Transformer Health Assessment and Techno-Economic End of Life Evaluation

by

Ahmed Elsayed Bayoumy Abu Elanien

A thesis
presented to the University of Waterloo
in fulfillment of the
thesis requirement for the degree of
Doctor of Philosophy
in
Electrical and Computer Engineering

Waterloo, Ontario, Canada, 2011

AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

Electrical power systems play a key role in production and services in both the industrial and commercial sectors and significantly affect the private lives of citizens. A major asset of any power delivery system is the transformer. Transformers represent extensive investment in any power delivery system, and because of the notable effect of a transformer outage on system reliability, careful management of this type of asset is critical. In North America, a large proportion of transformers is approaching the end of their life and should be replaced.

In many cases, unexpected transformer outages can be catastrophic and cause both direct and indirect costs to be incurred by industrial, commercial, and residential sectors. Direct costs include but are not limited to loss of production, idle facilities and labour, damaged or spoiled product, and damage to equipment. For commercial customers, the effects may include damage to electrical and electronic equipment, and in some cases damage to goods. For residential customers, outages may cause food spoilage or damage to electrical equipment. In addition to direct costs, there are several types of indirect costs may also result, such as accidental injuries, looting, vandalism, legal costs, and increases in insurance rates.

The main goal of this research was to assess the health and remaining lifetime of a working transformer. This information plays a very important role in the planning strategies of power delivery systems and in the avoidance of the potentially appalling effects of unexpected transformer outages. This thesis presents two different methods of assessing transformer end of life and three distinct methods of determining the health index and health condition of any working transformer. The first method of assessing transformer end of life is based on the use of Monte Carlo technique to simulate the thermal life of the solid insulation in a transformer, the failure of which is the main reason for transformer breakdown. The method developed uses the monthly average ambient temperature and the monthly solar clearness index along with their associated uncertainties in order to estimate the hourly ambient temperature. The average daily load curve and the associated uncertainties in each hourly load are then used to model the transformer load. The inherent uncertainties in the transformer loading and the ambient temperature are used to generate an artificial history of the life of the transformer, which becomes the basis for appraising its remaining lifetime.

The second method of assessing transformer end of life is essentially an economic evaluation of the remaining time to the replacement of the transformer, taking into consideration its technical aspects.

This method relies on the fact that a transformer fails more frequently during the wear-out period, thus incurring additional maintenance and repair costs. As well, frequent failures increase during this period also costs related to transformer interruptions. Replacing a transformer before it is physically damaged is therefore a wise decision. The bathtub failure model is used to represent the technical aspects of the transformer for the purposes of making the replacement decision. The uncertainties related to the time-to-failure, time-to-repair, time-to-switch, and scheduled maintenance time are modeled using a Monte Carlo simulation technique, which enables the calculation of the repair costs and the cost of interruptions. The repair, operation, and interruption costs are then used to generate equivalent uniform annual costs (EUACs) for the existing transformer and for a new transformer, a comparison of which enables the determination of the most economical replacement year. The case studies conducted using both methods demonstrate their reliability for determining transformer end of life for assessing the appropriate time for replacement.

Diagnostic test data for 90 working transformers were used to develop three methods of estimating the health condition of a transformer, which utilities and industries can use in order to assess the health of their transformer fleet. The first method is based on building a linear relation between all parameters of diagnostic data in order to determine a transformer health index, from which the health condition of the transformer can be evaluated. The second method depends on the use of artificial neural networks (ANN) in order to find the health condition of any individual transformer. The diagnostic data for the 90 working transformers together with the health indices calculated for them by means of a specialized transformer asset management and health assessment lab, were used to train an ANN. After the training, the ANN can estimate a health index for any transformer, which can be used in order to determine the health condition of the transformer. The third method is based on finding a relation between the input data and the given health indices (calculated by the specialized transformer asset management and health assessment lab) using the least squares method. This relation then can be used to find the health index and health condition of any working transformer. The health condition determined based on these methods shows excellent correlation with the given health condition calculated by the specialized transformer asset management and health assessment lab.

Acknowledgements

First of all, I would like to thank God Almighty for having made everything possible by giving me strength and courage to finish this work.

I wish to express my sincere gratitude and deep appreciation to Prof. Magdy Salama for his continued support and invaluable assistance, helpful suggestions, support and encouragement. His excellent guidance was crucial for the completeness of this thesis.

I would like also to thank Prof. Tarek Hegazy and Prof. Ray Bartnikas for their interest in my research and technical discussions during the course of this research.

Special thanks also to all colleagues and graduate friends, especially the Distribution Engineering group for sharing the literature, support, and fruitful discussions.

