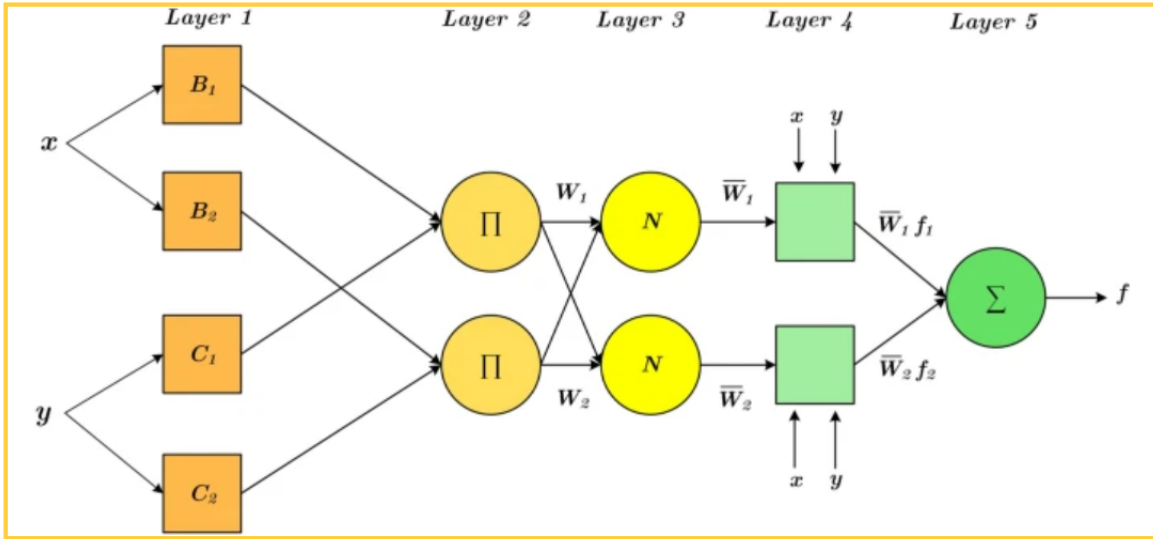


Figure 3.2: ANFIS Structural Layout

Practical implementation was conducted in MATLAB 2022a, where the data for inputs and outputs was saved in a .dat file and uploaded in the MATLAB-ANFIS Graphical User Interface for training. After successful mapping and training of the variables, a.fis file was created and the data was uploaded into the “rules” layer. An assumption for the worst possible state was defined in this layer, with an aim of creating a directed trend for the predictions. As a result, condition based parameters beyond 23 years of power transformer life were successfully achieved. Table 3.2 shows the hyperparameters used in the ANFIS tool and Figure 3.4 shows the flowchart for implementation.

Table 3.4: Hyper Parameters used in ANFIS Training

<b>Hyper parameter</b>	<b>Failure Condition Prediction</b>
Fuzzy Rules	3
Member functions	$\approx 3$
MF type	Gaussian or Bell
Learning Rate	$\leq 0.1$
Training Epochs	$\leq 3$
RMSE	[0.000314 0.000329]

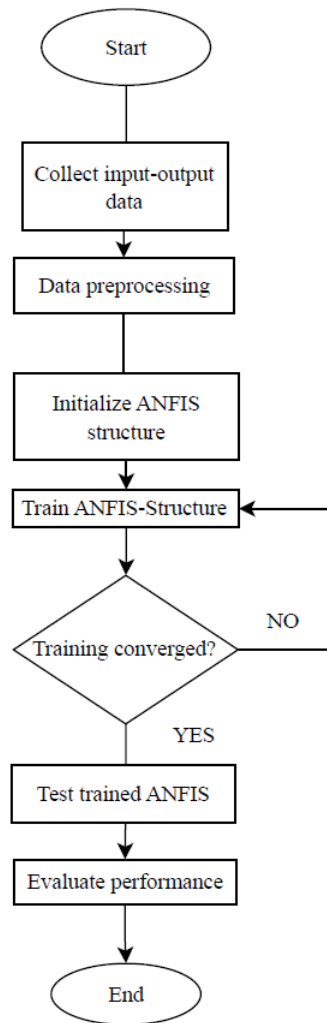


Figure 3.3: ANFIS flow chart

### 3.4.1 PSO-ANFIS Algorithm

Besides the conventional ANFIS model, this study employed the PSO-ANFIS hybrid algorithm to predict transformer degradation based on condition monitoring parameters such as BDV, moisture content, DGA, acidity, and oil color. The PSO-ANFIS approach was preferred over conventional ANFIS because it addresses key limitations such as sensitivity to initial membership function selection and the risk of convergence to local minima during training. By integrating PSO with ANFIS, the algorithm enhances the global search capability, automatically fine-tuning membership function parameters and optimizing the model structure for better predictive accuracy. This hybridization results in a more robust and generalizable model, especially critical for complex and non-linear degradation behaviors typically observed in transformer aging.

The PSO-ANFIS algorithm is considered novel in this context because it introduces a metaheuristic optimization layer into the traditional neuro-fuzzy framework, enabling superior performance without relying heavily on manual parameter tuning. Consequently, PSO-ANFIS represents an advanced, intelligent methodology for condition-based transformer life prediction, offering notable improvements in reliability and predictive capability over conventional techniques. Figure 3.5 parameterization flow chart.

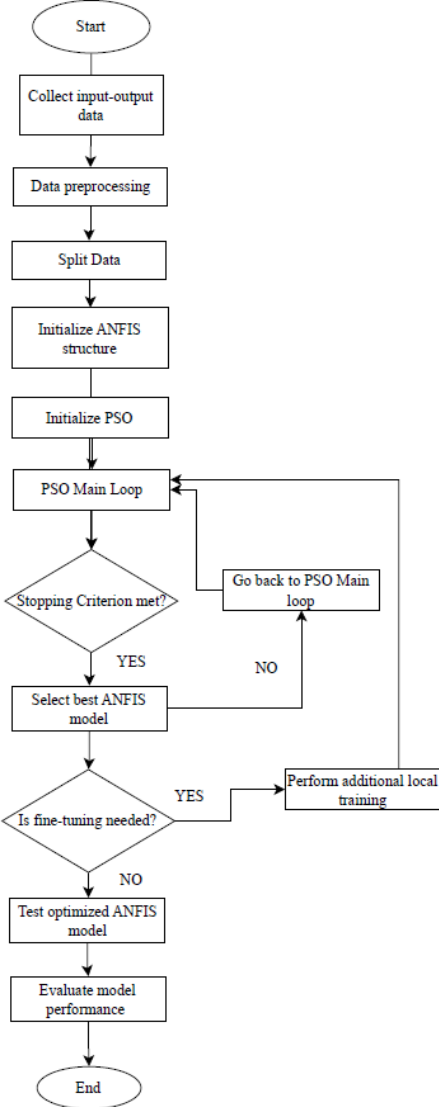


Figure 3.4: PSO-ANFIS flow chart

The hybrid Particle Swarm Optimization–Adaptive Neuro-Fuzzy Inference System (PSO–ANFIS) approach was selected because it effectively combines the strengths of swarm intelligence and fuzzy

logic to address the nonlinear and multi-parameter nature of transformer degradation. The ANFIS component provides adaptive learning and rule-based reasoning suitable for mapping complex relationships between condition-based parameters such as BDV, moisture, acidity, and IFT. However, ANFIS alone is prone to local minima and requires careful tuning of its membership functions. To overcome this limitation, Particle Swarm Optimization (PSO) was integrated to automatically optimize the ANFIS parameters, ensuring faster convergence and improved global search capability. Compared to standalone methods such as Artificial Neural Networks (ANN), Genetic Algorithms (GA), and Fuzzy Logic Systems, the PSO–ANFIS hybrid achieves higher prediction accuracy, better generalization on unseen data, and superior robustness under stochastic loading conditions. Furthermore, PSO is computationally efficient and requires fewer control parameters than other metaheuristics, making it ideal for real-time or large-scale predictive maintenance applications in UETCL’s operational environment.

### 3.4.2 Model Constraints

The optimization procedure incorporated several operational and technical constraints to ensure realistic and implementable maintenance decisions for the 132 kV power transformers. These constraints were defined as follows:

a) **Budgetary Constraint**

$$\sum_{i=1}^n (C_{m,i} + C_{r,i}) \leq B_{\text{annual}} \quad (3.21)$$

The total maintenance ( $C_{m,i}$ ) and replacement ( $C_{r,i}$ ) costs for all transformers  $i$  must not exceed the annual maintenance budget  $B_{\text{annual}}$ .

b) **Reliability Threshold Constraint**

$$R_i(t) \geq R_{\text{min}} \quad (3.22)$$

Each transformer reliability  $R_i(t)$  must remain above a minimum acceptable reliability level  $R_{\text{min}}$ , ensuring network operational security.

c) **Health Index (HI) Constraint**

$$HI_i(t) \leq HI_{\text{critical}} \quad (3.23)$$

Transformer interventions are triggered when the Health Index exceeds the critical limit  $HI_{\text{critical}}$ , thus preventing catastrophic failure.

d) **Resource Availability Constraint**

$$N_{\text{jobs}}(t) \leq N_{\text{crew}} \quad (3.24)$$

The number of scheduled maintenance jobs  $N_{\text{jobs}}(t)$  at any given time must not exceed the available maintenance teams  $N_{\text{crew}}$ .

e) **Service Life Constraint**

$$t \leq t_{\text{max-life}} \quad (3.25)$$

The service time  $t$  of each transformer is restricted to its maximum design or economic life  $t_{\text{max-life}}$ , derived from the Weibull scale parameter  $\eta$ .

Constraint violations were penalized within the PSO–ANFIS optimization using a quadratic penalty function:

$$F^*(x) = f(x) + \sum_{k=1}^m \lambda_k \max(0, g_k(x))^2 \quad (3.26)$$

where  $F^*(x)$  represents the penalized objective function,  $f(x)$  is the unconstrained fitness value,  $\lambda_k$  are penalty coefficients, and  $g_k(x)$  are the constraint functions. This formulation ensured convergence toward feasible and cost-effective maintenance schedules that adhered to the operational realities of the 132 kV transmission network.

## 3.5 Validation of the Developed Predictive Model under Diverse Loading Environments

### 3.5.1 Cross Validation

Validation was conducted with the aim of ensuring accuracy and consistency of the predictive model. In addition, the accuracy of conventional ANFIS was compared with PSO-ANFIS in order to determine the algorithm that provides the most accurate prediction for the condition-based factors under study. The key measurement parameters for validation included; percentage deviation between computed and predicted values, Mean Average Percentage Error (MAPE), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Factors such as moisture, acidity, interfacial tension, breakdown voltage, age and dissolved gases, with measured values, were analyzed and predicted first by linear and non-linear regression of measured operational parameters beyond 23 years of operation. The technique for

prediction of measured values was based on the linear and non-linear trend lines, which were projected from the 23-year transformer performance as shown in Section 4.2. The aim was to ensure that the maximum percentage error between the measured and simulated predictions (obtained from ANFIS) was less than 10%. This was achieved as shown in Section 4.4. The formulae for MAPE, MAE, PE, and RMSE are shown in Equation (3.15) to (3.18).

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100, \quad (3.27)$$

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|, \quad (3.28)$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}, \quad (3.29)$$

$$\text{Percentage Deviation} = \left( \frac{y_i - \hat{y}_i}{y_i} \right) \times 100, \quad (3.30)$$

In the above equations,  $y_i$  represents the actual measured value,  $\hat{y}_i$  is the predicted value obtained from the model, and  $n$  denotes the total number of data points used in the evaluation.

### 3.5.2 Validity Analysis

The validity analysis was carried out to ensure that the developed predictive models and the underlying data accurately represent the actual condition and failure behavior of 132 kV power transformers in Uganda's transmission network. The assessment focused on three key aspects: internal validation, data quality evaluation, and verification of model assumptions. The other objective was to ensure the accuracy and credibility of the developed PSO–ANFIS prediction model, to compare the model's outputs against independent datasets and established reliability indicators. The analysis employed both statistical and face validity checks. Statistical validity was tested by computing correlation coefficients between predicted and actual transformer condition parameters, yielding  $R^2$  values above 0.98 and p-values less than 0.05, indicating strong agreement and model significance. Furthermore, predictive validity was confirmed through cross-validation, where training and testing Mean Absolute Percentage Error (MAPE) differed by less than 3%, demonstrating the model's ability to generalize to unseen

data. Expert validity was also achieved by consulting UETCL maintenance engineers to confirm that predicted degradation patterns were consistent with observed transformer aging trends. These results collectively affirm that the proposed model reliably represents the operational behavior of 132 kV transformers and can be confidently applied for predictive maintenance decision-making.

Table 3.5: Summary of Validity Analysis Results for PSO–ANFIS Model

Validity Type	Indicator	Criterion	Result	Interpretation
Statistical Validity	$R^2$	$> 0.90$	0.982	Excellent fit
Predictive Validity	MAPE difference (Train/Test)	$< 5\%$	2.8%	Stable prediction
Construct Validity	Expert assessment	Consistent trends	Verified	Logical degradation pattern
Face Validity	UETCL data alignment	Qualitative agreement	Confirmed	Matches field experience

### 3.5.3 Internal Validation

Internal validation was performed to evaluate the robustness and generalization ability of the developed ANFIS and PSO-ANFIS models. The available dataset of transformer condition parameters—namely breakdown voltage (BDV), moisture content, and acidity level—was divided into training (70%) and testing (30%) subsets.

Performance indicators such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) were computed for both models. The PSO-ANFIS model consistently yielded lower RMSE and MAE values compared to the standalone ANFIS, indicating superior learning capability and prediction accuracy. Cross-validation was also applied to ensure the stability of the results and to confirm that model performance was not affected by overfitting or random variability.

### 3.5.4 Data Quality Evaluation

The reliability of the predictive analysis depends largely on the quality and consistency of the input data. Data were obtained from the Uganda Electricity Transmission Company Limited (UETCL) maintenance and transformer monitoring records. Prior to model training, the dataset underwent several preprocessing steps to enhance its integrity:

- **Completeness screening:** Missing or incomplete entries were identified and corrected using interpolation and expert validation.
- **Outlier analysis:** Extreme values were examined to distinguish true operational anomalies from measurement or recording errors.
- **Standardization:** All measurements were converted into consistent engineering units to remove scaling bias.

These steps ensured that the dataset used in model development accurately reflected the operational and degradation conditions of the transformers, making it suitable for reliability and failure prediction analysis.

### 3.5.5 Verification of Model Assumptions

Several assumptions were verified to confirm the validity of the developed models:

1. **Independence of observations:** Transformer failure events were assumed to be independent, based on distinct operational histories.
2. **Distributional fit:** Goodness-of-fit tests (Normal, Weibull, Gamma, Log-Normal, and Beta) were conducted for the time-to-failure data. The Weibull distribution exhibited the best fit, confirming its suitability for reliability modeling.
3. **Adequacy of predictors:** Predictor variables (BDV, moisture, and acidity) were tested for multicollinearity to ensure that each contributed uniquely to the model.
4. **Residual analysis:** Residual plots were examined for randomness and homoscedasticity, confirming unbiased and normally distributed errors.

The satisfaction of these assumptions validated the statistical soundness and predictive integrity of the developed models.

### 3.5.6 Summary of Validity

The results of the internal validation, data quality assessment, and assumption verification collectively confirm that the PSO-ANFIS model provides a valid and reliable framework for predicting transformer failure tendencies. The integration of high-quality empirical data, robust model calibration,

and consistent statistical performance ensures that the developed model can be confidently applied to inform transformer asset management and replacement strategies within the UETCL 132 kV network.

### 3.6 Developing a Cost-effective Replacement Strategy for Degrading 132 kV Transformers

Power transformer replacement was achieved at a time of operation  $t_p$  where the cost of failure  $C_f$  and the cost of preventive maintenance  $C_p$ , are at their minimum. The cost function  $C(t_p)$  guided the development of the most opportune replacement time  $t_p$ .  $\beta$  and  $\eta$  represent the shape and scale parameters respectively.  $H(p)$  is a function representing system behaviour, performance degradation or adjustment factor based on  $p$ . The Equation (3.19) represents the formulation of the cost estimates as well as the opportune time of power transformer replacement  $t_p$ , which is dependent on a time  $t$ . Equations (3.20) and (3.21) show the determination of the replacement strategy using constant-interval estimation method.

$$\frac{\delta(C_p)}{\delta p} = \frac{\delta}{\delta t_p} \left[ \frac{C_p + C_f \cdot H(p)}{t_p} \right] = 0. \quad (3.31)$$

After differentiating the process:

$$t_p = \frac{\frac{C_p}{C_f} + H(p)}{\frac{\delta H(p)}{\delta p}}, \quad (3.32)$$

Hence, incorporating Weibull predictors, the optimal time of replacement is achieved as:

$$t_p = \frac{\frac{C_p}{C_f} + 1 - \exp\left[-\left[\frac{t}{\eta}\right]^\beta\right]}{\frac{\beta}{\eta} \left[-\frac{t}{\eta}\right]^{\beta-1} \exp\left[-\frac{t}{\eta}\right]^\beta}. \quad (3.33)$$

The cost function will be  $C(t_p) = C_p + C_f \cdot \frac{1 - \exp\left[-\frac{t}{\eta}\right]^\beta}{\frac{\beta}{\eta} \left[-\frac{t}{\eta}\right]^{\beta-1} \exp\left[-\frac{t}{\eta}\right]^\beta}$ .

The replacement time was also be determined at a point in time when the risk index is minimum. The risk index is a function of the consequence of transformer failure as well as its useful life. The values of replacement time were be compared in order to identify the most effective.

### **3.7 Summary**

In this chapter, the methods for data collection and analysis have been discussed. The proposed model for predicting power transformer failure, PSO-ANFIS was selected due to its high level of accuracy even for low-size data sets. The Weibull model was selected as a tool for determining the opportune time of replacement, due to its high precision in aligning cost estimates with asset life. All the processes involved in developing the prediction model have been widely discussed.

# CHAPTER FOUR: PRESENTATION OF RESULTS

## 4.1 Introduction

This chapter presents findings related to 132 kV condition-based factors, prediction model for 132 kV transformer failure, and a replacement tool for critical transformers.

## 4.2 Determining Parameters Influencing 132 kV Transformer failure in Selected Substations

The failure records of transformers were analyzed by categorizing them into censored (healthy) and uncensored (failed) groups, considering their operational life from the time of installation to the present. This classification was crucial in evaluating the reliability and longevity of the transformers, particularly in MTTF, which provides insights into their expected service lifespan. Figure 4.1 presents the time-to-failure (in years) for UETCL power transformers based on their year of commissioning, revealing distinct trends in failure rates across different installation periods.

The analysis indicates that power transformers commissioned in different years exhibit varying lifespans until failure. Notably, transformers installed around the year 2000 have demonstrated longer operational lifespans, with many exceeding 14 years and some reaching up to 18 years before failure. In contrast, transformers commissioned in earlier years, such as 1970 and 1991, as well as more recent installations from 2018 and 2019, exhibit significantly shorter times to failure, typically ranging between 5 to 10 years. This variability suggests that factors such as improvements in technology, changes in manufacturing standards, variations in operational conditions, and maintenance practices have a substantial impact on transformer longevity. The findings highlight the importance of considering commissioning periods when assessing transformer reliability, as newer installations may not necessarily guarantee longer service life, possibly due to evolving design constraints, increased system

loading, or changing environmental conditions. These insights were also instrumental in determining the shape and scale parameters in Section 4.3, which are critical for probabilistic reliability modelling. The shape parameter helps define the failure rate trend over time, while the scale parameter represents the expected operational lifetime, enabling predictive maintenance planning and improved asset management strategies for power transformers.

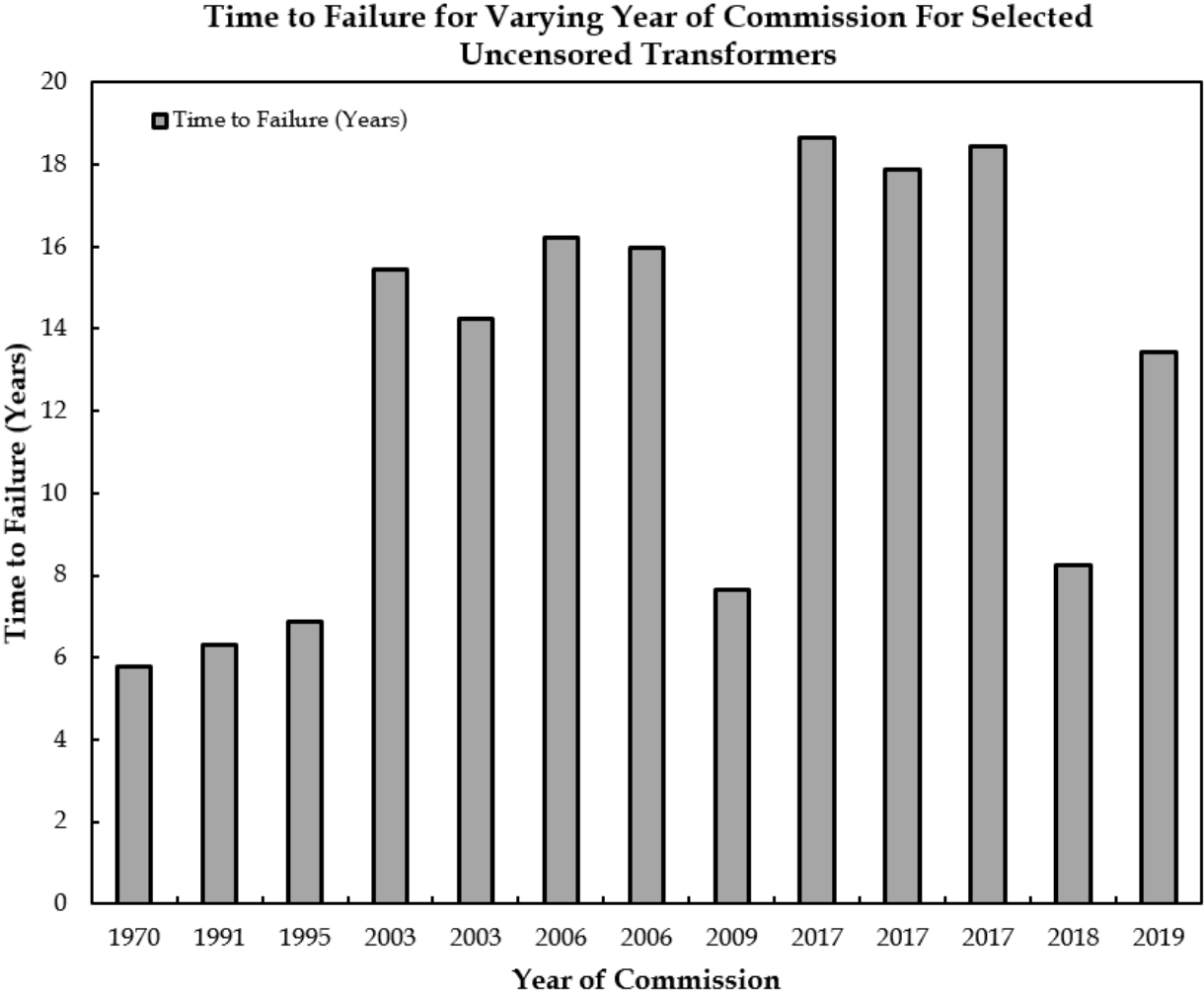


Figure 4.1: Time to Failure considering varying year of commission for power transformers

Figure 4.1 is based on the transformer inventory datasheet, where the failed transformers are denoted '1' and uncensored, and the health transformers '0' and censored, as shown in Appendix 11. The MTTF of the censored transformers was determined from Equation 3.5. For determining and analyzing reliability-based parameters, five key power transformers were selected which are uncensored, with failure status '1'. Their shape and scale parameters were determined based on methods in Section

3.2.3. Table 4.1 shows the parameterization of the selected power transformers in the critical state.

Table 4.1: Weibull Shape and Scale Parameters of Selected Power Transformers in Critical Condition

Transformer	Year of Installation	$\beta$	$\eta$
Namanve Transformer-3	2008	4.64	16.4
Mutundwe Transformer-1	1991	6.23	33
Mutundwe Transformer-2	1995	5.95	29.4
Fort Portal Transformer-5	2006	5.43	18.5
Kawanda Transformer-1	2009	3.7	36.8

These parameters guided into the analysis of the failure rate and the RUL of these selected power transformers as shown in Figure 4.2.

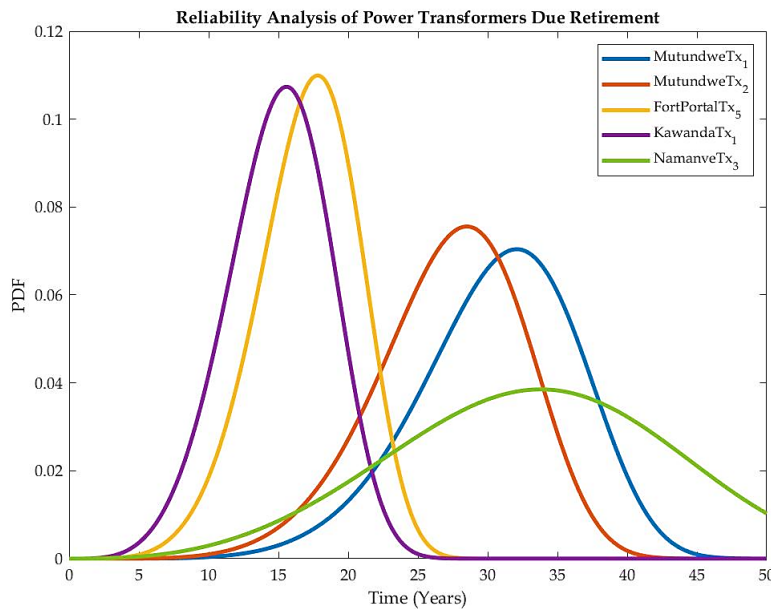


Figure 4.2: Reliability Analysis for Most Critical Transformers

The reliability plot demonstrates how the likelihood of transformer failure evolves over time for five key transformers in Uganda’s 132 kV network. Initially, all transformers operate with high reliability (above 98%), reflecting minimal chances of failure during their early years of service. However, each

transformer begins to experience noticeable reliability decline at different points, indicating varying life expectancies. Namanve Transformer 3 shows the earliest onset of failure, with reliability beginning to drop significantly around 6.5 years, suggesting a shorter operational lifespan. Fort Portal Transformer 5 follows, with failure tendencies emerging after approximately 10 years.

Kawanda Transformer 1 maintains reliability slightly longer but starts deteriorating after around 18 years. Mutundwe Transformer 2 shows a more prolonged period of high reliability, with significant degradation starting near the 23-year mark. Mutundwe Transformer 1 demonstrates the most extended reliability span, remaining above 90% until nearly 28 years and showing slower failure progression. These differences emphasize the need for condition-based maintenance and tailored asset management strategies, as transformer longevity clearly varies by location and operational context. This is shown in Figure 4.3

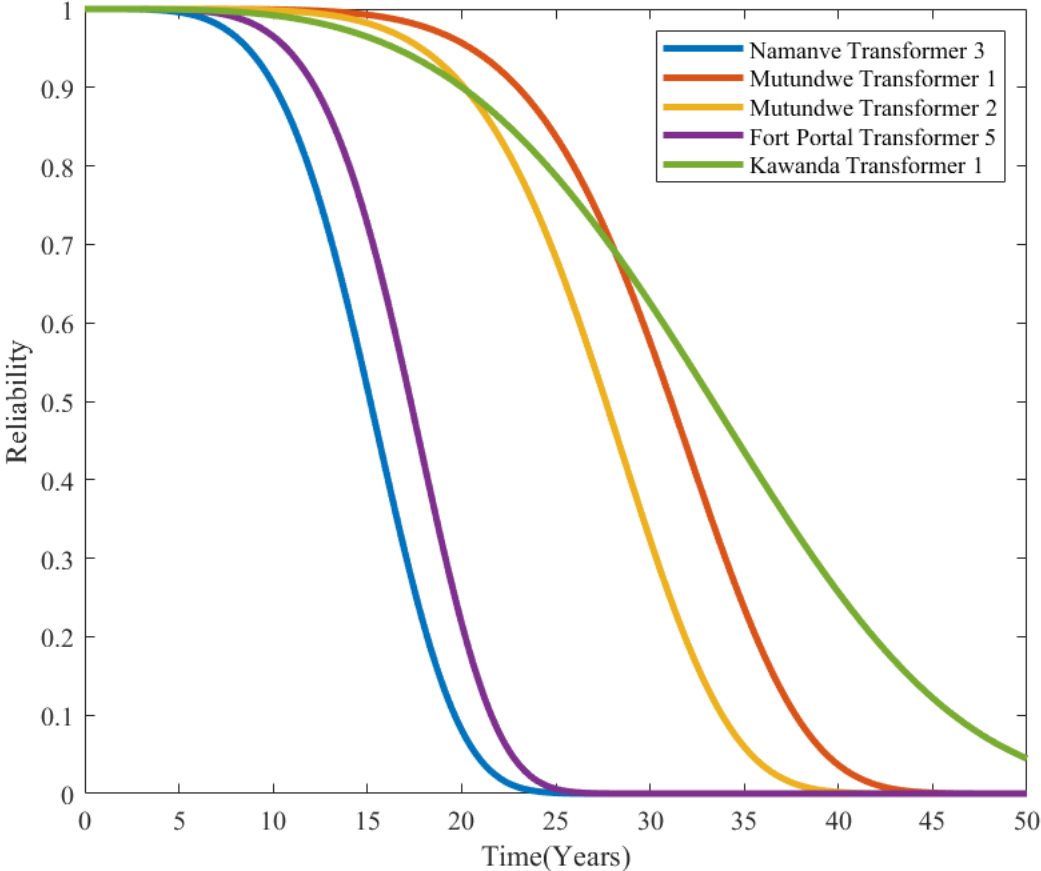


Figure 4.3: Reliability plot for the critical transformers

The hazard rate plot in Figure 4.4 provides critical insights into the aging and degradation trends of key transformers in Uganda’s 132 kV network by showing the rate at which failure becomes more likely over time. Initially, all transformers exhibit a flat, near-zero hazard rate, which is indicative of a stable operational phase with minimal failure probability. However, transition points emerge where the hazard rate begins to rise exponentially, marking the onset of accelerated degradation. Mutundwe Transformer 1 displays the earliest and steepest hazard rate escalation, peaking above 45% by year 50, indicating a sharp decline in reliability during its later years.

Namanve Transformer 3 also shows a pronounced hazard rate rise starting around year 20, reaching over 15% by year 50. Fort Portal Transformer 5 follows a similar trend with a more gradual increase. Meanwhile, Kawanda Transformer 1 and Mutundwe Transformer 2 maintain relatively flat hazard rates throughout the 50-year period, suggesting a longer period of operational stability with minimal degradation pressure. These trends highlight the need for prioritized maintenance planning, especially for transformers like Mutundwe 1 and Namanve 3, which exhibit earlier and sharper reliability deterioration.

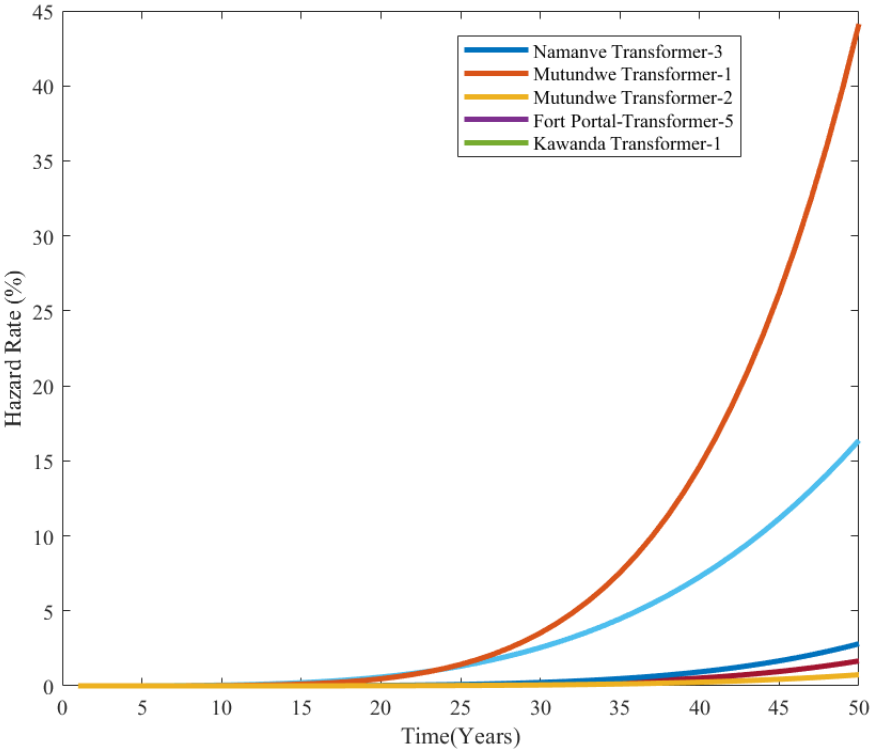


Figure 4.4: Hazard Rate for Critical Transformers

For determining operational-based parameters influencing power transformer performance, Mutundwe 132/33 kV Transformer - 1 and Lugogo 132/33 kV Transformer - 2 were used as a case for analysis, where six performance-based factors were analyzed namely; Break Down Voltage (BDV), Moisture Content (MC), Acidity, Interfacial Tension (IFT), Age and Furfural Dehyde (2-FD). Figure 4.6 shows the analysis for BDV over transformer operation life.

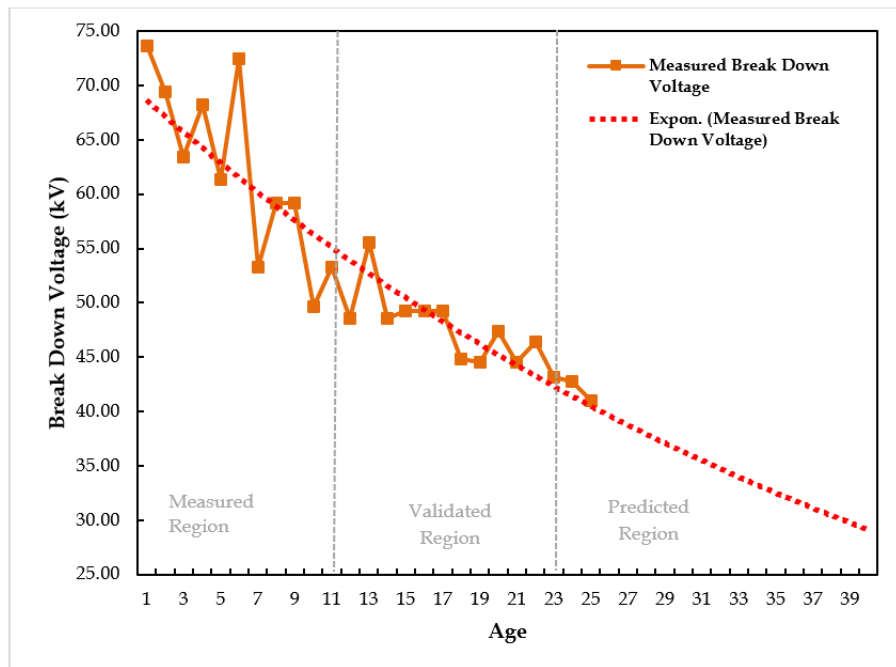


Figure 4.5: BDV Analysis for Mutundwe 132/33 kV Transformer-1

The BDV consistently decreases with transformer age. The first set of years i.e., 11 years indicate the measured value of BDV, whereas the next 11 years show the validated set, which shows consistency with the pattern of the first data set. It is observed that at 23 years of operation, the BDV will decline to values less than the threshold 45 kV value. The predicted region projects the expected pattern of the BDV based on the trend line, which takes a negative exponential trend. Similar results are shown for the Lugogo 132/33 kV Transformer plot in Figure 4.6.

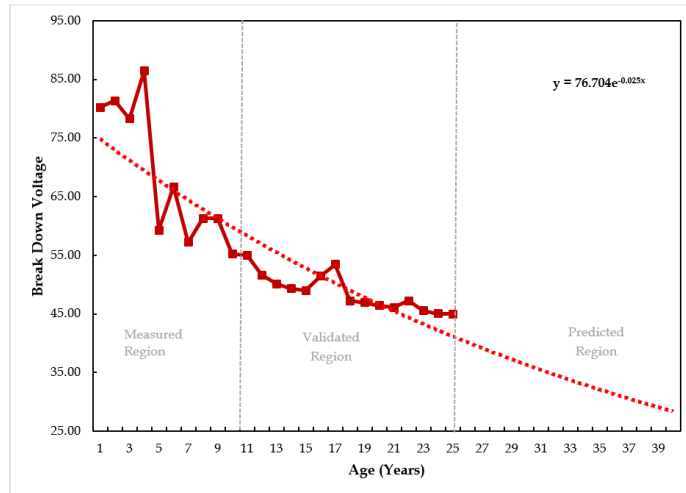


Figure 4.6: BDV Analysis for Lugogo 132/33 kV Transformer-2

The moisture content, as shown in Figure 4.7 increases steadily with age, having a logarithmic trend, from 11.23 ppm to 17.19 ppm and showing consistency between the measured and validated data set. In addition, the moisture content is still within the safety margins as defined by IEC 60422, which specify a minimum MC value of 30 ppm for transformer safety. Similar results are shown in Figure 4.8.

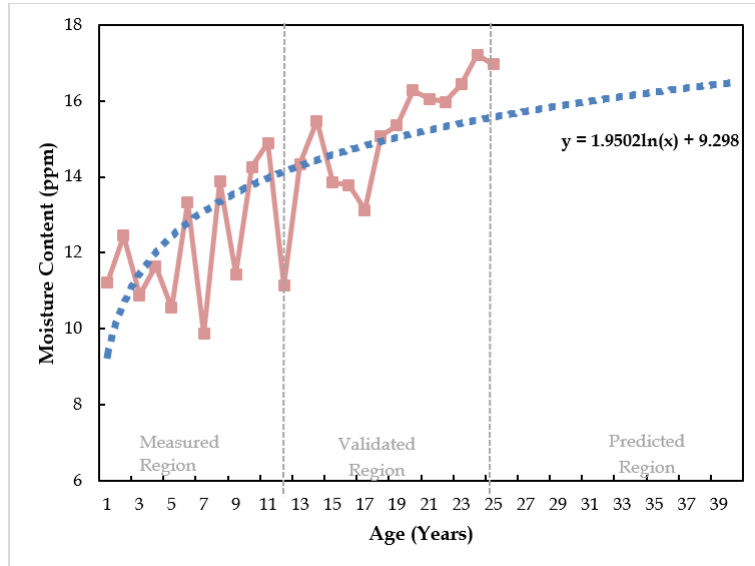


Figure 4.7: Moisture content for Mutundwe 132/33 kV Transformer-1

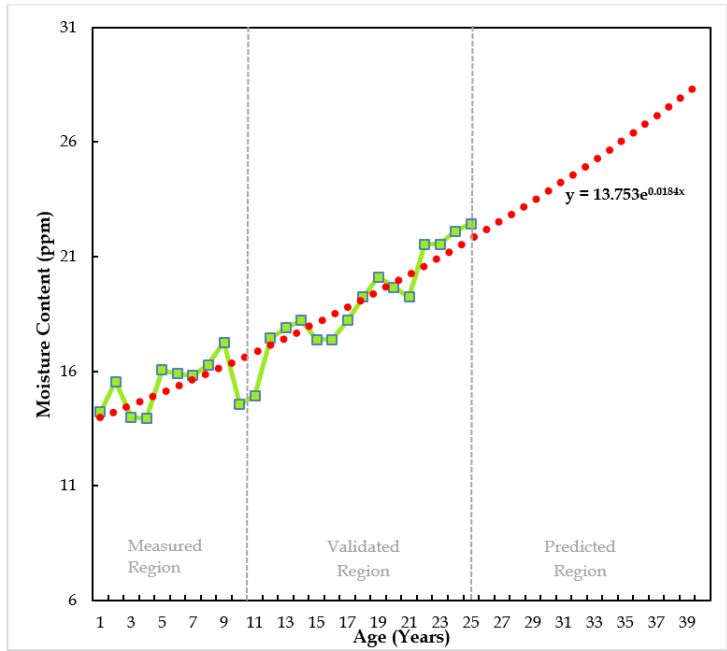


Figure 4.8: Moisture content for Lugovo 132/33 kV Transformer-2

In Figure 4.9, the acidity increases steadily with an exponential pattern. Exceptions are shown in the initial ages of the transformer, where the acidity acutely declines to a value of 0.028 mg KOH/g. After that, the acidity consistently increases for the next range of age. However, there is also a slight decrease in acidity values in the validation dataset, achieving a reduced value of 0.074 mg KOH/g. The trendline increases consistently for all data sets showing a projected increase in acidity value in the prediction region. Similar results for acidity are shown in Figure 4.7. The results also indicate that acidity levels are within the defined threshold of 0.03 to 0.1 mg KOH/g as defined by IEC 60296 which defines accepted acidity levels. In the last five years of observed transformer performance, the acidity level tends to approach the maximum IEC 60296 limit.

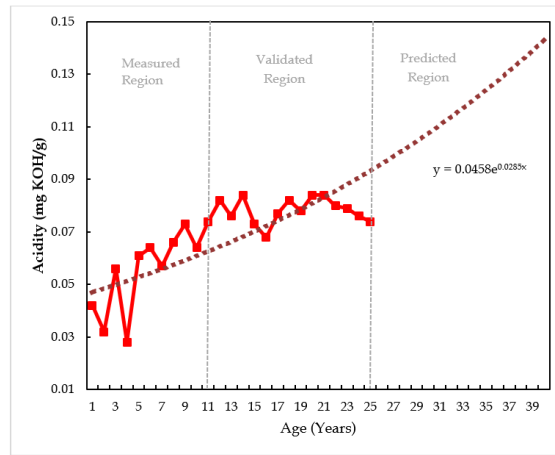


Figure 4.9: Acidity for Mutundwe 132/33 kV Transformer-1

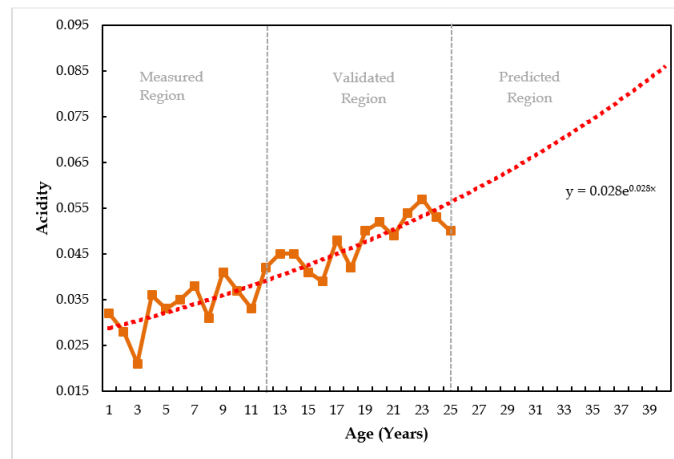


Figure 4.10: Acidity for Lugogo 132/33 kV Transformer-2

The IFT pattern, shown in Figure 4.11 is intermittent in nature, showing extreme variations and thus showing a less obvious establishment of trendline. However, the IFT slightly decreases with the age of the transformer, as evidenced by the exponential trendline. The measured and validated data sets are slightly consistent since the interfacial tension takes a sharp decline between transformer ages 15 and 19 years. Eventually, a step increase in interfacial tension is observed for the range of 19 to 24 years of transformer life. Similar results are shown in Figure 4.12. However, the trend of interfacial tension is consistent for both the measured and validated data set for the case of Lugogo 132/33 kV transformer-2. IEC 60422 standards define the minimum IFT level for in-service oil to be 15 mN/m. However, a sharp decline is observed between ages 15 and 19, with values below the defined threshold of 15 mN/m.