I wish to express my love and gratitude to my beloved parents; for their endless love, encouragement through the duration of my studies. I feel fortunate to have them always standing by my side.

Finally, I would like to thank my little son, Mohanad. His angel smile was always in front of me during the hard times of this work.

Dedication

This thesis is dedicated to my son Mohanad and my parents.

Table of Contents

List of Figures

List of Tables

Nomenclature

a	the variable repair cost per hour
A	empirical constant
A_m	the diurnal temperature swing (peak to peak) for month (m) in ^oC
(A/F,i,m)	the sinking fund factor for interest rate (i) and period equal to (m) in years
AI	Artificial Intelligent
ANN	Artificial Neural Network
B	empirical constant
b	the constant repair cost per outage
BDV	break down voltage
C	the capital cost of the asset
c	the number of simulation years until year c
C_o	the annual operating cost
$C_r(t)$	the annual repair cost for year t
CA	Condition Assessment
CH_4	methane
C_2H_4	ethylene content
C_2H_2	acetylene content
CBM	Condition Based Maintenance
CM	Condition Monitoring
$corr_i$	the correlation between the given health index and data category i
d	an index for the day of the month
d(j)	depreciation charge for year j
D_c	the monthly demand charge ($/kW)
DP	Degree of Polymerization
DGA	dissolved gas analysis
e	an index for the end day of the month, e.g., e = 31 for Jan
E(c)	the expectation of the estimate function at year c
E(F)	the expectation of the estimate function
EL_j	the expected lifetime using the equivalent aging factor for simulation year j
$\overline{EL}_c$	the average expected lifetime until year c of the simulation

EUAC	Equivalent Uniform Annual Cost
$EUAC_m$	the equivalent uniform annual cost for year m
F	the estimate function
$F^{-1}(U)$	the inverse of a selected cumulative probability distribution function
F_{AA}	the hourly aging acceleration factor
F_{AA_j}	aging acceleration factor for the temperature which exists during the time interval Δt_j
F_{eq}	the equivalent aging factor for the total time period
F_{eqj}	the equivalent aging factor for the simulation year j
$F_{eq\ k,j}$	the equivalent loss of life for load curve (k) and temperature curve j
(F/P, i, m)	the single-payment future-worth factor for interest rate i and period equal to m years
FA	furan analysis
FFANN	Feed Forward Artificial Neural Network
FRA	Frequency Response Analysis
FV_m	the future value of all transformer costs at the calculation year m minus the present worth of the transformer at year m
G_{sc}	the solar constant (=1367 W/m^2)
GCDF	group customer damage function
h	an index for the hour of the day, starting from zero at 12:00 midnight
H_2	hydrogen
$\overline{H}_m$	the mean value of the monthly average daily global solar radiation on a horizontal surface
$H_{m,I}$	the monthly average daily global solar radiation on a horizontal surface for month (m) in year (i) in J/m^2
HOD	a dimensionless expression for the hour of the day
HST	Hot Spot Temperature
$I_{d,h}$	the hourly radiation on a horizontal service for day d at hour h for month m in W/m^2
k_1	the maximum value of the scaling factor at the beginning of the infant period
k_2	factor represent the rate of exponential increase
K_i	the initial ratio of load *L* to rated load, per unit
K_U	the ultimate ratio of load *L* to rated load, per unit
K_{Tm}	the monthly solar clearness index

$\overline{K}_{Tm}$	the average solar index for month m
L(t)	the load at time t
LF	the load factor
$midday_m$	the middle day of month m
Lifetime	the expected useful asset lifetime in years
LOL_{ave}	the average loss of life
m	the year for which the EUAC is being calculated (the calculation year)
m(t)	the mean of the load
n	the total number of data years
N	the total number of samples (years)
ne	number of elements in series (x) or series (y)
NIL	the normal solid insulation lifetime based on 50% retained tensile strength and a continuous HST of 110^{o} C according to (7.42 years)
P	the reducing balance value (1.5 for 150% and 2 for 200% reducing balance depreciation)
P_l	the load losses (kW)
P_{au}	the auxiliary losses
P_{nl}	the no load power losses (kW)
P_x	the probability of transformer outage occurring for x hours
$P_{T,R}$	the total loss at rated load, watts
PD	Partial Discharge
Prob.	the probability of operation of the auxiliary equipment
PW (k)	the transformer's present worth at the end of year k
Q_k, Q_j	the corresponding probability values
R	the ratio of load loss at rated load to no-load loss
r_a	the average outage time per failure
r_j	the outage time for failure j
r_{xy}	the correlation coefficient between series of numbers (x) and series of numbers (y)
RCM	Reliability Centered Maintenance
RVM	recovery voltage measurement
S	the number of load sectors
S_r	the initial slope of the return voltage