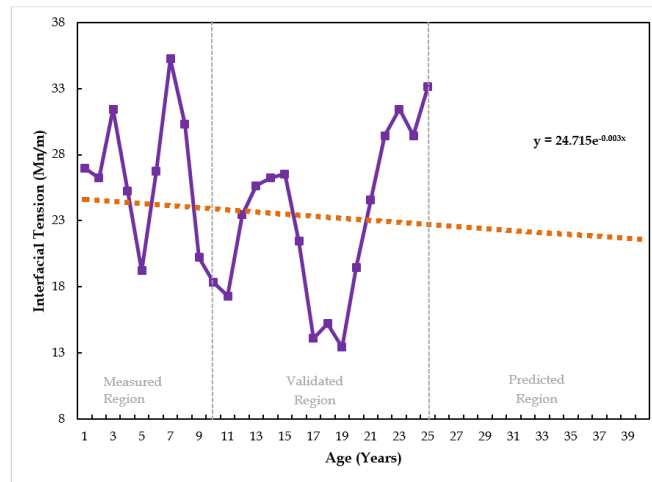


Figure 4.11: Interfacial tension for Mutundwe 132/33 kV Transformer-1

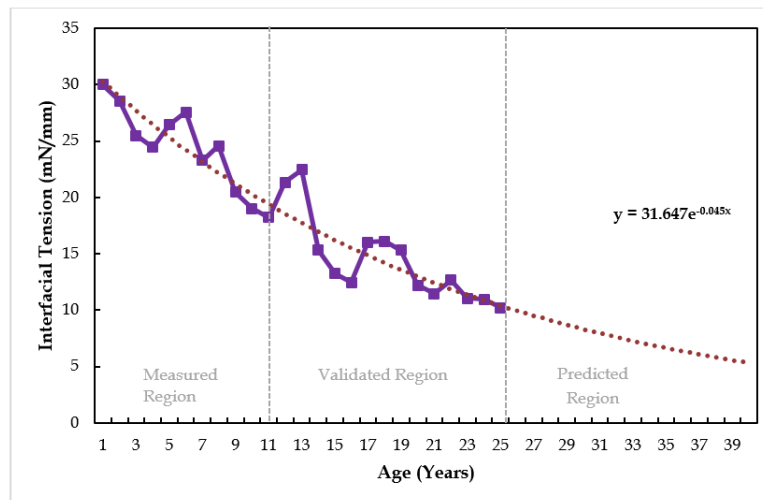


Figure 4.12: Interfacial tension for Lugogo 132/33 kV Transformer-2

The trend in color of oil increases steadily, showing visible change in color of transformer oil with age as shown in Figure 4.13. A slope of 0.174 represents a significant change in color observed as the transformer ages. There is also consistency between the values in the measured and validated region. The defined threshold limit for inservice oil is 1.0 to 2.5 g/cc based on the ASTM D1500 scale. Thus, from 11 years of transformer life, the values of color are observed to be above the minimum safety margins that define degradation.

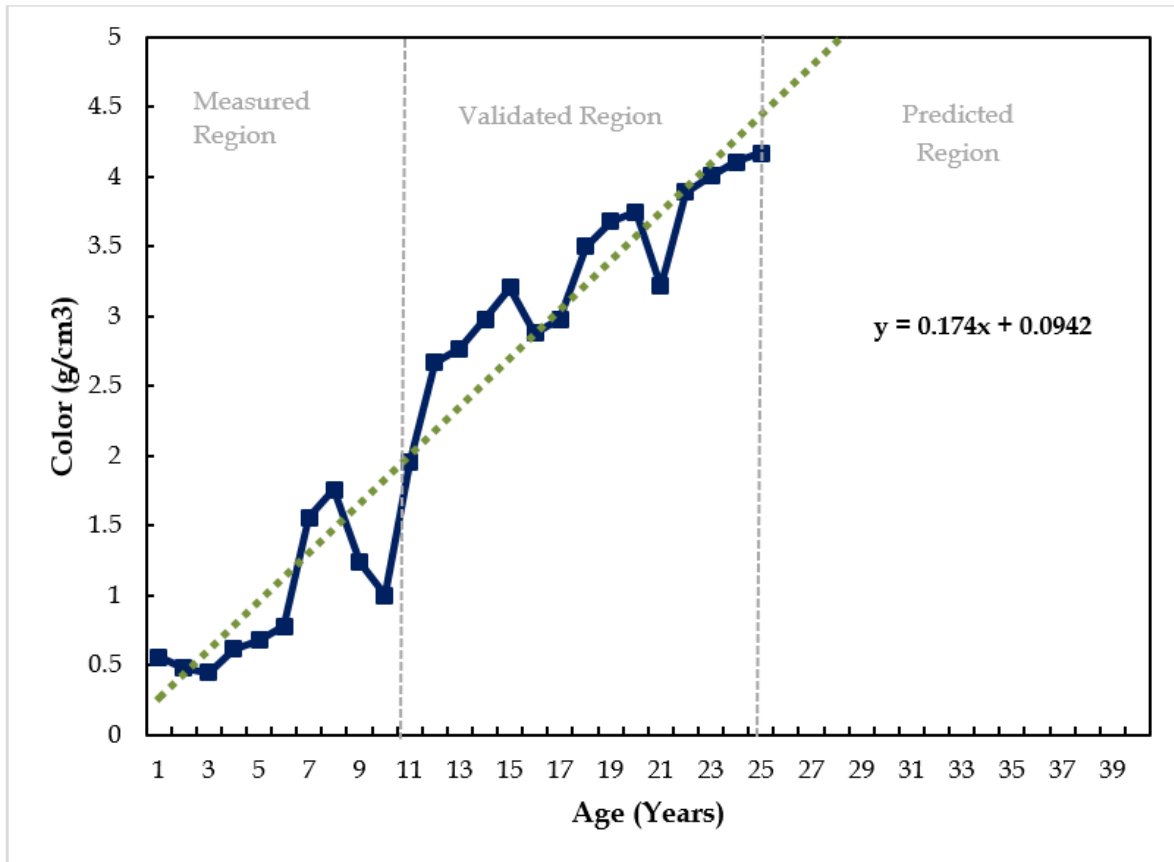


Figure 4.13: Color of Oil for Mutundwe 132/33 kV Transformer-1

A linear increase in furfural dehyde with age is observed for Mutundwe transformer-1 and Lugogo transformer-2. However, there is a slight consistency in values of the measured and simulated dataset since a large proportion of the measured values are below the trendline from 3 to 10 years of Mutundwe transformer-1 operation. Generally, a steady linear increase for furfural dehyde is observed with transformer age. This is shown in Figure 4.14. Similar results are observed in Figure 4.15.

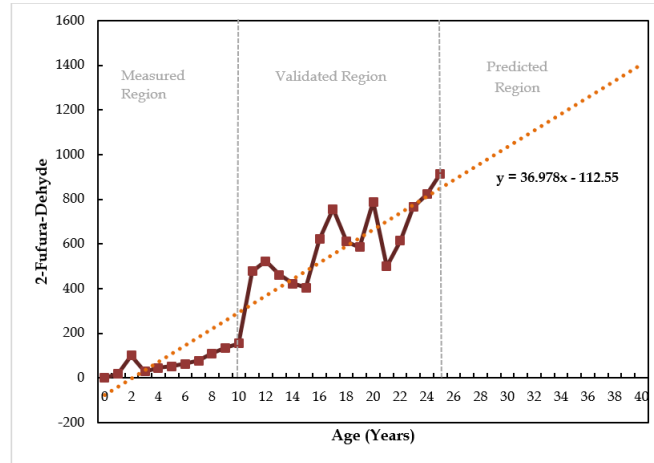


Figure 4.14: Furfural Dehyde for Mutundwe 132/33 kV Transformer-1

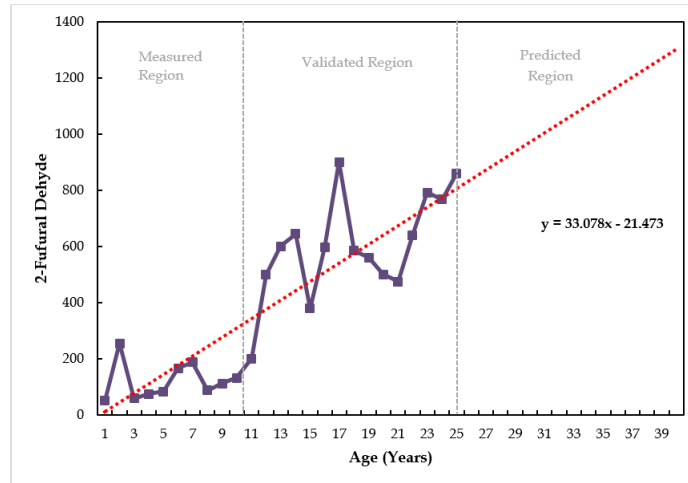


Figure 4.15: Furfural Dehyde for Lugogo 132/33 kV Transformer-2

Results for Dissolved Gas Analysis (DGA) tests taken in the course of operation of Mutundwe 132/33 kV transformer-1 are shown in preceding figures. For instance, the concentration of hydrogen in the transformer as shown in Figure 4.13 is more significant in its early years of operation. Between 0 and 9 years of transformer life, the hydrogen concentration decreases from 98 to 48 ppm. However, a consistency in decline of hydrogen concentration is noted even in the validation dataset, showing less significant amounts of hydrogen between 12 and 25 years of operation of the transformer. A negative decline in hydrogen concentration is projected for the prediction dataset. Results are shown in Figure 4.16. Based on IEC 60599, the transformer is reliable for the observed duration of transformer operation.

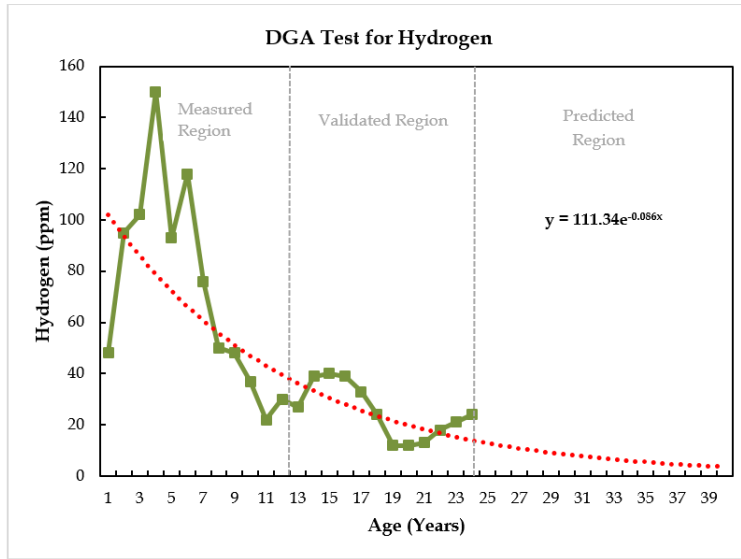


Figure 4.16: Hydrogen concentration for Mutundwe 132/33 kV Transformer-1

The concentration of methane decreases exponentially with transformer life. Between 0 to 13 years of transformer life, an intermittent pattern in methane is observed. However, there is a sharp decline in concentration levels at particular ages of the transformer, for instance at 2 and 7 years. Conversely, the validated region shows a consistent decline in methane concentration for the next set of transformer years. This is shown in Figure 4.17.

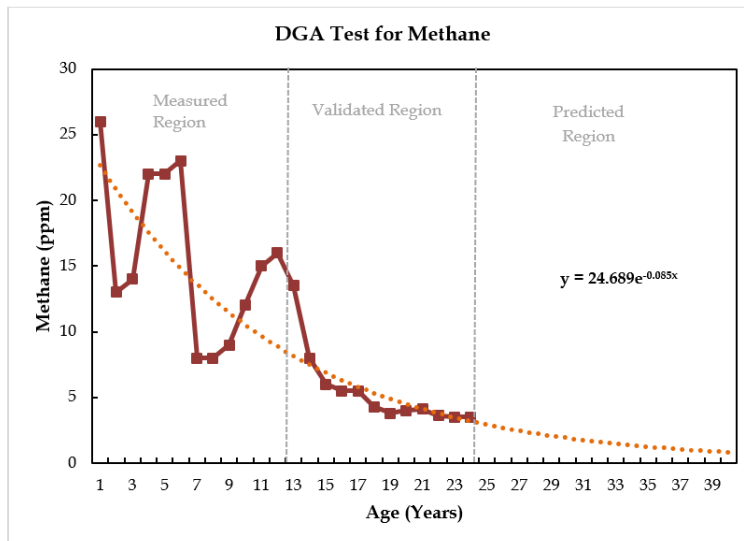


Figure 4.17: Methane concentration for Mutundwe 132/33 kV Transformer-1

The trend of carbonmonoxide slightly increases exponentially with transformer age, with the exception of a decrease in concentration observed between 22 and 25 years of transformer age

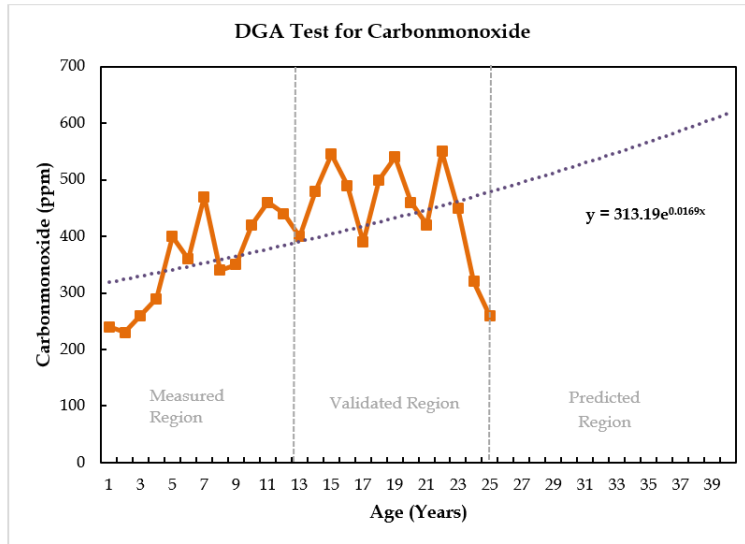


Figure 4.18: Carbon monoxide concentration for Mutundwe 132/33 kV Transformer-1

The trend of carbon dioxide increases significantly for the first 13 years of transformer operation. In the validation region, the concentration of carbon dioxide is consistent from 13 to 20 years of transformer life. There is a significant decline in carbon dioxide concentration between 20 and 25 years. However, the pattern of carbon dioxide concentration still shows a slight increase in the trend throughout the transformer life. It should also be noted that this trend is influenced by majority data points showing a positive increase in carbon dioxide over transformer age. Results are shown in Figure 4.19.

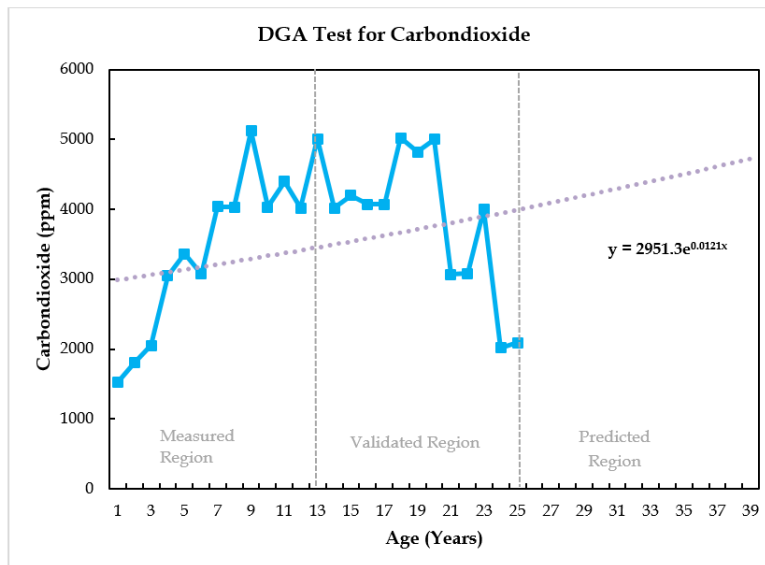


Figure 4.19: Carbon dioxide concentration for Mutundwe 132/33 kV Transformer-1

The trend for ethylene is observed as a linear steady increase with low concentrations observed for the first 12 years of transformer life. For the next data set, there is intermittency in values of ethylene concentration. However, a significant increment (21 to 41 ppm) is noticed between 20 and 24 years of transformer life. Results are shown in Figure 4.20.

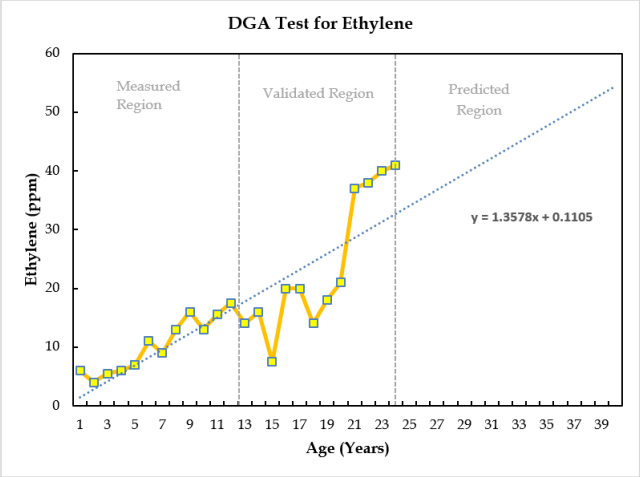


Figure 4.20: Ethylene concentration for Mutundwe 132/33 kV Transformer-1

The concentration of ethane decreases exponentially with transformer age. Intermittent patterns are observed for the first 12 years of transformer life, following a consistent drop in concentration as shown in the validation region. The concentration of ethane is predicted to be the least significant at a later age of the transformer. Results are shown in Figure 4.21

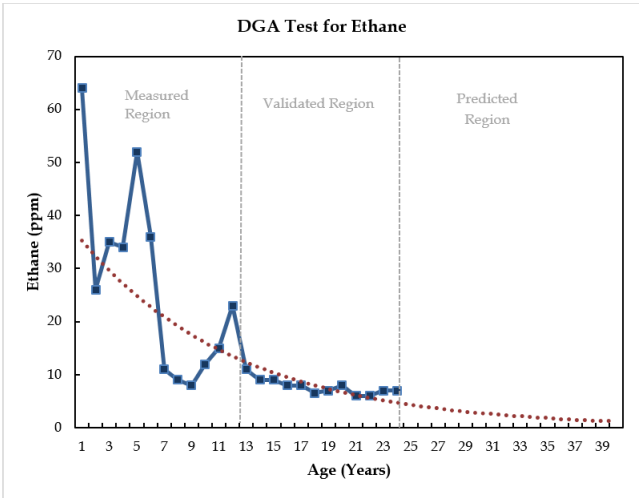


Figure 4.21: Ethane concentration for Mutundwe 132/33 kV Transformer-1

The concentration of acetylene takes a positive logarithmic trend, increasing slightly with the transformer age. However, a steep decline in acetylene concentration is observed (25ppm to 7.5ppm) between 11 and 13 years of transformer operational life. A sharp increase (7.5 to 23.6 ppm) is observed from 13 to 24 years of transformer operational life. This trend is shown in Figure 4.22.

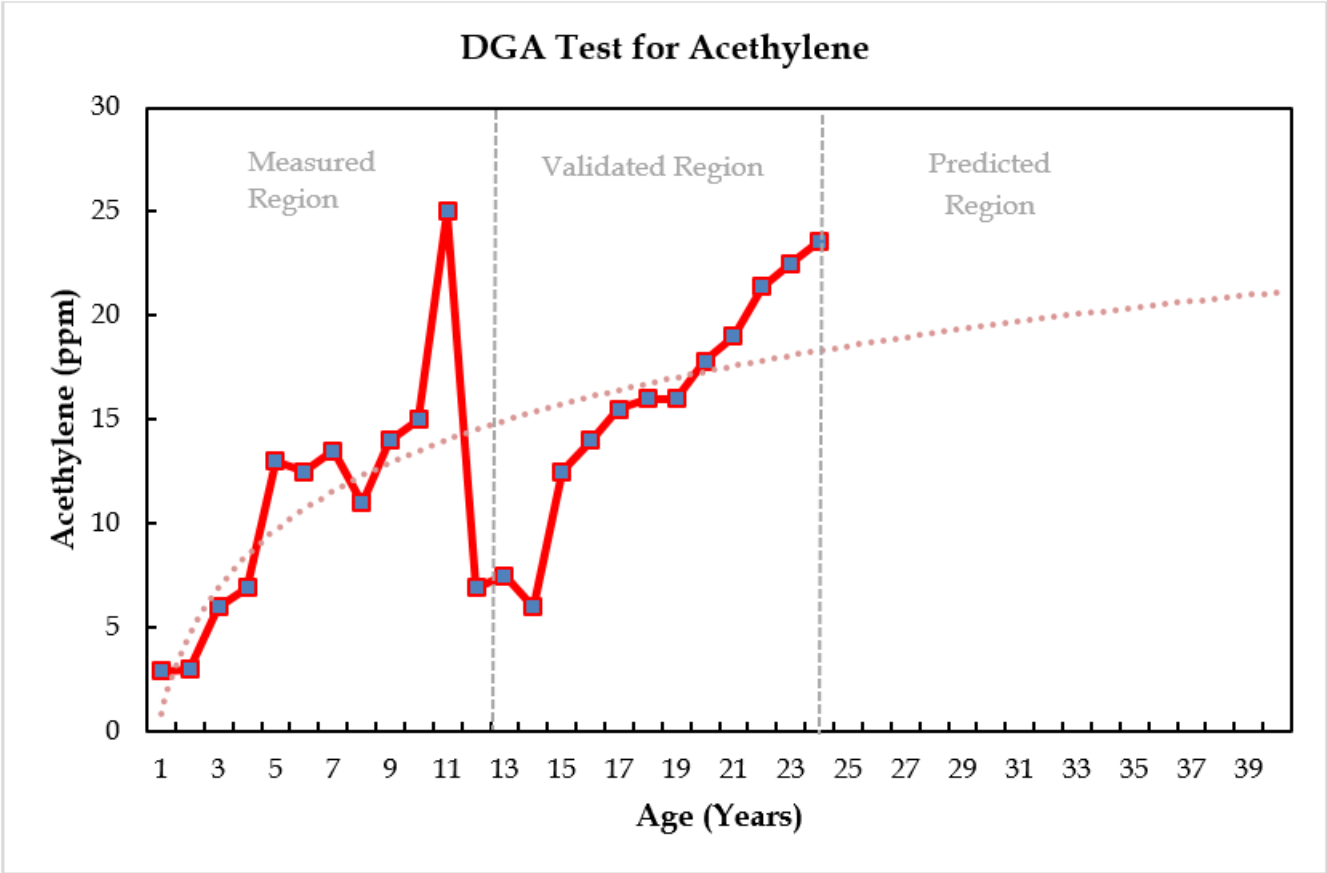


Figure 4.22: Acetylene concentration for Mutundwe 132/33 kV Transformer-1

Table 4.2 provides a detailed analysis of the variation of key operational parameters of transformers with age and their implications. Parameters such as BDV, IFT and Hydrogen follow a negative exponential trend, indicating a steady decline over time, leading to reduced insulation strength and increased degradation risk. Conversely, Moisture Content, Acidity, and Carbon Monoxide exhibit a positive exponential trend, implying a steady increase with age, which accelerates insulation deterioration. Furfural Dehyde and Ethylene show a linear trend, indicating a gradual increase, highlighting the progressive aging of transformer oil and paper insulation. Acetylene follows a positive logarithmic trend, showing a sharp exponential increase with transformer age, signaling potential arcing faults. These trends help

in assessing transformer health, predicting failures, and optimizing maintenance strategies.

Table 4.2: Description of the operation-based parameters

<b>Operation-Parameter</b>	<b>Variation with Age</b>	<b>Implication</b>
BDV	Negative exponential trend	Decreases steadily with age
Moisture Content	Positive exponential trend	Increases steadily with age
Acidity	Positive exponential trend	Increases steadily with age
IFT	negative exponential trend	Decreases slightly with transformer age
Furfural Dehyde	linear trend	Increases linearly with transformer age
Hydrogen	negative exponential trend	Decreases steadily with transformer age
Carbon monoxide	positive exponential trend	increases slightly with transformer age
Ethylene	linear trend	Increases linearly with transformer age
Ethane	positive linear trend	Increases linearly with transformer age
Ethane	negative exponential trend	Decreases slightly with transformer age
Acetylene	positive logarithmic trend	Increases exponentially with transformer age

#### 4.2.1 Results for Health Index

The earlier described in Section 3.3.1, the health index for the representative transformers was determined as shown in Figure 4.23. These Health Index (HI) graphs illustrate the degradation patterns of the four selected transformers—Fort Portal-5, Mutundwe-2, Mutundwe-1, and Namanve-3—over a 40-year operational horizon. In all cases, the computed HI (solid markers/lines) and the predicted HI (dashed markers/lines) show a consistent declining trend with increasing age, indicating progressive deterioration of transformer condition parameters such as BDV, moisture, acidity, interfacial tension, and dissolved gases. The relatively close alignment between computed and predicted curves validates the accuracy of the predictive model, showing that it captures the key ageing dynamics. Differences be-

tween transformers reflect unique operational histories and stress conditions; for instance, Mutundwe-1 exhibits more fluctuations in HI due to variations in condition parameters, while Namanve-3 and Mutundwe-2 show smoother degradation paths, indicating relatively stable but gradual ageing.

Overall, these plots demonstrate the ability of the model to track both measured and forecasted health trajectories, which is critical for anticipating end-of-life scenarios and planning replacements. The fact that the predicted HI closely follows the computed HI confirms the robustness of the PSO–ANFIS hybrid model in replicating real condition-based data. Practically, this means asset managers can use the predicted HI values to proactively identify transformers approaching critical deterioration thresholds (e.g., HI 40), rather than relying solely on corrective maintenance. This proactive insight provides a sound basis for implementing cost-effective replacement strategies and strengthening the resilience of Uganda’s 132 kV network.

## Health Index Comparison of Transformers

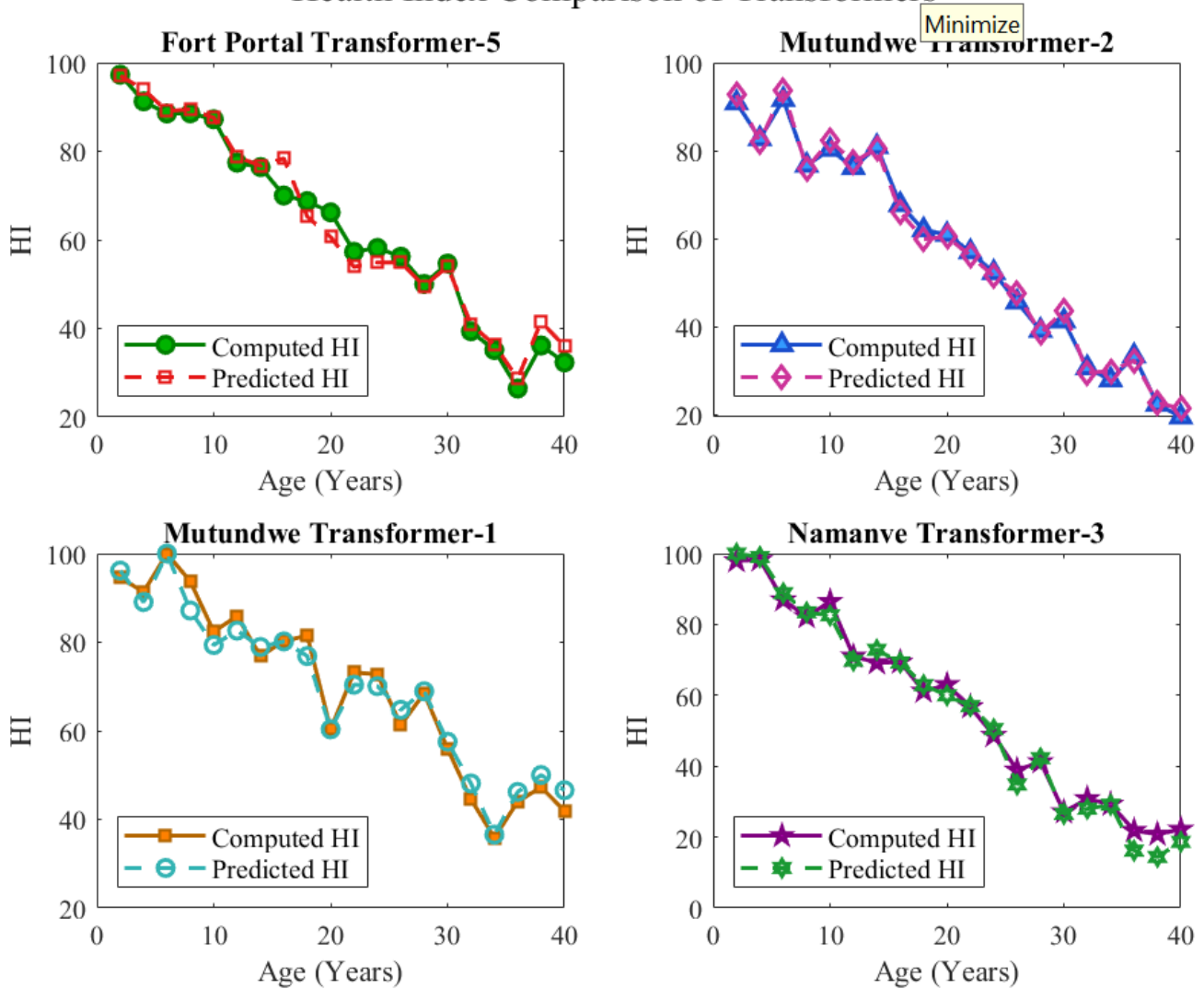


Figure 4.23: Results of health index for representative transformers

### 4.3 Prediction Model for Condition Based Factors Affecting Transformer Performance

In order to understand the degree of failure of the transformer due to different operational factors, Probability Density Function (PDF) graphs were developed using the Weibull Model, analyzing the failure rates ignited by selected operational factors. The purpose of this analysis was to analyze the operational factors that influence transformer failure from the factor of with the highest to the least impact. In addition, Figure 4.20 shows the anticipated failure rate and RUL of the transformer based on these operational factors. The figure is based on the failure rate and RUL of six operational factors

namely; moisture, furfural dehyde, BDV, IFT, acidity and color for the projected life of Mutundwe Transformer-1. Each of these factors was considered to have varying failure rate and expected to yield varying impact on the RUL of the transformer.

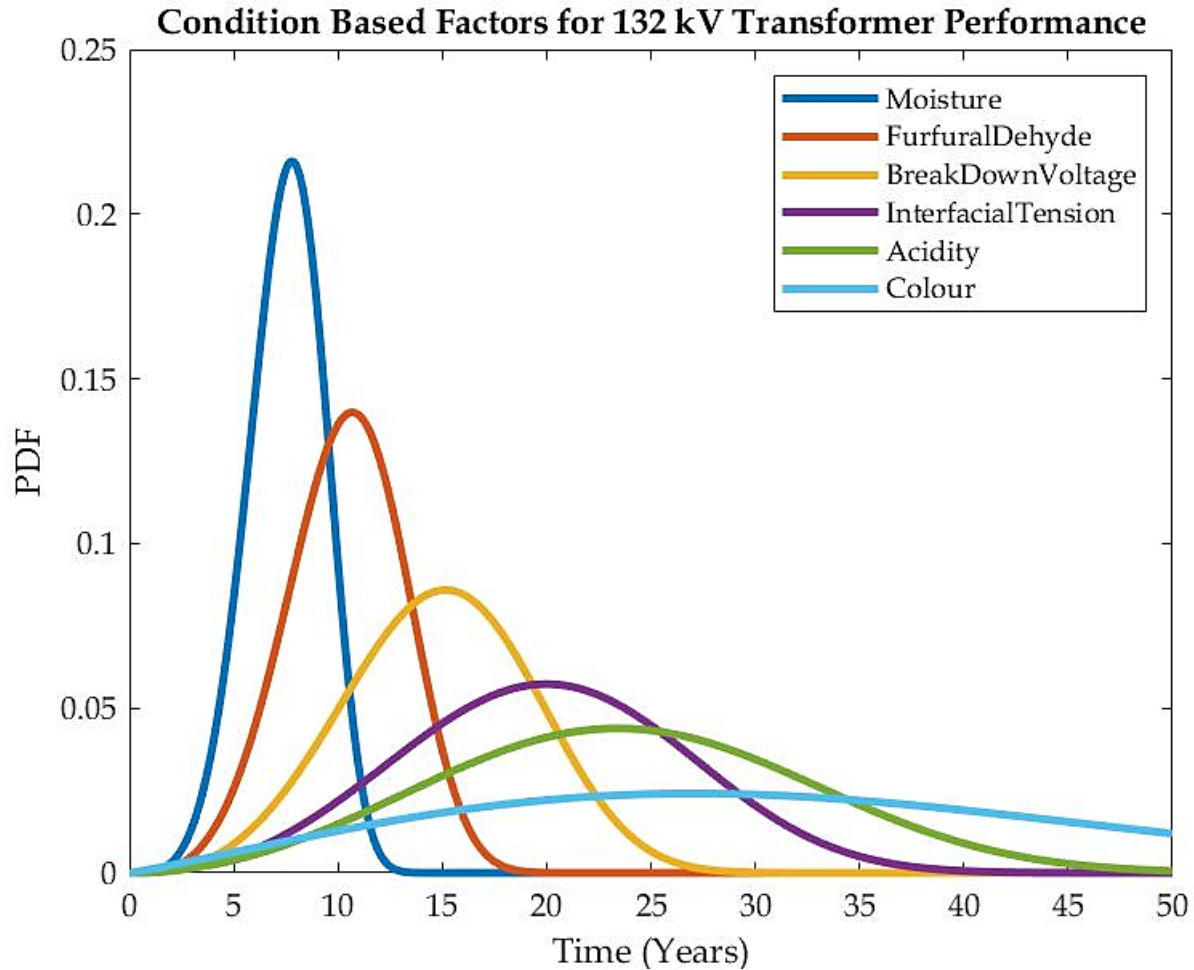


Figure 4.24: Condition Based Factors Influencing 132 kV Mutundwe transformer-1 Reliability

Figure 4.23 represents the failure rates of various operational factors influencing the performance and remaining useful life (RUL) of a 132 kV transformer. Moisture exhibits the highest initial failure rate, peaking sharply within the a RUL of 5 years, making it the most critical factor affecting transformer degradation early in its lifespan. Furfuraldehyde and breakdown voltage show moderate failure rates, peaking around 10 to 15 years, reflecting their increasing impact as the transformer ages.

Interfacial tension has a slower, more prolonged effect, with its failure rate rising gradually and peaking around a RUL of 23 years, indicating a longer RUL compared to the others. Acidity and color exhibit

the least influence, with broad, lower peaks extending beyond 25 years, suggesting that they contribute to long-term degradation but with the least immediate impact on failure rates. Overall, the operational factors show varied influences on RUL, with moisture having the shortest RUL and interfacial tension and color contributing to longer RULs.

### 4.3.1 Prediction of 132 kV Transformer Failure using ANFIS

Prediction of 132 kV transformer failure was carried out using ANFIS model, where each operational factor was analyzed. The basis for analysis was the transformer operation status, regarded as failed “1” or healthy “0”. The reliability of the transformer was also analyzed, considering varying loading of the transformer with age. Results were then developed showing the effect of this relationship on selected operational factors. Figure 4.24 shows the BDV schematic diagram developed using ANFIS model.

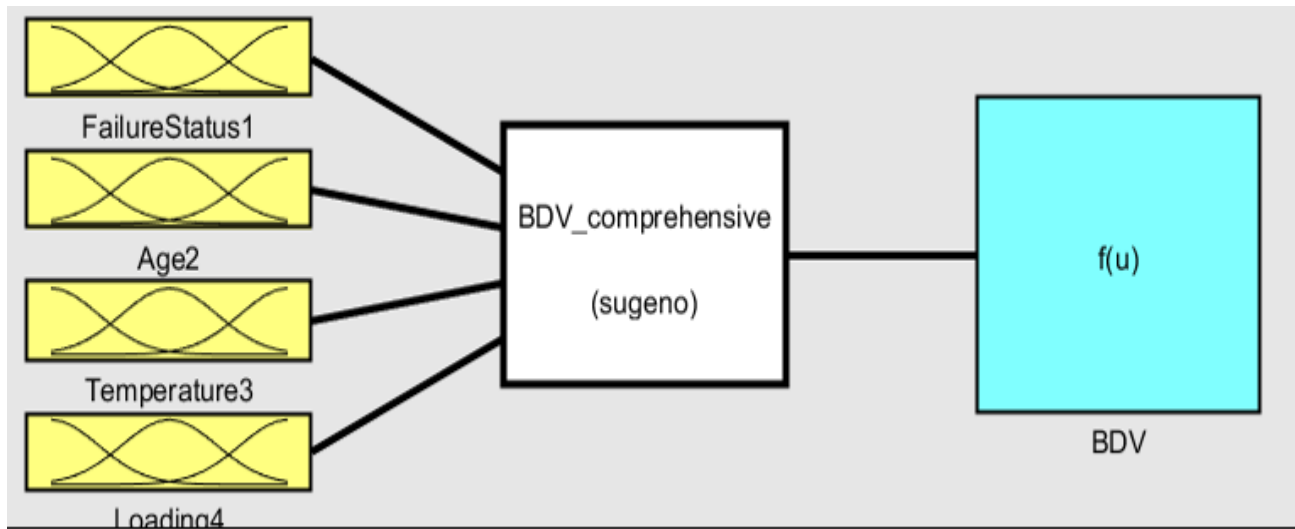


Figure 4.25: Schematic Diagram for BDV prediction showing inputs and outputs using ANFIS

The inputs for the model included the failure status of the transformer and varying load levels of the transformer, seeking to determine the effect of these parameters on the BDV of the transformer and consequently its reliability. As earlier discussed the data of transformer BDV with time was analyzed. A summary of this analysis was developed and benchmarked against the transformer status and loading as inputs. The output included the transformer BDV. These variables were thus trained and used to inform the ANFIS prediction model. Results were categorized into two cases namely; prediction of transformer failure when in present healthy state and online (loaded) denoted as (0, loading, BDV) and prediction of transformer failure when in present critical state denoted as (1, loading, BDV). Figure 4.25 shows results for the ANFIS data training process.

```

ANFIS info:
  Number of nodes: 23
  Number of linear parameters: 9
  Number of nonlinear parameters: 12
  Total number of parameters: 21
  Number of training data pairs: 5
  Number of checking data pairs: 0
  Number of fuzzy rules: 3

Warning: number of data is smaller than number of modifiable parameters

Start training ANFIS ...

  1      0.000314188
  2      0.000329117

Designated epoch number reached --> ANFIS training completed at epoch 2.

Minimal training RMSE = 0.000314

```

Figure 4.26: BDV training process using ANFIS

It is observed that the ANFIS training was successful with an RMSE value of 0.000314. This demonstrated high accuracy in the relationship between the mentioned variables, thus making room for an accurate prediction model. Figure 4.26 shows the results of the base case scenario, considering a healthy transformer at high loading and having a BDV value above the minimum UETCL safety threshold i.e., 45 kV. A high loading was considered as an assumption that transformer failure is common in occurrence at high loadings or utilization factors. This case can also be summarized as (0,70%,49.6). Input-1 represents the failure status, input-2 represent the loading and output-1 represents the predicted BDV value.

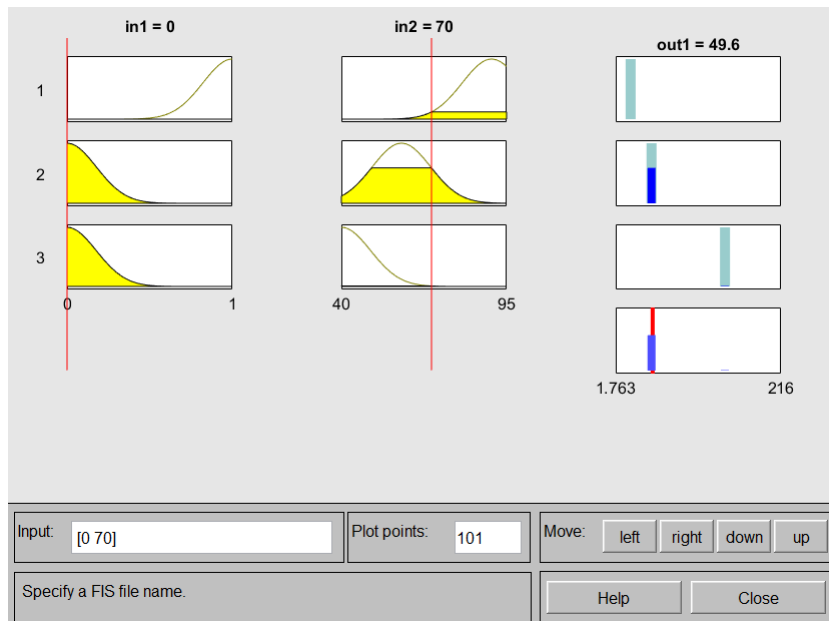


Figure 4.27: BDV model showing base case scenario

In the second scenario, the transformer status is “1”, for an increase in loading to 70%. It is observed that the predicted BDV value reduces to 49.5 kV. When the loading is further increased to 80%, the BDV value reduces to 45.4%. Figure 4.26, 4.27, 4.28, 4.29 and Table 4.3 show the predicted cases. Lower values of BDV are observed for PSO-ANFIS based predictions.