SCDF	sector customer damage function
$SCDF_{jk}$	the sector customer damage function for load type k and duration index j
SD_x	standard deviation of series of numbers (x)
SD_y	standard deviation of series of numbers (y)
SOYD	sum of years digits depreciation
SUM	sum of the years digits of the lifetime
SRT	scheduled repair time
SV	the transformer salvage value
t_c	RVM charging time
t_d	RVM discharging time
t_{infant}	the infant period in years
$\overline{T}_m$:	the mean value of the average ambient temperature for month m in ^oC
T_{peak}	the time at which the maximum return voltage is occurred
t_{wo}	the duration of the wear-out region in years
tariff	the energy tariff ($/kWh)
TBM	Time Based Maintenance
TC	the thermal capacity of the transformer, Watt-hours/°C and it depends on the weights of core , winding, and tank, and the volume of oil
TI	the total number of time intervals (usually 24 hrs for one day or 8760 hrs for one year)
TO	the total number of transformer outages during the simulation period (artificial history)
TO_x	the total number of transformer outages of x hours during the simulation (artificial history)
TTF	The time to failure
TTS	time to switch
TTSM	the time to scheduled maintenance
TTR	time to repair
U	random number sequence
UHF	Ultra High Frequency
V_r	the maximum value of the return voltage
V(c)	the variance in the estimate function at year c

V(F)	the variance of the estimate function
W_i	weights of the linear relationship
w_k	the weighting factor for load type k
$\bar{x}$	mean of series of numbers (x)
$\bar{y}$	mean of series of numbers (y)
Z	a standard normal random variable
Θ_{HS}	temperature of hot spot in ^{o}C
Θ_A	ambient temperature in ^{o}C
$\Delta\Theta_{TO}$	top oil temperature rise over ambient in ^{o}C
$\Delta\Theta_H$	winding HST rise over top oil in ^{o}C
$\Delta\Theta_{TO,R}$	rise in top oil temperature over ambient at the rated load in °C
$\Delta\Theta_{HS,R}$	rise in hottest spot conductor temperature over top oil temperature, at the rated load in °C
$\Delta\Theta_{TO,U}$	the ultimate top oil temperature rise over ambient for load L in ^{o}C,
$\Delta\Theta_{TO,i}$	the initial top oil temperature rise over ambient for t=0 in ^{o}C,
τ_{TO}	the top oil time constant for load L in hrs
$\Delta\Theta_{TO,U}$	the ultimate top oil temperature rise over ambient for load L in ^{o}C,
$\Delta\Theta_{TO,i}$	the initial top oil temperature rise over ambient for t=0 in ^{o}C,
$\tau_{TO,R}$	the top oil time constant at rated load in hrs
τ_w	the winding time constant at hottest spot location in hrs
$\Delta\Theta_{H,U}$	ultimate winding HST rise over top oil in ^{o}C at load L
$\Delta\Theta_{H,I}$	initial winding HST rise over top oil in ^{o}C at at t=0
$\Delta\Theta_{H,R}$	rated winding HST rise over top oil in ^{o}C at load L
Δt_j	time interval, hours
φ	the latitude of the site (weather station)
δ	the solar declination
ω_s	the main sunshine hour angle for the month
ε(c)	the coefficient of variation at year c of the simulation
λ(t)	the failure rate at year t
λ_n	the failure rate of the normal region of the bathtub curve
α(t)	the exponential time-varying scaling factor

β	a factor that is calculated by substituting unity for $\alpha(t)$ at the end of the infant region
γ	factor represent the rate of exponential increase
α_{max}	the maximum value of the scaling factor at the end of the wear-out region
μ_j	the mean of the normal distribution j
σ_j	the standard deviation of the normal distribution j

Chapter 1
Introduction

1.1 Preface

In a deregulated/reformed environment, electric utilities are under constant pressure to reduce operating costs, to enhance the availability of transmission and distribution equipment, and to improve the quality of power and service provided to the customer. Running the system at its optimum limit has become a reality, and the risk involved in running the system without proper attention to the assets in service has therefore become very significant, as well, the probability of losing equipment vital to the transmission and distribution system, such as power and distribution transformers, is also increasing. Today, the operation scenario has changed and efforts are now being directed at exploring new approaches and techniques for the maintenance, life span assessment, and condition evaluation of power system assets.

Because of the substantial investment in power transformers and their importance as a major factor that affects system reliability, transformer asset management can be assumed to be one of the most important areas of equipment asset management [1]. In most cases, unscheduled transformer outages due to unexpected failures are disastrous.