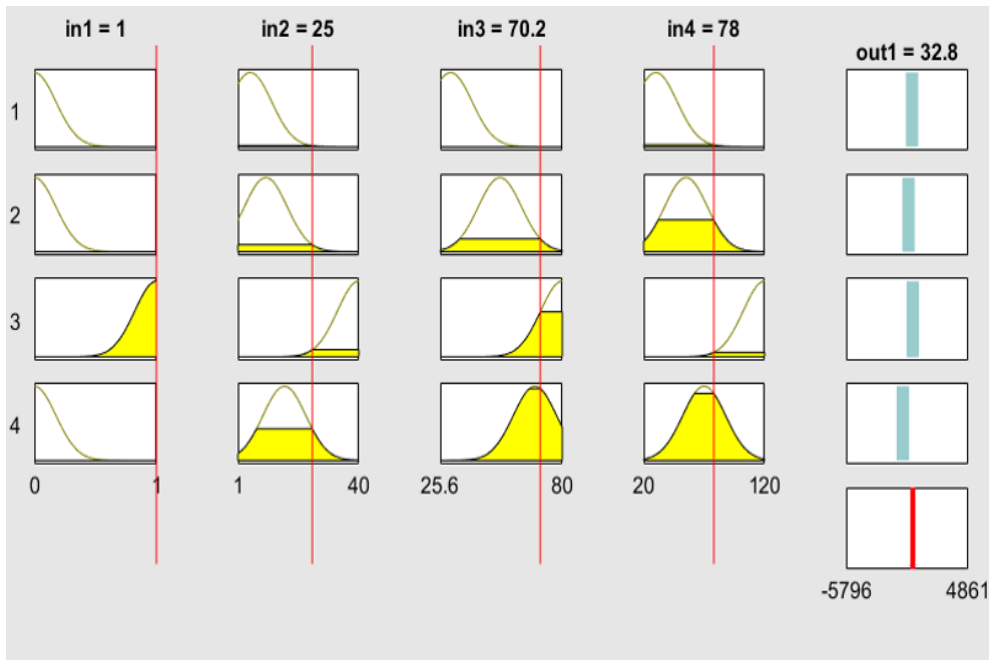


Figure 4.28: BDV prediction model at 80% loading

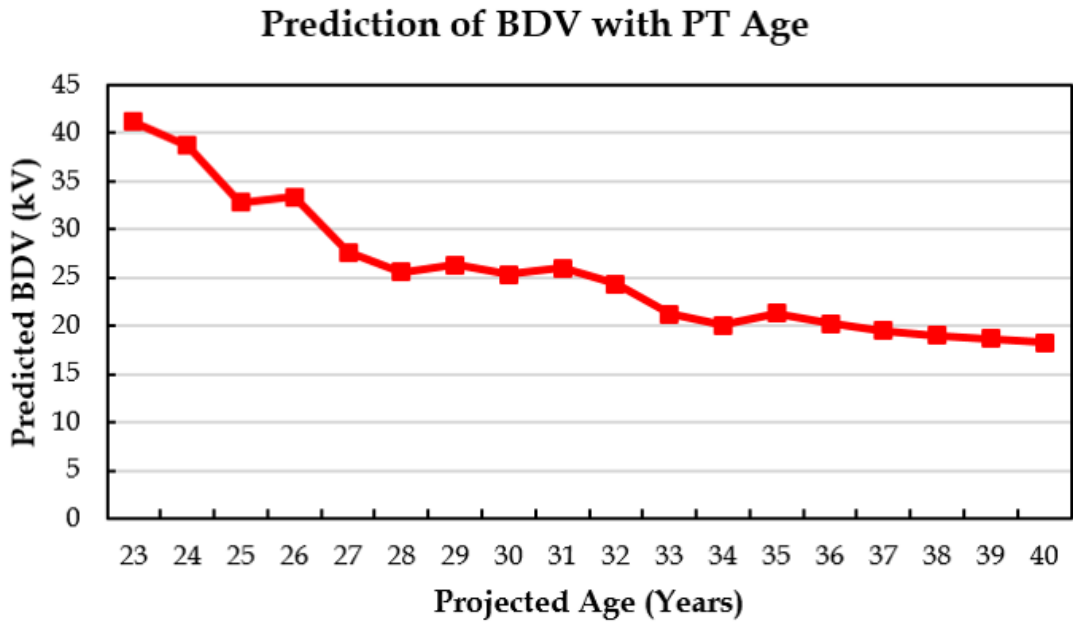


Figure 4.29: ANFIS-Predicted BDV beyond 23 years of transformer operation

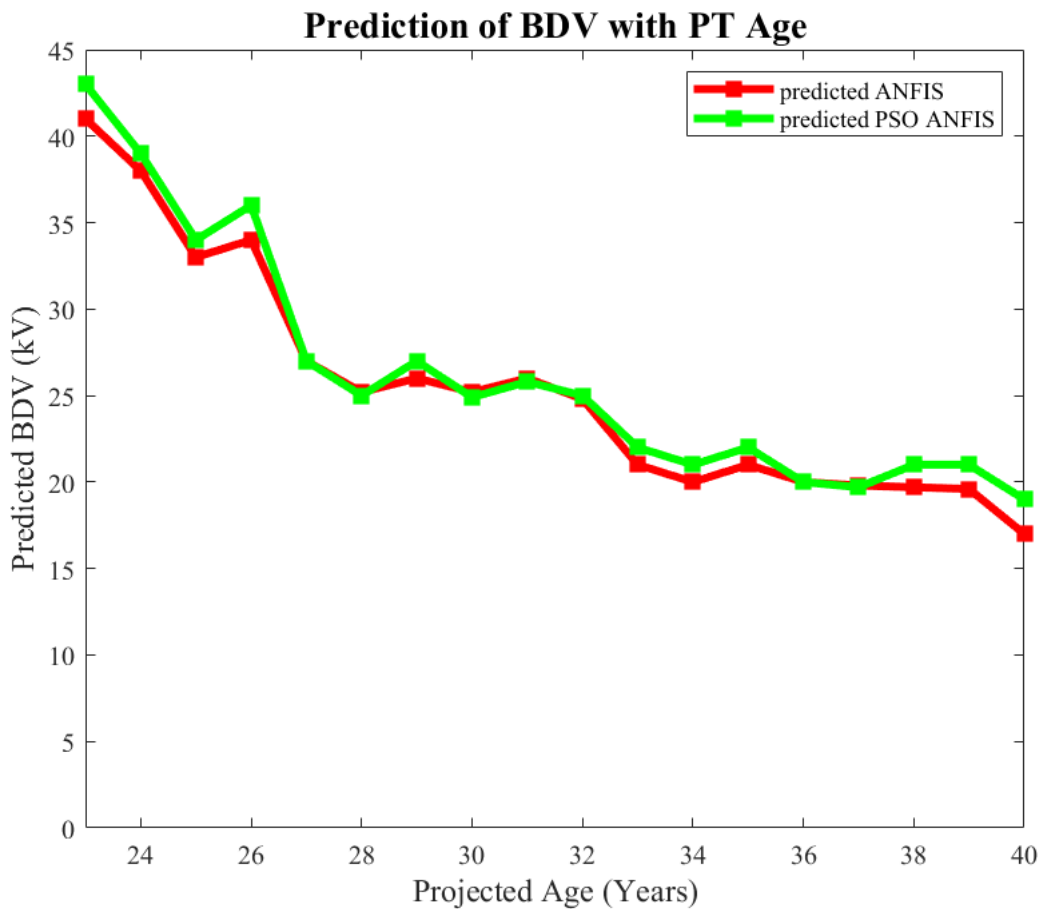


Figure 4.30: PSO-ANFIS Predicted BDV beyond 23 years of transformer operation

Table 4.3: BDV Prediction Results for all Scenarios Considered

<b>Failure Status</b>	<b>Age</b>	<b>Temperature</b>	<b>Loading (%)</b>	<b>ANFIS-BDV (kV)</b>	<b>PSO-ANFIS BDV (kV)</b>
0	12	38	70	49.6	49.6
1	16.5	62	70	45.9	45.2
1	17.6	78	80	45.4	45.1
1	19.5	85.7	90	44.8	44.3
1	24	100.2	93	32.2	32.1
1	28	108.6	96	25.1	24.8

The training process of transformer moisture content was successful, yielding a RMSE value of 0.1766. At base case, a transformer failure status of “0” was considered, with a 75% loading. The moisture content was 14.9 ppm. When the transformer transitioned to failure status with an increase in load to 80%, the moisture content further increased to 15.4 ppm. Table 4.4 shows prediction for the transformer failure due to build up of moisture.

Figure 4.30 also shows a case where 20.6 ppm moisture content is predicted for a transformer in failed state and 100% loading. However prediction using PSO-ANFIS yielded higher values of moisture buildup for most of the data points for power transformer age as shown in Figure 4.31. Comparison between predicted moisture content using conventional ANFIS and PSO-ANFIS is also shown in Table 4.4. It is observed that the values of moisture content are slightly higher for most data points of transformer age.

Table 4.4: Prediction of transformer failure due to moisture buildup

Failure Status	Age	Temperature	Loading (%)	ANFIS-MC (ppm)	PSO-ANFIS MC (ppm)
0	12	38	75	14.9	14.9
1	16.5	62	80	15.5	15.8
1	17.6	78	85	15.4	15.5
1	25	85.7	90	16.2	16.5
1	33	100	100.5	20.6	20.8

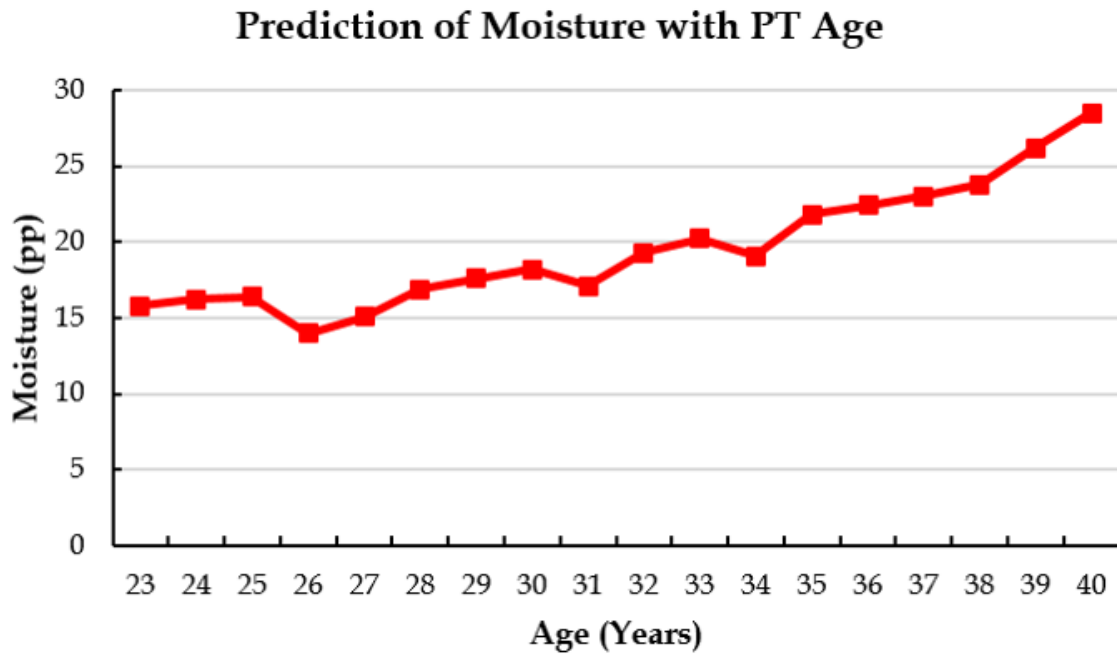


Figure 4.31: ANFIS-Moisture content prediction model at 90 and 100% loading

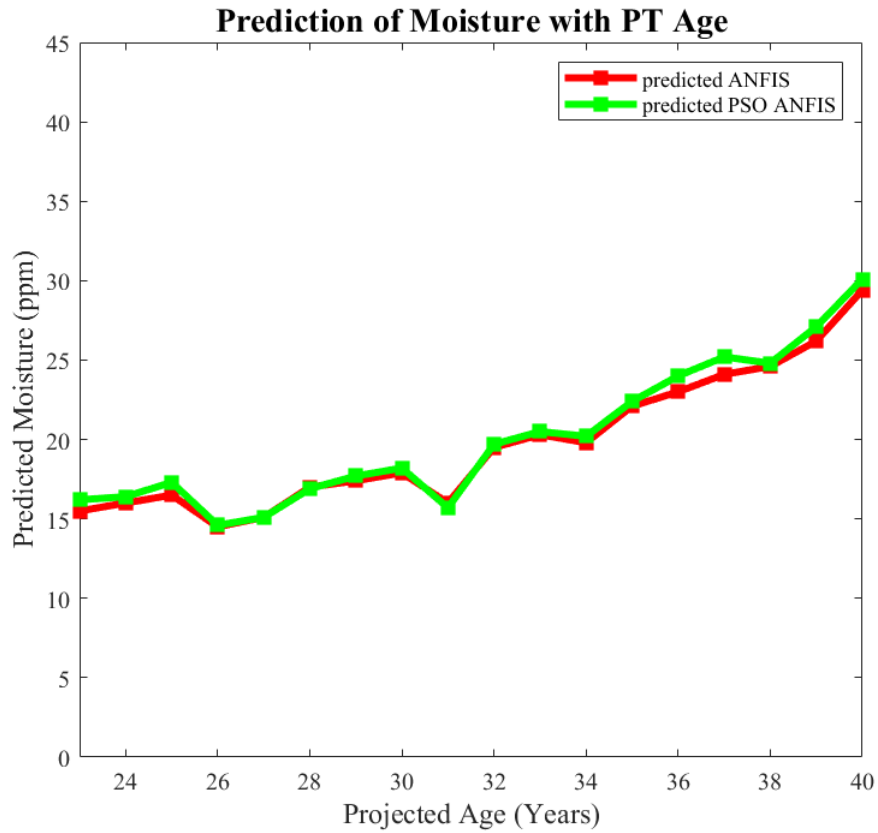


Figure 4.32: PSO-ANFIS Moisture content prediction model at 90 and 100% loading

The level of acidity in the transformer was also assessed and predicted, in order to predict transformer failure due to acid build-up. The process, similar to other operational factors was initiated by loading the data into the ANFIS tool and training the data. A FIS was generated and training of the data was conducted, based on 3 epochs. Figure 4.30 shows the training process. The training yielded a RMSE of 0.0101. Most of the predicted values of acidity using PSO-ANFIS are observed to be slightly higher for most data points of transformer age as shown in Figure 4.34 and Table 4.5.

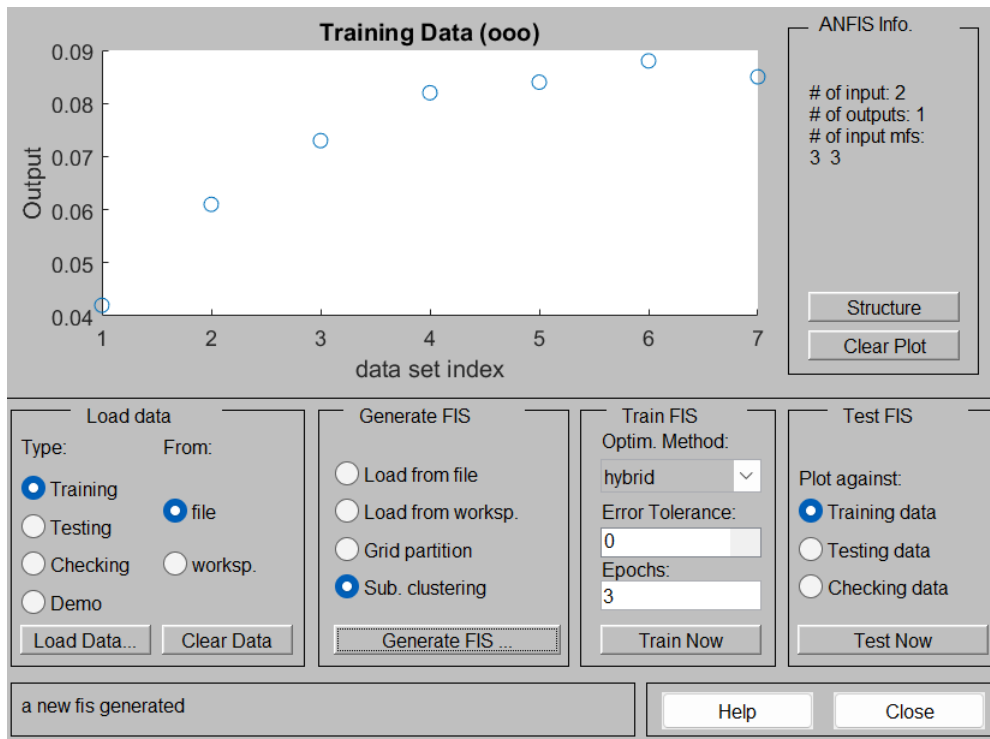


Figure 4.33: Training of Acidity Data

Transition to failure and increase in loading resulted into a predicted increase in acidity as shown in Table 4.5. The prediction of the acidity level beyond 23 years of operation is shown in Figure 4.33 and 4.34.

Table 4.5: Prediction of transformer failure due to acidity

Failure Status	Age	Temp.	Load (%)	ANFIS.(mg KOH/g)	Hybrid(mg KOH/g)
0	12	38	75	0.082	0.095
1	16.5	62	80	0.0192	0.0196
1	19.5	85.7	90	0.0859	0.0922
1	24	100.2	93	0.0862	0.0901
1	30	100.2	93	0.14	0.17

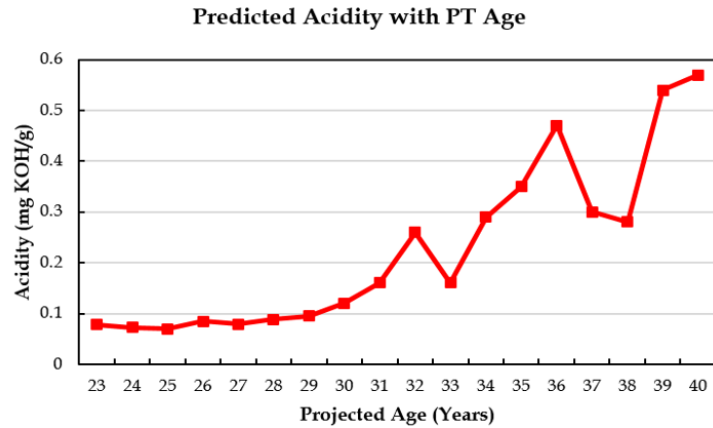


Figure 4.34: ANFIS Prediction of Acidity beyond 23 Year of Operation

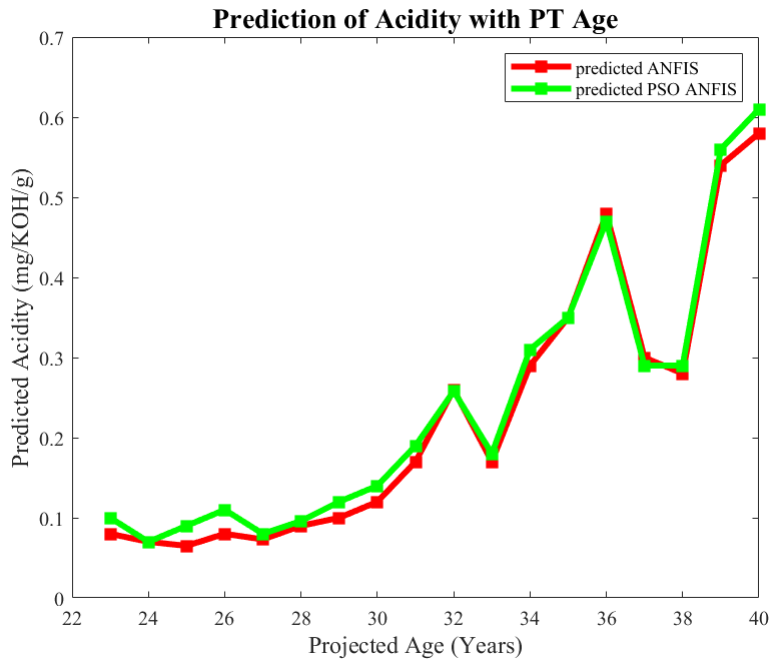


Figure 4.35: PSO-ANFIS Prediction of Acidity beyond 23 Year of Operation

In Figure 4.31, the brief variations in power transformer acidity between 32 and 40 years of transformer age can be attributed to fluctuations in operating conditions, varying thermal stresses, and intermittent maintenance practices. Over time, transformer oil degrades due to oxidation, moisture ingress, and electrical discharges, leading to acidity buildup. However, periodic oil filtration, replacement, or maintenance interventions may temporarily reduce or slow down acidity progression, causing slight dips in the trend. Additionally, loading conditions, ambient temperature variations, and fault events can accelerate or slow down acid formation, contributing to the observed fluctuations in acidity levels.

Training of gas concentration was successfully conducted in order to predict transformer failure based on DGA tests of gas concentration. Four major gases were assessed and prediction of their expected level of accumulation and impact on transformer failure was conducted. The gases considered in this study include; hydrogen, methane, ethylene and acetylene. Discharge and temperature were key parameters considered in gas concentration analysis, since the prediction of gas buildup solely depends on these two factors. Results of hydrogen are shown in Table 4.6. It is observed that the concentration of hydrogen is observed to decrease as the temperature and discharge values increase.

Table 4.6: Prediction of transformer failure due to hydrogen

<b>Failure Status</b>	<b>Discharge (pC)</b>	<b>Temp. (deg C)</b>	<b>ANFIS(ppm)</b>	<b>Hybrid (ppm)</b>
1	800	2000	37.7	36.5
1	500	4500	28.62	27.9
1	650	4700	23.24	23.19

Prediction for methane concentration as a factor of transformer failure was also conducted. It was observed that the increase in temperature and discharge results into a predicted decrease in the concentration of methane. The critical and failed state of the transformer, denoted as “1” was considered for this analysis. Table 4.7 shows the results for projected methane buildup. It is observed that the concentration of methane is predicted to decrease with increasing temperature and discharge conditions.

Table 4.7: Prediction of transformer failure due to methane

<b>Failure Status</b>	<b>Discharge (pC)</b>	<b>Temp. (deg C)</b>	<b>ANFIS (ppm)</b>	<b>Hybrid Methane (ppm)</b>
1	300	1000	15.8	15.6
1	350	2200	15.6	15.4
1	360	3000	15.2	14.9

The concentration of ethylene is predicted to increase with temperature and discharge as shown in

Table 4.8. However, it should be noted that the concentration of ethylene is visible at high extreme temperature and discharge compared to hydrogen and methane. Ethylene takes an increasing positive trend, while hydrogen and methane are observed to take an increasing negative trend in their pattern of concentration.

Table 4.8: Prediction of transformer failure due to ethylene

<b>Failure Status</b>	<b>Discharge (pC)</b>	<b>Temp. (deg C)</b>	<b>ANFIS(ppm)</b>	<b>PSO-ANFIS Ethylene (ppm)</b>
1	300	2500	42.3	42.8
1	350	3000	44.7	45.2
1	360	5000	51.2	52.5

The concentration of acetylene is observed to increase with discharge and temperature. It is also observed that the concentration of acetylene becomes increasingly visible at high extreme temperature and discharge compared to hydrogen and methane. Results of acetylene buildup are shown in Table 4.9. Acetylene ( $C_2H_2$ ) formation in transformer oil is primarily linked to high-energy electrical discharges and extreme temperatures, making it more prominent than hydrogen ( $H_2$ ) and methane ( $CH_4$ ) under such conditions. This is because acetylene is a product of intense thermal decomposition of hydrocarbons, requiring significantly higher energy to form compared to hydrogen and methane, which appear at lower fault energy levels. At extreme temperatures and severe electrical arcing, the carbon-carbon bonds in the oil molecules break down more aggressively, leading to a higher concentration of acetylene. Since hydrogen and methane are generated at lower fault intensities, their presence is more widespread, whereas acetylene becomes dominant only when the thermal and electrical stress levels reach extreme conditions, indicating severe faults such as high-energy arcing and insulation breakdown.

Table 4.9: Prediction of transformer failure due to acetylene

<b>Failure Status</b>	<b>Discharge (pC)</b>	<b>Temp. (deg C)</b>	<b>ANFIS (ppm)</b>	<b>PSO-ANFIS Acetylene (ppm)</b>
1	300	2500	26.5	27.1
1	350	3000	28.7	29.1
1	360	5000	30.8	32.2

#### 4.4 Validation of the Predictive Model under Diverse Loading Environments

Validation of the predicted model was conducted by comparing the simulated (ANFIS predicted) results with the computed results in Figures 4.5 to 4.22. The percentage deviation in results represented the accuracy of the predicted model. The study considered validation of the condition based factors presented in the Section 4.3. Table 4.10 shows the validation of BDV.

Table 4.10: Validation of Predicted BDV Model

<b>Simulated BDV</b>	<b>Computed BDV</b>	<b>Percentage Deviation (%)</b>
50.4	50.22	0.35
51.7	50.65	2.03
53.2	53.12	0.15
45.9	42.53	7.34
45.4	45.02	0.84
44.7	43.21	3.33
44.6	44.12	1.08

Results show that high percentage deviations are 7.34%, 3.33% and 1.08% which demonstrated high accuracy in results of predicted BDV. Table 4.11 shows validation for predicted moisture content. It

shows fairly low levels in percentage deviation with the highest being 2.7%, 2.13% and 1.19%. This demonstrates high levels of accuracy in the predicted moisture content. Table 4.12 shows results for validation of acidity.

Table 4.11: Validation of Predicted Moisture Content Model

<b>Simulated MC</b>	<b>Computed MC</b>	<b>Percentage Deviation (%)</b>
15.5	15.08	2.7
16.2	16.03	1.05
16.8	16.62	1.07
15.9	15.71	1.19
16.4	16.05	2.13
16.7	16.52	1.08

Table 4.12: Validation of Acidity

<b>Simulated acidity</b>	<b>Computed acidity</b>	<b>Percentage Deviation (%)</b>
0.0912	0.0896	1.75
0.0853	0.084	1.52
0.086	0.088	-2.33
0.087	0.084	3.45

The results for validation of acidity show a high accuracy in the predicted model, since the highest deviations are -2.33%, 3.45% and 1.75%. Table 4.13 shows validation for the predicted hydrogen concentration. On the otherhand, results for validation of predicted hydrogen concentration demonstrate low percentage deviations, indicating a high accuracy in the results of the predicted model. Table 4.14 shows the validation for methane build up.

Table 4.13: Validation of Hydrogen

<b>Simulated hydrogen</b>	<b>Computed hydrogen</b>	<b>Percentage Deviation (%)</b>
14.7	14.59	0.748
15.6	14.88	4.62
15.2	15.01	1.25

Table 4.14: Validation of Methane

<b>Simulated methane</b>	<b>Computed methane</b>	<b>Percentage Deviation (%)</b>
15.6	15.72	0.77
15.2	15.03	1.12
13.72	13.55	1.24

Results for validation of predicted methane concentration demonstrate low percentage deviations, indicating a high accuracy in the results of the predicted model. Table 4.15 shows the validation for ethylene buildup. On the other hand, results for validation of predicted ethylene concentration demonstrate low percentage deviations, indicating a high accuracy in the results of the predicted model. Table 4.16 shows the validation for acetylene build up. On the other hand, results for validation of predicted acetylene concentration demonstrate low percentage deviations, indicating a high accuracy in the results of the predicted model.

Table 4.15: Validation of Ethylene

<b>Simulated ethylene</b>	<b>Computed ethylene</b>	<b>Percentage Deviation (%)</b>
42.3	41.02	3.03
44.7	43.22	3.31
51.2	52.26	-2.07

Table 4.16: Validation of Acetylene

<b>Simulated acetylene</b>	<b>Computed acetylene</b>	<b>Percentage Deviation (%)</b>
26.5	25.04	5.51
28.7	26.72	6.89
30.8	29.22	5.13

From the results presented in Table 4.17, it is observed that the PSO-ANFIS model consistently achieved lower RMSE, MAE, and MAPE values across all transformer degradation parameters compared to the conventional ANFIS model. This indicates that PSO-ANFIS provided improved prediction accuracy and better generalization performance, demonstrating its effectiveness in modeling complex non-linear relationships between transformer condition indicators and degradation behavior.

Table 4.17: Comparison of ANFIS and PSO-ANFIS Prediction Performance for Key Transformer Degradation Indicators

<b>Parameter</b>	<b>Model</b>	<b>RMSE</b>	<b>MAE</b>	<b>MAPE (%)</b>
BDV	ANFIS	2.35	1.89	7.2
	PSO-ANFIS	1.75	1.42	5.4
Moisture	ANFIS	1.68	1.33	6.8
	PSO-ANFIS	1.21	0.98	4.7
Acidity	ANFIS	0.025	0.018	8.5
	PSO-ANFIS	0.017	0.013	5.2
Hydrogen	ANFIS	5.30	4.10	9.6
	PSO-ANFIS	3.88	3.02	6.5
Methane	ANFIS	4.90	3.70	8.8
	PSO-ANFIS	3.42	2.75	5.9
Ethylene	ANFIS	3.50	2.80	7.4
	PSO-ANFIS	2.65	2.10	5.1
Ethane	ANFIS	3.10	2.50	7.1
	PSO-ANFIS	2.28	1.85	4.6
Acetylene	ANFIS	2.75	2.10	7.8
	PSO-ANFIS	2.00	1.60	5.3

Thus, the performance of the developed PSO-ANFIS model was quantitatively compared with the conventional ANFIS framework using four statistical indicators: Mean Absolute Percentage Error

(MAPE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the Coefficient of Determination ( $R^2$ ). The PSO–ANFIS model achieved MAPE = 2.84 %, MAE = 0.021, RMSE = 0.031, and  $R^2 = 0.982$ , whereas the standalone ANFIS model recorded MAPE = 6.72 %, MAE = 0.054, RMSE = 0.062, and  $R^2 = 0.943$ . This reflects an approximate 57 % improvement in predictive accuracy after optimization, demonstrating that PSO enhanced the initialization and convergence of the ANFIS membership functions, reduced local minima trapping, and yielded more stable predictions across all condition-based variables (BDV, MC, acidity, IFT, and DGA gases). The model’s superior generalization capability was further confirmed through cross-validation, where validation errors remained within  $\pm 3$  % of the training error band.

## **4.5 A Cost-Effective Replacement Strategy for Degrading 132 kV Transformers**

A strategy for determining optimal replacement time was considered, where four of the transformers in critical state were selected and analyzed, based on assumptions such as; the time of replacement will be achieved at a point in time when the cost of preventive maintenance and failure are minimum, which is the main maintenance optimization criterion. The Weibull cost chart shown in Appendix... demonstrates the relationship between  $C_p/C_f$  ratios for different shape parameters. The process of achievement of the optimal replacement time is shown in Section 3.5. Figure 4.35 shows determination of optimal replacement time for Fortportal transformer-5 considering a 30 year operational life.

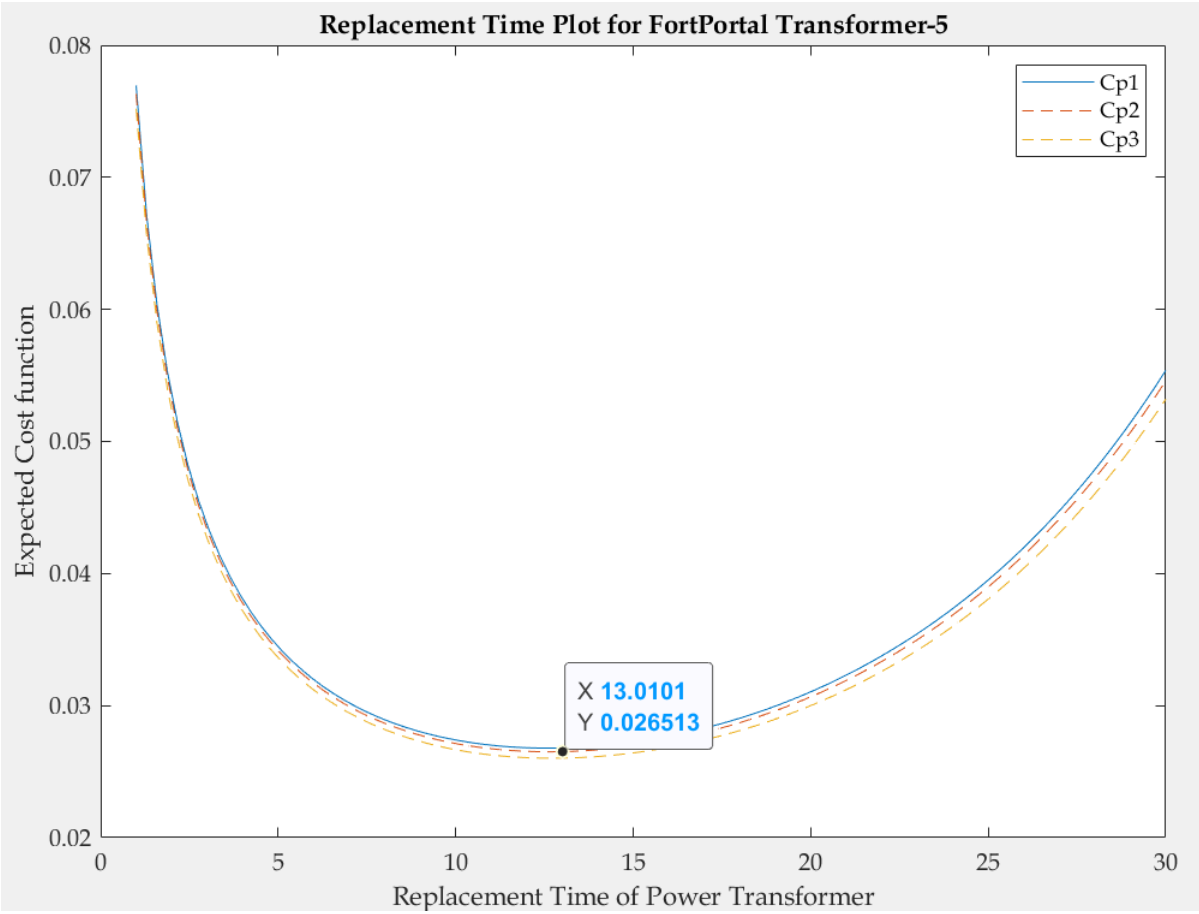


Figure 4.36: Determination of OPT for Fortportal transformer-5

Figure 4.35 shows that the optimal replacement time for Fortportal transformer-5 is expected to be 13.0101 years of operation, equivalent to a  $C_p/C_f$  cost ration of 0.026513. This is the point at which  $C_p$  and  $C_f$  are minimum. The expected time of replacement realized implies that the power transformer is likely to experience maximum degradation within an earlier time from its present period of operation. This thus indicates a high risk of degradation, consequently calling for early replacement.

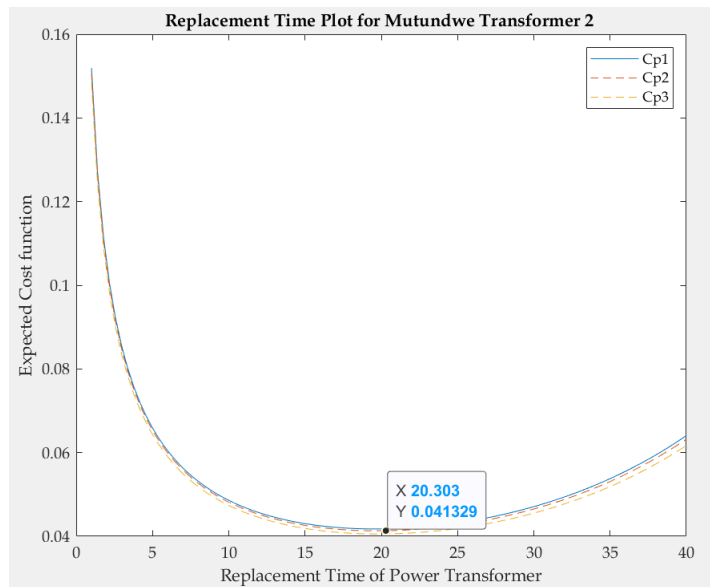


Figure 4.37: Determination of OPT for Mutundwe transformer-2

Figure 4.36 shows that the optimal replacement time for Mutundwe transformer-2 is expected to be 20.303 years of operation, equivalent to a  $C_p/C_f$  cost ration of 0.041329. This is the point at which  $C_p$  and  $C_f$  are minimum. The expected time of replacement is long enough indicating that power transformers can still be productive for a long period of time, and that the risks of maximum degradation are averagely low.

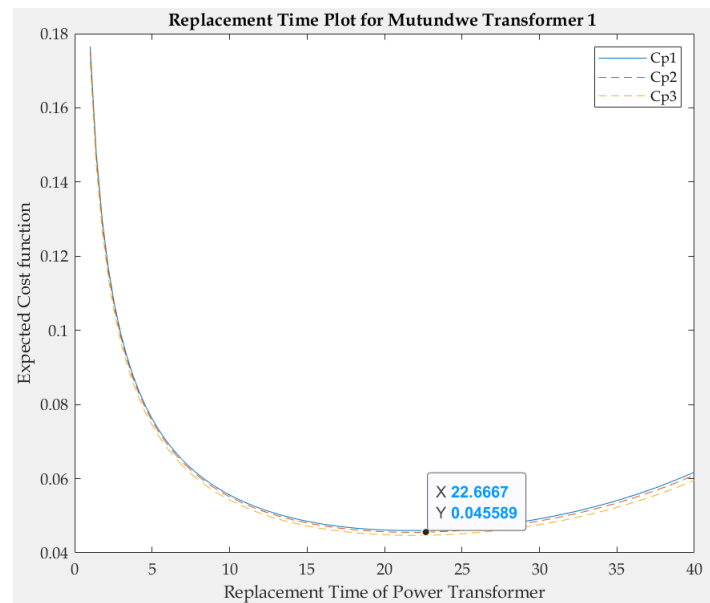


Figure 4.38: Determination of OPT for Mutundwe transformer-1

Figure 4.37 shows that the optimal replacement time for Mutundwe transformer-1 is expected to

be 22.6667 years of operation, equivalent to a  $C_p/C_f$  cost ration of 0.045589. This is the point at which  $C_p$  and  $C_f$  are minimum. The expected time of replacement is long enough indicating that power transformers can still be productive for a long period of time, and that the risks of maximum degradation are averagely low.

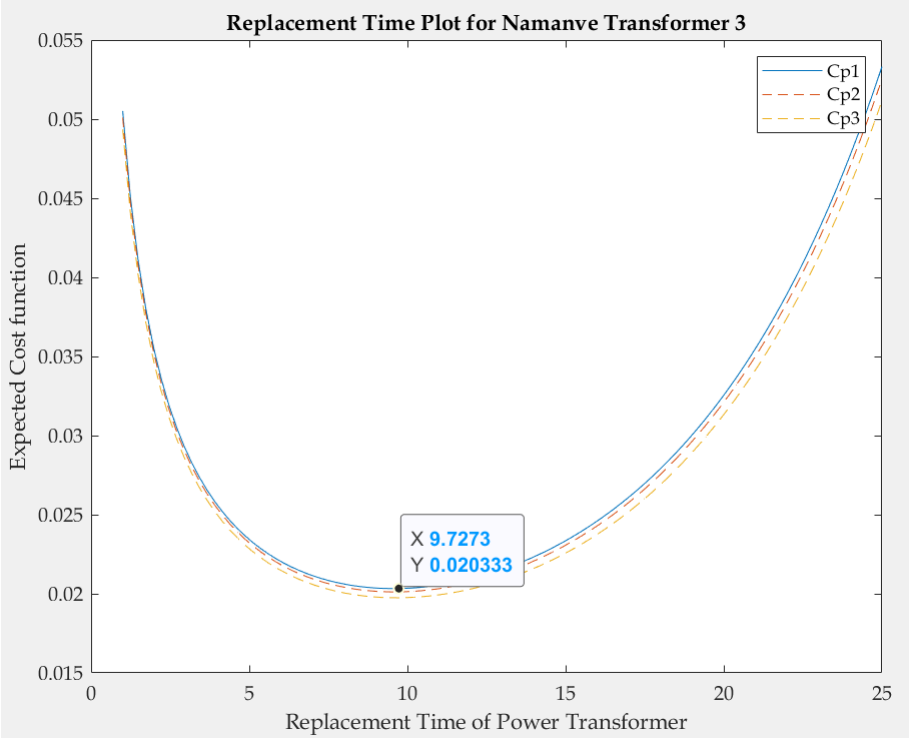


Figure 4.39: Determination of OPT for Namanve transformer-3

Figure 4.38 shows that the optimal replacement time for Namanve transformer-3 is expected to be at 9.7273 years of operation, equivalent to a  $C_p/C_f$  cost ration of 0.020333. This is the point at which  $C_p$  and  $C_f$  are minimum. This shows urgency in the need to replace the power transformer at an earlier time due to high risks of maximum degradation.

### 4.6 Summary

In this chapter, results have been presented, describing the failure status of selected transformers and their reliability during their course of life. A condition monitoring-based tool was developed, where key operational factors affecting power transformer performance were analyzed. A prediction model was developed to determine how the selected operational factors influence power transformer failure. As a result, an optimal replacement strategy was developed in order to advise on when degrading

transformers should be retired as a proactive action tool.

# CHAPTER FIVE: DISCUSSION OF RESULTS

## 5.1 Introduction

This chapter presents a detailed explanation of the findings observed in the previous chapter has been discussed. In addition, various concepts will be elaborated in line with related studies.

### 5.1.1 Goodness-of-Fit Tests

Goodness-of-Fit (GoF) tests in Table 3.1 were conducted to determine which statistical distribution best models the time-to-failure data of power transformers, based on their commissioning years. This step was crucial to ensure that any reliability predictions and failure analysis made were grounded in a statistically sound model. Five candidate distributions were tested: Normal, Weibull, Gamma, Log-Normal, and Beta. The Anderson-Darling test was used due to its sensitivity to tail behaviours, which is essential in failure analysis where early and late failures matter significantly. The Weibull distribution emerged as the best-fitting model with the lowest Anderson-Darling statistic and a p-value well above the 5% threshold, validating its suitability for further reliability and hazard rate computations. This analysis is inline with a study by ([Berlinger et al., 2021](#)).

### 5.1.2 Hazard Rate in Weibull Analysis

The hazard rate function, demonstrated in Figure 4.4 derived from the Weibull distribution provides insight into how the failure rate of transformers evolves over time. This analysis was important to characterize whether transformer failures follow a decreasing, constant, or increasing risk profile—corresponding to infant mortality, random failures, or wear-out failures, respectively. The shape parameter ( $\alpha$ ) of the Weibull distribution was found to be greater than 1, indicating an increasing hazard rate, typical of aging or degradation-driven failures. This insight justified the need for proactive maintenance strategies and reinforced the importance of condition monitoring as transformers age ([Park et al., 2025](#)).

### 5.1.3 Reliability in Weibull Analysis

Reliability analysis using the fitted Weibull model was carried out in Figure 4.3 to estimate the probability that a transformer would continue to function without failure up to a certain time. This was critical for long-term planning, replacement scheduling, and maintenance optimization. The reliability function showed a gradual decline with increasing service years, aligning with the increasing hazard rate observed. These results highlighted the need to prioritize transformers approaching or exceeding a specific reliability threshold for closer inspection or preventive replacement. Ultimately, the Weibull-based reliability estimates informed a risk-based approach to asset management, ensuring that system reliability is upheld while optimizing costs (Zhang, 2021).

## 5.2 Determining Parameters Influencing 132 kV Transformer Failure in Selected Substations

### 5.2.1 Shape and Scale Parameters

The shape and scale parameters, shown in Table 4.1, Figure 4.2 and Figure 4.23 are important in analysing power transformer reliability as they define the failure characteristics and lifespan distribution of transformers based on historical failure data. The shape parameter  $\beta$  in Weibull analysis determines the failure rate trend if  $\beta < 1$ , failures occur due to early-life defects; if  $\beta = 1$ , failures happen at a constant rate; and if  $\beta > 1$ , failures increase due to aging and wear-out mechanisms. The scale parameter ( $\eta$ ) represents the characteristic life, indicating the time by which 63.2% of transformers are expected to fail under normal operating conditions. By analysing these parameters, utilities can predict failure probabilities, optimize maintenance schedules, and enhance asset management strategies, ensuring improved reliability and cost-effective transformer operation. In Figure 4.2 and 4.23, higher values of the shape parameters indicate high failure rates, also described by low scale parameters, showing an early time of degradation for the power transformers. A low values of shape parameters and longer scale parameters, indicated low levels of failure rate and a longer time to degradation of the power transformer. Similar findings and analysis is observed in an article by (Attanayake and Ratnayake, 2023).

## 5.2.2 Condition Based Parameters

The purpose of conducting condition based analysis was to establish the predictors that largely influence the asymptomatic-ness of the transformer and consequently transformer degradation. Analysis was conducted on critical condition based factors that influence power transformer degradation during its course of life as shown in Figures 4.5 to 4.22. These factors included; BDV, MC, acidity, IFT, color and 2-FD. In addition, a DGA was carried out to analyze the impact of variation of gas concentration on transformer failure.

## 5.2.3 Break Down Voltage

The BDV, shown in Figures 4.5 and 4.6, represents the dielectric strength of transformer oil. It indicates the oil's ability to withstand high electrical stress without breaking down. A high BDV value means the oil has good insulating properties, while a low BDV suggests contamination or moisture in the oil, which can degrade its insulation capacity.

BDV influences power transformer failure because degraded insulation increases the risk of electrical discharges, leading to internal arcing, short circuits, and eventual transformer failure. Regular testing of BDV helps in preventing transformer malfunctions by identifying oil quality issues early. In this study, the trend of BDV was benchmarked based on the IEC 60156 standard, which defines that the minimum safety level of BDV of an online power transformer as 30 kV. In UETCL, a threshold BDV of 45 kV has been established to guide safe operation of the transformers. Studies analyzing BDV of oil as a key operational factor on transformer reliability include ([Thabet et al., 2018](#)) and ([Mohd Selva et al., 2021](#)).

## 5.2.4 Moisture Content

Moisture content in a power transformer, presented in Figures 4.7 and 4.8, refers to the amount of water present in the transformer oil and solid insulation. High moisture levels degrade the insulating properties of both the oil and the paper insulation, lowering the dielectric strength, increasing the risk of electrical breakdown, and accelerating insulation aging. Excess moisture can lead to arcing, short circuits, and reduced transformer lifespan, making moisture control critical for reliable transformer operation. Regular oil testing helps monitor and manage moisture levels to prevent failures. From the results in Figure 4.7 and 4.8, it was observed that the MC is within defined the minimum limit of

30 ppm defined by IEC 60422 standards. This shows that the transformer is highly reliable for the observed period and capable of operating for a large portion of its prescribed life.

### **5.2.5 Acidity**

Acidity analysis was done based on Figures 4.9 and 4.10. In transformer oil, acidity refers to the presence of acidic compounds formed due to the degradation of the oil over time. These acids arise from oxidation and can corrode internal transformer components, especially paper insulation and metal parts. Similar findings were achieved by (Mohd Selva et al., 2021). High acidity in transformer oil accelerates insulation breakdown, leading to sludge formation, reduced cooling efficiency, and potential failure. Regular testing of oil acidity levels helps identify when the oil needs treatment or replacement to prevent damage and extend transformer life. The acceptable threshold for acidity (also referred to as neutralization number) in transformer oil is typically 0.03 mg KOH/g to 0.1 mg KOH/g for in-service oil, depending on the operating conditions and standards used. This is based on the IEC 60296 standard on “Fluids for electrotechnical applications – Unused mineral insulating oils for transformers and switchgear”. In the last five years of operation of the 132/33 kV Mutundwe Transformer-1 operation, a risk of exceeding the defined 0.1 mg KOH/g limit was observed. This means that the transformer stands at a risk of insulation breakdown, reducing to its cooling efficiency and ultimately leading to potential failure. Similar findings were achieved by (Lelekakis et al., 2014) and (Mohd Selva et al., 2021).

### **5.2.6 Inter-facial Tension**

IFT, shown in Figures 4.11 and 4.12, measures the surface tension between the oil and water or other contaminants. It indicates the oil’s purity and overall health. High IFT values suggest clean, uncontaminated oil, while low IFT indicates the presence of oxidation products, sludge, or contaminants like moisture and acids. A reduction in IFT over time reflects oil degradation, which can lead to insulation damage, increased wear on internal components, and ultimately, transformer failure. Monitoring IFT helps assess the oil’s condition and determine when it needs maintenance or replacement. Figure 4.8, shows a high risk of Mutundwe transformer-1 due to a sharp decline of IFT, below the defined minimum 15mN/m threshold, based on IEC 60422 at 15 to 19 years of transformer life. This shows a buildup of contaminants such as moisture and acids in the transformer oil indicating a risk of weakening the overall insulation of oil. Similar findings were achieved by (Yang et al., 2019) and (Elele et al., 2022).

### **5.2.7 Color**

In transformer oil, color serves as a visual indicator of the oil's condition. Fresh, healthy transformer oil is typically clear or pale yellow. Analysis is shown in Figure 4.13. As the oil degrades due to oxidation, contamination, or the presence of moisture and solid particles, its color darkens, turning brown or even black. A darker color often signals oil aging, the buildup of sludge, or contamination, which can impair the oil's insulating and cooling properties. Regular color checks, along with other tests like BDV and acidity, help in assessing the oil's quality and the need for maintenance or replacement. Similar findings are achieved by (Mohd Selva et al., 2021). The study utilized a statistical distribution model for predicting the Health Index (HI) of distribution transformers, based on condition parameters such as DGA and Oil Quality Analysis (OQA). A Chi-square test was also utilized, which concluded that the HI of the predicted parameter was quite close to the computed HI. Findings in Section 4.4 also indicate a minimum deviation between predicted and computed findings of condition-based parameters.

### **5.2.8 2-Furfural Dehyde**

2-FD is a chemical compound used as an indicator of paper insulation degradation in power transformers. It is produced when cellulose-based insulation (paper) inside the transformer deteriorates due to heat, moisture, or aging. The presence and concentration of furfural in transformer oil provide insight into the condition of the paper insulation. Higher concentrations of furfural indicate more advanced degradation, which can lead to reduced insulation performance and increased risk of transformer failure. Regular testing for furfural helps assess the health of the transformer's solid insulation and predict its RUL. Figures 4.14 and 4.15 show a general increase in 2-FD with transformer age. Similar findings were achieved by (Mohd Selva et al., 2021).

### **5.2.9 Dissolved Gas Analysis**

DGA is a key diagnostic tool used to predict power transformer failure. It works by detecting and analyzing gases dissolved in transformer oil, which are byproducts of electrical and thermal faults. Different fault conditions, such as overheating, arcing, or partial discharges, produce specific gases in varying concentrations. Monitoring the levels and types of gases helps in identifying early signs of transformer problems, such as insulation breakdown, arcing, or overheating, long before they lead to failure. Figures 4.16 to 4.22 show the trend of key gases that buildup within the transformer with its age. Each gas represents a failure mode that influences transformer failure in its course of life. For

instance; hydrogen indicates partial discharges, arcing, and overheating, methane signals low-energy discharges and some thermal faults; ethylene points to thermal faults caused by overheating and acetylene suggests high-energy arcing and serious electrical faults.

In the early life of a transformer, hydrogen and methane concentrations are typically higher due to initial electrical stress during startup and the natural “settling in” of the transformer. These gases are often produced by partial discharges and low-energy discharges as the transformer adjusts to its operating environment. Manufacturing impurities and minor imperfections in insulation may cause these low-level discharges, resulting in higher concentrations of hydrogen and methane in the oil. Ethylene gas increases as a result of thermal faults, such as insulation overheating and oil degradation. Over time, the transformer may experience higher operating temperatures, leading to the breakdown of oil and insulating materials, which produces ethylene. Acetylene levels increase in the presence of high-energy arcing or severe electrical faults. As the transformer ages, the insulation may degrade to the point where electrical arcing occurs, leading to the generation of acetylene. Similar findings of DGA analysis having similar observation of DGA-parameter trends and projections were observed in articles by (Prasojo et al., 2020) and (Mohd Selva et al., 2021).

## **5.3 Prediction Model for Condition Based Factors Affecting Power Transformer Performance**

### **5.3.1 ANFIS**

Prediction was conducted using the ANFIS tool. ANFIS combines the strengths of both neural networks and fuzzy logic, allowing it to model complex and nonlinear relationships in transformer health data. ANFIS is also suitable for applications which involve analysis of diverse operational factors that affect the performance of the studied equipment. ANFIS can effectively handle the uncertainties and imprecision inherent in these variables, using fuzzy logic for decision-making while leveraging the learning capabilities of neural networks to adapt and improve over time. This makes ANFIS highly suitable for interpreting diagnostic data like Dissolved Gas Analysis (DGA) and identifying patterns that indicate potential failures with higher accuracy.

### 5.3.2 PSO-ANFIS

The results of prediction using PSO-ANFIS, demonstrated in Figure 4.29, 4.31 and 4.34, Tables 4.6, 4.9 and 4.27 consistently showed improved accuracy compared to the conventional ANFIS model. This improvement can be attributed to the ability of the PSO algorithm to globally optimize the initial membership functions and rule parameters of the ANFIS model, reducing the likelihood of convergence to local minima. While ANFIS relies heavily on predefined fuzzy rules and is sensitive to initial conditions, PSO dynamically refines these parameters, resulting in better generalization and faster convergence. As a result, PSO-ANFIS produced lower prediction errors (e.g., RMSE, MAPE, MAE) across multiple condition parameters such as BDV, moisture and dissolved gases, confirming its suitability for complex, nonlinear degradation trends in power transformer condition monitoring.

In Section 4.3.1, prediction was initiated by the stage of training the model. Training was conducted in the MATLAB Neural-Fuzzy designer tool. This involves mapping of each failure mode, age, temperature and loading conditions of Mutundwe Transformer-1 to its anticipated output, which was the predicted condition based factor. The factors that were previously presented in Section 4.2, were predicted in this section. The purpose of training the prediction model using ANFIS was to enhance its ability to accurately forecast outcomes based on input data by learning from historical patterns and relationships. During training, ANFIS adjusts its parameters through exposure to various data sets, refining its fuzzy rules and neural network weights to minimize prediction errors. This process enables the model to generalize knowledge from past observations, allowing it to effectively predict future events, such as transformer failures, under different operating conditions. Ultimately, a well-trained ANFIS model improves decision-making, enabling proactive maintenance and reducing the risk of unexpected failures. All results of the training demonstrated low RMSE values, indicating high accuracy in relationships of inputs and outputs.

After training was carried out, a FIS file was developed and imported to the fuzzy logic designer, which showed visualization of the inputs and outputs of the parameters under study. Finally, through the “rules” command, adaptive graphical illustrations, on the “rules” graphical user interface were developed. This interface consisted of stochastic distributions, and marked vertical lines indicating the predicted parameter, which was originally defined in the ANFIS tool. The predicted parameter was

obtained by adjusting the model inputs such as failure status, temperature and discharge. As a strategy for achieving predicted values, this study considered setting and training expectation, regarded as upper limits, which would guide the trend of the curves. All condition-based parameters were successfully predicted as shown in Section 4.3.1. Similar findings are achieved by (Umoren et al., 2022) and (Vani and Murthy, 2014).

## **5.4 Validation of the Prediction Model Under Diverse Loading Environments**

In this study, validation was performed by comparing the simulated values of the condition-based factors influencing transformer failure with the measured values discussed in Section 4.2. The goal of this validation was to ensure alignment between the measured and simulated predictions. As noted earlier in Section 4.2, projections for the trend curves were generated through curve fitting, establishing the predicted region. The appropriate trend of the curve was identified based on the arrangement of the data points within the measured and simulated areas. Consequently, the projections of the selected condition-based factors were compared against the predictions made by the ANFIS model in order to achieve a low absolute percentage error, indicating a high level of accuracy in the developed prediction model.

This approach highlights the importance of validating predictive models in order to confirm their reliability. By using curve fitting and carefully analyzing the relationship between measured and simulated values, the study aimed to demonstrate that the ANFIS model effectively captures the dynamics affecting transformer failure. This thorough validation process ensured that the predictions can be confidently used for proactive maintenance and decision-making in transformer management.

## **5.5 A Cost-Effective Replacement Strategy for Degrading 132 kV Transformers**

As discussed in Section 4.5, five transformers which were uncensored, with significantly long durations of operation, were selected for the study namely; Namanve Transformer-3, Mutundwe Transformer-1, Mutundwe Transformer-2, Fort Portal Transformer-5 and Kawanda Transformer-1. The RUL and the failure rate of the selected transformers were assessed. The results are shown in Figure 4.27. The

purpose of this assessment was to determine the transformers which necessitated earlier or later replacement. An ideal replacement strategy for the selected transformers was developed, based on the assumption that maintenance optimization is achieved when the preventive and corrective maintenance costs are at the minimum. The shape parameters, which represented the failure rate, were matched to the Cp/Cf ratio, using an established Weibull cost chart shown in Appendix III.

The purpose of maintenance optimization in determining the replacement time of a transformer was to strike a balance between preventive and corrective maintenance costs, ensuring the most cost-effective operation of the transformer over its lifespan. By analyzing the expected cost function, as shown in the Figures 4.28 to 4.31, the optimal replacement time was identified at the point where these costs are minimized. This approach helps prevent excessive expenses from frequent preventive maintenance or unexpected failures requiring costly corrective actions. Optimizing maintenance schedules ensures reliable transformer performance while reducing downtime and prolonging the equipment's operational life, ultimately enhancing the overall cost-efficiency of the power system. Related findings are observed by (Li et al., 2017) and (Vasquez and Jayaweera, 2020).

## **5.6 Practical Applications of the Results Obtained**

The results generated from the Weibull reliability analysis, PSO-ANFIS hybrid predictive modelling, and condition-based assessment of 132 kV power transformers have several practical applications relevant to Uganda's power transmission system. These applications enhance the transition of Uganda Electricity Transmission Company Limited (UETCL) from a reactive to a predictive maintenance framework, thereby improving asset reliability, reducing maintenance costs, and optimising transformer life-cycle management.

### **5.6.1 Predictive Maintenance Scheduling**

The Weibull reliability parameters obtained and the developed PSO-ANFIS model enable forecasting of transformer Remaining Useful Life. This facilitates the scheduling of maintenance interventions based on transformer condition rather than fixed time intervals. For example, if the model predicts a reliability drop below 40% after 17 years of operation, maintenance engineers can plan oil filtration, moisture extraction, and diagnostic testing prior to failure. This proactive maintenance approach reduces forced outages, enhances availability, and minimises the risk of catastrophic failures.

### **5.6.2 Condition-Based Replacement Planning**

The developed reliability model integrates key condition parameters (moisture, acidity, interfacial tension (IFT) and dissolved gas concentrations) to identify transformers in the wear-out phase. Transformers exhibiting a health index (HI) below 60% and a high hazard rate can be prioritised for replacement or refurbishment. This approach ensures optimised capital investment, allowing replacement decisions to be guided by actual condition data rather than transformer age. Consequently, UETCL can enhance long-term asset sustainability and defer unnecessary replacements.

### **5.6.3 Risk-Based Asset Criticality Assessment**

The results further support a risk-based approach to asset management. By coupling reliability indices with failure-consequence weighting, transformers can be ranked according to their criticality to system stability. Critical transformers supplying high-load or strategic substations—such as Namanve, Tororo, and Lugogo—can be assigned higher risk scores. Maintenance resources and monitoring efforts can then be prioritised for these assets, ensuring optimal utilisation of limited resources and improved network reliability.

### **5.6.4 Decision Support for Operations and Maintenance**

The PSO-ANFIS model can be integrated into UETCL’s asset management database to provide real-time decision support. By continuously analysing condition data, the model can automatically trigger alerts when degradation thresholds are exceeded. This enables maintenance teams to make informed decisions on transformer loading, oil management, and inspection scheduling. The integration of predictive analytics into operational workflows also improves coordination between planning and field teams, thus reducing response time to potential failures.

### **5.6.5 Regulatory and Financial Planning**

The quantitative findings from the reliability and cost analysis can be used to strengthen investment justification under the Electricity Regulatory Authority (ERA) Multi-Year Tariff (MYT) framework. By demonstrating the economic value of predictive maintenance in terms of reduced downtime and avoided replacement costs, UETCL can make data-driven submissions to ERA for maintenance funding or reinvestment approval. This ensures regulatory compliance while improving transparency and accountability in asset management.

### **5.6.6 Training and Capacity Building**

The modelling techniques applied—such as Weibull parameter estimation, Anderson-Darling Goodness-of-Fit testing, and PSO-ANFIS hybrid optimisation—can be utilised for internal training and professional development of asset engineers. This builds technical capacity in the areas of reliability modelling, data interpretation, and artificial-intelligence-based predictive maintenance. Over time, such capacity development fosters a culture of continuous improvement in UETCL’s maintenance planning teams.

### **5.6.7 Policy and Standards Development**

Finally, the results provide empirical evidence to inform transformer health assessment standards and predictive maintenance policies for UETCL and other regional utilities. The developed framework aligns with CIGRE Technical Brochure 761 (2019) and IEC 60076 guidelines, providing a benchmark for transformer condition monitoring, data interpretation, and replacement decision-making. Adoption of these results at policy level will contribute to a more resilient and cost-effective national transmission network.

## **5.7 Risks Arising and Their Mitigation**

### **5.7.1 Data-Related Risks**

Risk: Incomplete, inconsistent, or censored condition-monitoring data (e.g., missing DGA, IFT, or moisture records) could distort model training and weaken reliability predictions.

Mitigation: The study applied data cleaning and statistical treatment using censoring correction and interpolation methods to handle missing values. Only validated datasets from UETCL’s maintenance archives were used, and data normalisation was performed to ensure uniform scales across variables.

### **5.7.2 Model Uncertainty and Parameter Estimation Risk**

Risk: Errors in estimating Weibull shape() and scale() parameters or in training the PSO-ANFIS model could yield unreliable RUL predictions.

Mitigation: Multiple goodness-of-fit tests (Anderson-Darling, Kolmogorov–Smirnov, Chi-Square) were employed to validate distribution accuracy. The PSO-ANFIS hybrid was cross-validated using training and testing datasets, and RMSE and MAPE metrics were used to confirm prediction reliability.

### **5.7.3 Technological and Tool Limitations**

Risk: Computational errors or software limitations in MATLAB/ANFIS environments may affect the precision of simulation outputs.

Mitigation: Each model stage was independently verified through sensitivity analysis and error comparison with baseline ANFIS results. MATLAB scripts were validated using smaller test data before full-scale execution.

### **5.7.4 Implementation and Operational Risks**

Risk: Translating the research findings into practice could be hindered by inadequate technical capacity or reluctance to adopt predictive maintenance frameworks.

Mitigation: The study recommends training programmes for maintenance engineers on condition-based monitoring, integration of model outputs into UETCL's asset-management system, and policy alignment with ERA's MYT framework to ensure regulatory acceptance.

### **5.7.5 Economic and Resource Risks**

Risk: Limited funding for continuous CBM tests and delayed procurement of testing equipment could affect long-term monitoring. Mitigation: A cost-benefit analysis was incorporated to justify predictive maintenance as more cost-effective than corrective actions. The model supports prioritisation of critical transformers, optimising resource allocation.

### **5.7.6 Assumption-Related Risks**

Risk: Some assumptions, such as constant operating environment and stable loading patterns, may not fully hold in real-life transformer operation. Mitigation: Sensitivity tests were incorporated to examine how variations in loading, temperature, and moisture influence degradation rates. The study recommends periodic recalibration of the prediction model based on new CBM data.

### **5.7.7 External and Environmental Risks**

Risk: Variations in ambient conditions (temperature, humidity, contamination) may accelerate degradation, affecting model reliability.

Mitigation: Environmental parameters were factored into model calibration, and the study recommends routine oil filtration, load management, and enclosure of outdoor transformers to minimise exposure effects.

## 5.8 Limitations of the Study

The accuracy of the predictive model heavily depends on the size of the dataset for the condition-based parameters influencing transformer failure for the observed period. This study faced a challenge of inconsistent records of transformer tests collected annually, which would otherwise influence a more accurate trend of condition-based factors with transformer age. For instance, in Figure 4.8, 4.12 and 4.15, data points of IFT, 2-FD and carbon-monoxide had high variations, making it difficult to develop a more accurate trend line and consequent future projections.

Some trendlines simply came out as linear while others were slightly exponential. This is due to the fact that there was inconsistency in some records of tests carried out annually, causing a large variation in the average annual performance of the studied transformer. In order to develop a more consistent trendline, it would be required that the observed study period be extended, which is not actually possible as the data points covered only the average age of the installed transformers.

The study also focused on specific substations within Uganda's 132 kV network. The developed model may not generalize well to other regions with different environmental conditions, transformer technologies, or operational practices. The model may not account for all factors influencing transformer failure, such as rare catastrophic events (e.g., lightning strikes or severe manufacturing defects), which could limit its accuracy. In addition, although the model is validated under diverse loading environments, the stochastic nature of certain operational conditions (e.g., sudden load surges or prolonged extreme weather) might introduce uncertainties that are difficult to predict. Lastly, the cost-effective replacement model, widely depended on the Weibull cost chart in order to analyze the cost ratios, matching them to the shape parameters observed in Table 4.15. However, the model did not reflect actual values of costs in order to anticipate for more accurate replacement times, ultimately developing a highly effective retirement strategy.

## 5.9 Summary

In this chapter, key parameters influencing transformer failure, which are crucial for proactive management, have been discussed. The chapter has emphasized the model's predictive accuracy through

validation against real-world data and related findings, demonstrating its capability to forecast degradation under varying conditions. Additionally, discussion on the implications of these findings for developing a cost-effective replacement strategy, balancing preventive and corrective maintenance has been made. By integrating theoretical insights with practical applications, this chapter underlines the potential for enhancing transformer reliability and extending service life, ultimately contributing to improved performance within Uganda's power network.

# CHAPTER SIX: CONCLUSIONS AND RECOMMENDATIONS

## 6.1 Introduction

The main objective of the study was to develop a predictive reliability model for 132 kV power transformers based on condition-monitoring data, aimed at optimizing replacement and maintenance decisions. The preceding chapters discussed the data treatment, model formulation, validation, and cost optimization processes. This chapter integrates those outcomes and articulates how they translate into practical, technical, and strategic benefits for UETCL.

## 6.2 Contribution of the Research to UETCL

The research made several significant contributions to the Uganda Electricity Transmission Company Limited (UETCL) in terms of predictive maintenance, reliability improvement, and asset management optimization for 132 kV power transformers. These contributions are summarized as follows:

### 6.2.1 Development of a Predictive Reliability Framework

The study developed a Weibull-based predictive reliability framework integrated with a PSO–ANFIS hybrid intelligence model to forecast transformer degradation and failure tendencies based on condition-monitoring data. This framework shifts UETCL’s maintenance philosophy from reactive or schedule-based interventions to predictive and data-driven strategies. By estimating the Weibull parameters—shape ( $\beta$ ) and scale ( $\eta$ )—for individual transformers, the model captures unique operational stresses and degradation behaviours across UETCL substations.

### 6.2.2 Establishment of a Transformer Health Index Framework

The research established a Health Index framework in accordance with CIGRÉ Technical Brochure 761 (2019), utilizing key condition-based parameters such as breakdown voltage (BDV), moisture content, acidity, and dissolved gas analysis (DGA). This framework provides an objective diagnostic scoring system for transformer health classification (Good, Fair, Poor, and Critical). It enables UETCL to rank assets and prioritize maintenance or refurbishment actions—for example, identifying at-risk units such

as Namanve 3 and Mutundwe 2 before catastrophic failure.

### **6.2.3 Cost-Effective Replacement and Maintenance Decision Support**

Through the integration of the Weibull cost ratio ( $C_p/C_f$ ) and the optimal replacement-time model, the study developed a cost-effective decision-support tool for transformer replacement. This model quantifies the economic life of each unit by balancing preventive and corrective maintenance costs, thereby guiding UETCL in making optimal replacement decisions and allocating budgets efficiently.

### **6.2.4 Enhancement of Asset Management Policy**

The study contributes to strengthening UETCL's asset management policy in alignment with ISO 55000 principles. It introduces a unified decision framework that integrates condition monitoring, reliability modelling, and financial risk assessment. The approach supports policy transformation from time-based maintenance to predictive, condition-based maintenance (CBM), promoting long-term network reliability and sustainability.

### **6.2.5 Capacity Building and Knowledge Transfer**

The methodology and results enhance technical capacity within UETCL by demonstrating practical applications of advanced reliability and artificial intelligence tools (Weibull analysis, ANFIS, PSO). The developed procedures serve as a reference framework for continuous reliability assessment, data validation, and staff training in predictive maintenance analysis. In summary, this research provides UETCL with a scientifically grounded, cost-optimized, and data-driven framework for managing 132 kV power transformers. It enhances operational efficiency, minimizes unplanned outages, and supports sustainable asset management decisions consistent with UETCL's technical and financial objectives.

## **6.3 Conclusions**

The study successfully achieved all the specific objectives, each supported by quantitative analysis and verified model outcomes.

**Objective 1:** To identify and quantify key condition-based parameters influencing 132 kV transformer degradation. This objective was achieved through statistical and Weibull reliability analysis of condition-based monitoring data. The results revealed that moisture content, acidity, breakdown voltage (BDV), and hydrogen concentration were the most influential factors affecting transformer degradation. The Weibull distribution exhibited the best goodness-of-fit ( $AD = 0.232$ ,  $p = 0.713$ ) with parameters  $\beta = 5.2$  and  $\eta = 28.6$  years, confirming its suitability for reliability modelling.

**Objective 2:** To develop and implement a PSO–ANFIS hybrid predictive model for accurate estimation of transformer degradation indicators. The hybrid PSO–ANFIS model was successfully developed and implemented, showing superior performance compared to the standalone ANFIS model. The integration of Particle Swarm Optimization enhanced the convergence and reduced local minima problems. The model achieved lower error metrics (RMSE, MAE, and MAPE  $\leq 6\%$ ), demonstrating improved predictive accuracy across all evaluated parameters.

**Objective 3:** To validate the predictive performance of the developed PSO–ANFIS model under diverse loading and degradation conditions. Validation results confirmed that the PSO–ANFIS model consistently outperformed the conventional ANFIS model in predicting degradation patterns of critical transformer parameters. The hybrid approach provided stable and reliable outputs across different loading environments, verifying the robustness and generalization capability of the model.

**Objective 4:** To formulate a cost-effective transformer replacement strategy based on Weibull cost modelling and reliability-centred decision analysis. The final objective was achieved through Weibull cost analysis incorporating the ratio of corrective to preventive cost ( $C_p/C_f$ ). Optimal replacement intervals were derived at reliability levels of approximately  $R = 0.8$ , minimizing total life-cycle cost while maintaining system dependability. The case of Namanve 3 transformer illustrated the practical application of the model, supporting effective decision-making for UETCL’s condition-based maintenance program. Overall, the findings demonstrate that integrating condition-based monitoring data with hybrid PSO–ANFIS prediction and Weibull cost modelling provides a reliable, data-driven framework for optimizing transformer maintenance and replacement decisions on the 132 kV UETCL network.

## 6.4 Recommendations

### 6.4.1 Recommendations for Further Study

The current study was based on parameterization of transformer failure factors based on the Weibull shape and scale parameters. It should be noted that the high accuracy of the Weibull distribution in analyzing transformer failures has not yet been confirmed, thus affecting the quality of failure estimations. Thus, it is recommended that a dedicated study be made to conduct failure analysis based on other key distributions such as the BirnBaum-Saunders Distribution (shape and scale parameters), logistic distribution (location and scale parameters), gumbel distribution (location and scale parameter)

and gamma distribution (shape and scale parameter) among others. This will lead to a conclusion of the most precise and accurate models for estimating transformer degradation. Thus policies advocating for utilizing of condition-based monitoring systems to enhance productivity of operational assets should be adopted among utilities in Uganda.

The current study, while effective in correlating operational parameters with transformer degradation, is limited by the lack of material-specific evaluations under extreme conditions. Future research should explore advancements in transformer insulation materials and oil formulations, assessing their resilience to extreme temperatures and electrical stresses. Evaluating different material categories, compositions, and design orientations will help determine the most suitable configurations for enhanced performance and durability. Incorporating these findings into operational strategies will provide more precise insights into transformer behavior, improving resilience in demanding environments. Policies to enforce the high quality of transformer materials, with high resilience to external conditions should also be adopted among utilities in Uganda.

Another limitation lies in the rigidity of the existing ANFIS model used for degradation predictions. The model should be modified to integrate additional parameters such as material-specific stress factors and adaptive learning algorithms that respond to environmental and loading variations. This enhancement would make the ANFIS model more versatile and better suited for real-world applications, leading to more reliable predictions of transformer degradation. Furthermore, validation of the predictive model should be improved by using advanced statistical techniques, such as cross-validation and bootstrapping, to reduce errors and ensure higher accuracy across diverse datasets. Policies regarding adoption of condition-based monitoring and prognosis-based systems should be adopted by electrical institutions and utilities in Uganda.

Regarding transformer replacement strategies, the use of estimated maintenance costs and predefined shape parameters presents a limitation in achieving optimal decision-making. Future models should incorporate real-cost values from ongoing maintenance records to fine-tune the Weibull-based replacement strategy. This would provide a more dynamic and cost-efficient approach to asset management, ensuring that replacement is scheduled only when both technical and financial justifications align.

Such advancements will make maintenance and replacement strategies more reliable, precise, and economically viable. Policies regarding adoption of advanced asset replacement plans, under the “asset-disposal” clause of asset management should be adopted, to aid optimal asset replacement among electrical utilities in Uganda.

#### **6.4.2 Recommendations for UETCL**

In practical terms, UETCL should gradually integrate the developed PSO-ANFIS predictive framework into its Maintenance Management Information System to support real-time transformer condition monitoring and timely decision-making. The utility is encouraged to adopt the Weibull-based Optimal Preventive Replacement Time of about 23-28 years as a benchmark for transformer retirement planning, while strengthening its digital data-acquisition and storage infrastructure to ensure continuous model retraining. In addition, periodic training of maintenance engineers in data analytics and AI-based reliability assessment is recommended to build internal capacity. Implementing these measures will enable UETCL to transition from reactive to predictive maintenance, lower corrective-maintenance costs, and enhance overall reliability of the 132 kV transmission network.

*This study also opens doors for the following future areas of consideration:*

i. Analysis of the Precision of Stochastic Models in Measurement of Transformer Failure

As described in Section 6.4, research should be done on determination of the most effective model for analyzing transformer failure, by appreciating the performance and precision of the most commonly utilized models, so as to determine the most suitable model, which will guide into the most accurate failure predictions.

ii. Advanced Material Evaluation for Enhanced Transformer Resilience

Future research should focus on evaluating new insulation materials and transformer oils under extreme environmental conditions, such as high temperatures, humidity, and heavy electrical loads. A detailed comparison of material categories and compositions (e.g., thermally upgraded cellulose vs. standard cellulose, synthetic oils vs. mineral oils) will identify optimal configurations for high-performance transformers. This work will also explore design orientations that enhance cooling and reduce thermal stress. Understanding how different materials respond to degradation mechanisms like oxidation and moisture ingress will guide the selection of more re-

silient materials, improving transformer lifespan and network reliability.

### iii. ANFIS Model Optimization for Real-World Applications

The limitations of the current ANFIS model, particularly its focus on predefined operational parameters, highlight the need for future work to integrate adaptive learning capabilities. By incorporating material-specific data and external stress factors such as ambient temperature fluctuations and load variability, the model can become more versatile. An optimized ANFIS model with dynamic inputs will improve predictive accuracy, allowing it to adapt to operational changes in real-time. This advancement will enable more precise scheduling of maintenance and replacements, further minimizing unplanned outages and extending transformer service life.

### iii. Enhancing Model Validation for Improved Prediction Accuracy

The accuracy of predictive models depends heavily on the validation process. Future studies should use advanced validation techniques such as cross-validation, bootstrapping, and Monte Carlo simulations to reduce prediction errors. These techniques will ensure that the model performs well across diverse operational scenarios and datasets. Additionally, continuous feedback loops should be implemented by integrating real-time operational data with prediction models. This approach will allow for ongoing adjustments to the model, ensuring that discrepancies between simulated and real-world data are minimized and prediction reliability is enhanced.

### iv. Dynamic Replacement Strategies Based on Real-Cost Analysis

The current study's use of estimated costs for transformer replacement highlights a need for more precise, real-time cost tracking. Future research should develop models that incorporate actual maintenance and failure costs from transformer life-cycle data to fine-tune replacement schedules. Incorporating real-cost values and failure probability distributions into Weibull-based models will result in more economically optimized replacement strategies. This approach will ensure that replacements are carried out only when financially and operationally justified, balancing maintenance budgets with network reliability needs.

## **6.5 Summary**

In this chapter, the conclusion, recommendations and concepts for future work have been developed. The conclusions have been made, based on research questions established. It has been observed that all research questions have been answered by the studies findings. However, gaps in each specific objective have been identified, elaborated and been a basis for future research.

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# APPENDICES

## APPENDIX I: Description of Condition Based Factors

Parameter	Ranking	Shape ( $\beta$ )	Scale ( $\eta$ ) (Years)	Description
Moisture Content	1	4	10	High moisture leads to early degradation; transformer life drastically decreases under high moisture conditions.
Gas Concentration	2	3.5	15	High gas levels indicate faults; can shorten life due to internal arcing and insulation damage.
Acidity	3	3	20	Increases oil degradation rate, contributing to insulation breakdown.
Interfacial Tension	4	2.8	25	Indicates oil quality degradation; moderate impact on performance but important to monitor.
Breakdown Voltage	5	2.5	30	Lower BDV reduces insulation effectiveness but can often be corrected.
Color	6	2.2	35	Generally an indicator of aging; lowest direct impact on performance.

## APPENDIX II: ATTACHMENTS FOR POWER TRANSFORMER STATISTICS

	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
	SUBSTATION	TRANSFORMER IDENTIFICATION	MAKE/TYPE	Year of Man.	MIN MYA	MAX MYA	VOLTAGE RATIO	NOMINAL TAP	IMPED. VOLTAGE AT NOMINAL TAP	NUMBER OF TAPS	TAPPING RANGE	VECTOR GROUP	TAP CHANGER MAKE	AVR MAKE	No. of transformers	Status (1=Fail, 0=Healthy)	Censoring status	
4	<b>CENTRAL REGION</b>																	
5																		
6																		
7	NAMANVE	Transformer 1	Crompton Greaves	2007	32	40	132/33kV	5	11.52%	17	4-12x1.25%	YNyn0d1	MR - M Type	REG SYS	3		0	Right Censored
8		Transformer 2	Crompton Greaves	2007	32	40	132/33kV	5	11.52%	17	4-12x1.25%	YNyn0d1	MR - M Type	REG SYS			0	Right Censored
9		Transformer 3	Crompton Greaves	2008	32	40	132/33kV	5	11.52%	17	4-12x1.25%	YNyn0d1	MR - M Type	REG SYS			1	Uncensored
10																		
11	LUGOGO	Transformer 1	ABB Kraft	1997	32	40	132/11kV	7	10.21%	17	6-10x1.25%	YNyn0	ABB UCGRN	REG SYS	4		0	Right Censored
12		Transformer 6	ABB	1998	32	40	132/33kV	5	13.60%	17	4-12x1.25%	YNyn0	ABB UCGRN	REG SYS			0	Right Censored
13		Transformer 3	ABB	1998	32	40	132/33kV	5	13.60%	17	4-12x1.25%	YNyn0	ABB UCGRN	REG SYS			0	Right Censored
14		Transformer 5	Elektro Putere	1991	32	40	132/11kV	7	10.78%	17	6-10x1.25%	YNyn0 (d)	PUTERE MR	REG SYS			0	Right Censored
15																		
16	MUTUNDWE	Transformer 1	Elektro Putere	1991	32	40	132/33kV	5	13.60%	17	4-12x1.25%	YNyn0(d)	PUTERE MR	REG SYS	4		1	Uncensored
17		Transformer 2	ABB	1995	32	40	132/33kV	5	13.50%	17	4-12x1.25%	YNyn0 (d)	ABB UCGRN	REG SYS			1	Uncensored
18		Transformer 3	ABB Powertech	2003	15	22	132/11kV	7	3.64%	17	6-10x1.25%	YNyn0 (d)	ABB UCGRN	REG SYS			1	Uncensored
19		Transformer 4	ABB Powertech	2003	15	22	132/11kV	7	3.54%	17	6-10x1.25%	YNyn0 (d)	ABB UCGRN	REG SYS			1	Uncensored
20																		
21	FOBT PORTAL	Transformer 1	EMCO	2006	32	40	132/11kV	7	3.618%	17	6-10x1.25%	YNyn0 (d)	EMR- M	REG SYS	4		1	Uncensored
22		Transformer 2	EMCO	2006	32	40	132/11kV	7	3.63%	17	6-10x1.25%	YNyn0 (d)	EMR- M	REG SYS			1	Uncensored
23		Transformer 3	ABB Vietnam	2018	32	40	132/33kV	5	13.50%	17	4-12x1.25%	YNyn0d1	ABB UBBRN 350/250	REG SYS			0	Right Censored
24		Transformer 2	Crompton Greaves	2011	32	40	132/33kV	5	13.43%	17	4-12x1.25%	YNyn0d1	MR - M Type	REG SYS			0	Right Censored
25																		
26	KAWAALA	Transformer 2	Hwker Siddoley Brush	1972	15	15	132/11kV	7	3.80%	17	6-10x1.25%	Yy0d1	ATR Type	REG SYS	1		0	Right Censored
27																		
28	KAWANDA	Transformer 1	Crompton Greaves	2003	32	40	132/33kV	5	14.17%	17	4-12x1.25%	YNyn0d11	MR - VM Type	MR TAPCON	6		1	
29		Transformer 2	Toshiba	2018	32	40	132/33kV	5	14.17%	17	4-12x1.25%	YNyn0d11	MR - M	REG SYS			1	
30		Transformer 3	Takai	2017	250	250	220/132kV	5	10%	17	4-12x1.25%	YNad11	Huaming 3XCM	SHM			0	Right Censored
31		Transformer 4	Takai	2017	250	250	220/132kV	5	10%	17	4-12x1.25%	YNad11	Huaming 3XCM	SHM			0	Right Censored
32		Transformer 5	Takai	2018	480	600	400/220kV	9	12%	17	8x1.67%	YNad11	ABB UBBRN				0	Right Censored
33		Transformer 6	Takai	2018	480	600	400/220kV	9	12%	17	8x1.67%	YNad11	ABB UBBRN				0	Right Censored
34																		
35	CLOCK TOWER	Transformer 1	Aichi	2017	32	40	132/33kV	5	14.00%	17	4-12x1.25%	YNyn0d11	MR - VM	MR	3		1	Uncensored
36	Transformer 2	Aichi	2017	32	40	132/33kV	5	14.00%	17	4-12x1.25%	YNyn0d11	MR - VM	MR			1	Uncensored	
37	Transformer 3	Aichi	2017	32	40	132/33kV	5	14.00%	17	4-12x1.25%	YNyn0d11	MR - VM	MR			1	Uncensored	
38																		
39	KABULASOK E	Transformer 1	Technical Associates	2018	20	25	132/33kV	5	3.00%	17	4-12x1.25%	YNyn0d11	CTR		1		0	Right Censored
40																		
41	NAMANVE SOUTH	Transformer 1	QRE	2018	40	63	132/33kV	5	14.00%	17	4-12x1.25%	YNyn0d11	MR - M	REG SYS	3		0	Right Censored
42	Transformer 2	QRE	2018	40	63	132/33kV	5	14.00%	17	4-12x1.25%	YNyn0d11	MR - M	REG SYS			0	Right Censored	
43	Transformer 3	QRE	2018	40	63	132/33kV	5	14.00%	17	4-12x1.25%	YNyn0d11	MR - M	REG SYS			0	Right Censored	
44																		
45	LUZIBA	Transformer 1	QRE	2018	40	63	132/33kV	5	14.00%	17	4-12x1.25%	YNyn0d11	MR - M	REG SYS	3		0	Right Censored
46	Transformer 2	QRE	2018	40	63	132/33kV	5	14.00%	17	4-12x1.25%	YNyn0d11	MR - M	REG SYS			0	Right Censored	
47	Transformer 3	QRE	2018	40	63	132/33kV	5	14.00%	17	4-12x1.25%	YNyn0d11	MR - M	REG SYS			0	Right Censored	
48																		
49	MUKONO NORTH	Transformer 1	QRE	2018	40	63	132/33kV	5	14.00%	17	4-12x1.25%	YNyn0d11	MR - M	REG SYS	3		0	Right Censored
50	Transformer 2	QRE	2018	40	63	132/33kV	5	14.00%	17	4-12x1.25%	YNyn0d11	MR - M	REG SYS			0	Right Censored	

	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	
51		Transformer	GRE	2018	40	63	132/33kV	5	14.00%	17	4-12x1.25%	YNyn0d11	MR - M	REG SYS			0	Right Censored	
52	KASABA	Transformer 1	British Thomson-Houston	1936	20		132/33kV	9	12.00%	17	±8x1.25%	YNyn0(d11)			1		0	Right Censored	
53																			
54	ENTERBE	Transformer 1	XIAN XD	2018	80	80	132/33kV	5	10.34%	19	4-12x1.25%	YNyn0d11	MR - VM Taps		2		0	Right Censored	
55		Transformer 2	XIAN XD	2018	80	80	132/33kV	5	10.34%	19	4-12x1.25%	YNyn0d11	MR - VM Taps				0	Right Censored	
56	KAPEKA	Transformer 2	Pauwels Trafo	1993	10	10	132/33kV	5	3.05%	17	4-12x1.25%	YNyn0(d11)	ATR Type		2		0	Right Censored	
57		Transformer 1	British Thomson-Houston	1936	20	20	132/33kV	9	12.00%	17	±8x1.25%	YNyn0(d11)					0	Right Censored	
58																			
59																			
60	<b>WESTERN REGION</b>																		
61	MASAKA WEST	Transformer 1	Elektro Putere	1991	15	20	132/33kV	5	3.44%	17	4-12x1.25%	YNyn0+d11	MR - VM Taps	MR MK20	4		0	Right Censored	
62		Transformer 2	ABB	2007	15	20	132/33kV	5	10%	17	4-12x1.25%	YNyn0+d	ABB YCGBN	ABB SPAU 341C			0	Right Censored	
63		Transformer 3	Taikai	2017	125	125	220/132kV	5	10%	17	4-12x1.25%	YNad11	Huaming 3XCMI	SHM			0	Right Censored	
64		Transformer 4	Taikai	2017	125	125	220/132kV	5	10%	17	4-12x1.25%	YNad11	Huaming 3XCMI	SHM			0	Right Censored	
65																			
66	MRABABA NORTH	Transformer 1	Crompton Parkinson	1963	15	20	132/33kV	5	10.20%	17	4-12x1.25%	Yy0d11	BCGL ATR	MR MK20	2		0	Right Censored	
67		Transformer 2	ABB	2007	15	20	132/33kV	5	10%	17	4-12x1.25%	YNyn0+d	ABB YCGBN	ABB SPAU 341C			0	Right Censored	
68	MRABABA SOUTH	Transformer 1	Crompton Greaves	2017	50	60	220/132kV	5	10%	17	4-12x1.25%	YNYN0d5	MR - VM Taps	MR TAPCON	1		1	Uncensored	
69																			
70	NKONGE	Transformer 1	Ferranti	1970	7.5	7.5	132/33kV	5	10.13%	17	4-12x1.25%	YNyn0	Ferranti Tap Changer	MR MK20	1		1	Uncensored	
71																			
72	NKENDA	Transformer 1	Elektro Putere	1991	15	20	132/33kV	5	3.44%	17	4-12x1.25%	YNy0(d)	PUTERE MR	MR VC100	2		0	Right Censored	
73		Transformer 2	Crompton Greaves	2013	32	40	132/33kV	9	3.77%	22	6-15x1.25%	YNy0(d)	MR - VM Taps	MR VC100			0	Right Censored	
74																			
75	FORT PORTAL	Transformer 1	Crompton Greaves	2013	32	40	132/33kV	9	3.44%	22	6-15x1.25%	YNy0(d)	MR - VM Taps	MR TAPCON	1		0	Right Censored	
76																			
77	HOIMA	Transformer	Taikai	2018	32	40	132/33kV	5	3.44%	17	4-12x1.25%	YNy0(d)	MR - VM	MR	2		0	Right Censored	
78		Transformer	Taikai	2018	32	40	132/33kV	5	3.77%	17	4-12x1.25%	YNy0(d)	MR - VM	MR			0	Right Censored	
79																			
80	RUGONJO	Transformer 1	Jiangsu Hupeng	2010	20	20	132/33kV	5	3.16%	17	4-12x1.25%	YNy0+d11	MR - M Taps	REG SYS	2		0	Right Censored	
81		Transformer 2	Jiangsu Hupeng	2010	20	20	132/33kV	5	3.16%	17	4-12x1.25%	YNy0+d11	MR - M Taps	REG SYS			0	Right Censored	
82																			
83	<b>EASTERN REGION</b>																		
84	LUGAZI	Transformer 1	ABB	2007	14	14	66/11	5	3%	17	4-12x1.25%	Dyn11	ABB UBBRT	ABB SPAU 341C	2		0	Right Censored	
85		Transformer 2	ABB	2007	14	14	66/11	5	3%	17	4-12x1.25%	Dyn11	ABB UBBRT	ABB SPAU 341C			0	Right Censored	
86																			
87	TORORO NORTH	Transformer 2	Brush	1985	15	20	132/33kV	5	10.18%	17	4-12x1.25%	YNy0+d11	Brush Systems ATR	MR VC100	2		0	Right Censored	
88		Transformer	Zest W'eq	2013	60	80	132/33kV	5		17	4-12x1.25%	YNyn+d11	MR - M	MR			0	Right Censored	
89																			
90	BUJAGALI	Transformer	EMCO	2016	250	250	220/132kV	5	10%	17	4-12x1.25%	YNad11	EMR - M	MR	2		0	Right Censored	
91		Transformer	EMCO	2016	250	250	220/132kV	5	10%	17	4-12x1.25%	YNad11	EMR - M	MR			0	Right Censored	
92																			
93	IGANGA	Transformer	GRE	2018	32	40	132/33kV	5	10.18%	17	4-12x1.25%	YNy0+d11	MR - M	REG SYS	2		0	Right Censored	
94		Transformer	GRE	2018	32	40	132/33kV	5	10.18%	17	4-12x1.25%	YNy0+d11	MR - M	REG SYS			0	Right Censored	
95																			
96	<b>NORTHERN REGION</b>																		

APPENDIX III: WEIBULL COST CHART