Existing methods for assessing the end of life for any transformer depends on the physical features of the asset, such as the electrical quantities and experimental measurements. However, these methods provide only a general overview of the health of the transformer and are used to determine whether the transformer has reached its end of life. They do not offer any numerical values for indicating the expected remaining lifetime of the transformer. The need for a clear idea of the remaining lifetime of the transformer is increasing because this knowledge can prevent expensive and unexpected outages of power transformers, which are sometimes catastrophic. Moreover, most existing methods for calculating the health index of a transformer do not take into consideration all factors that affect the health of a transformer. Furthermore, some existing methods have not been tested with actual working transformers in order to verify their results.

Consideration of asset failure is not limited to the maintenance or even the changing of the failed part; rather, it extends to the consequences of the failure, which are classified as consequences for the asset itself and consequences for the system. The consequences for the asset itself include the price of changing or maintaining the failed part. The consequences for the system include the cost of power interruptions, which may be either negligible, for residential and agricultural applications, or of considerable value, for large industries and commercial activities. Thus, determining dollar value for the asset facet of life assessments is critical. The decision-making process for any engineering system is based mainly on economic considerations, and as result, the economic evaluation of all physical and technical issues will help the decision makers make appropriate choices based on the probable consequences of any expected problem. This economic perspective of transformer end of life is completely different from that of the financial and accounting group, who identify the end of life of an asset as the point when its value depreciates to zero or to a very low salvage value without considering any of the technical aspects, such as the operating conditions or the rate of failure of the asset.

1.2 Research Objectives

This research had three main objectives. The first was to use Monte Carlo simulation technique to build a solid insulation thermal model so that the remaining lifetime of the solid insulation of a transformer can be accurately estimated and then used to determine the remaining lifetime of the transformer. This approach is based on the fact that determination of the solid insulation is the main cause of transformer failure and end of life [2-5]. The real problem in applying this insulation model for end of life lies in determining the correct treatment of the transformer load and the ambient temperature, including associated uncertainties. The model developed takes into consideration the loading and ambient temperature histories of an existing transformer and aslo the uncertainties associated with them.

The second objective was to develop a techno-economic technique for replacing transformers. This technique builds a bridge between the engineering and the financial aspects of operating a transformer and helps business administrators make appropriate decisions, especially in the deregulated power market, which must operate an asset for the longest possible time without unexpected harmful failures. In this technique, an economic evaluation based on the technical aspects of both an existing transformer and a new transformer is carried out to determine the most economic time to replace the existing transformer with the new transformer.

The third objective of this research was to develop a systematic method for determining the health condition of any transformer. This method can be used by electrical utilities and industries to provide clear idea about the health of their working transformers. This goal was achieved by developing three methods for calculating a health index for a transformer, which is then used to classify the condition of the transformer (good, moderate, or bad).

The first objective of the research was addressed through consideration of the following items:

1. Correct estimation of the ambient temperature using the monthly average ambient temperature and the monthly solar clearness index. This correct estimation of the ambient temperature is used in thermal modeling of the transformer insulation to result in correct estimation of the transformer end of life point.

2. Use of past data about the transformer load to generate an average daily load curve and to calculate the standard deviations of the hourly loads.

3. Use of inherent uncertainties in the estimated ambient temperature and daily loads to build an artificial history of the transformer using Monte Carlo technique. The history was then used to determine the remaining lifetime of the insulation.

The second objective of the research was addressed through consideration of the following items:

1. Calculation of the present worth of existing and new transformers at each year of their useful lifetime. To calculate the profile of the present worth, a new depreciation model that takes into consideration the stages of the lifetime of the asset (infant, normal, and wear-out) was developed. This model differs from existing depreciation models that are built entirely from a financial perspective. Instead, the new model is based on the engineering and economic factors.

2. Modeling of the transformer failure rate in all stages of the useful lifetime of a transformer according to a bathtub curve. The failure rate model was used in the calculation of the annual costs of new and existing transformers, which in turn, form the basis of a replacement decision.

3. Development of a transformer outage model using a Monte Carlo simulation. The main sources of uncertainty in a Monte Carlo simulation for a transformer are the time to failure, time to repair, time to switch, and scheduled repair time. The outage model takes into consideration the following items:

    a. The planned outage of the transformer at regular intervals for maintenance.

b. The forced outage of the transformer.

4. Calculation of the new and existing transformer repair costs based on the failure rate model, followed by the calculation of the annual costs of interruptions based on the failure rate and outage models, as the basis for the determination of the annual costs.

5. Generation of a model for the equivalent uniform annual costs for new and existing transformers based on the calculated annual costs.

6. Determination of the most economical replacement time based on the calculated equivalent uniform annual costs.

The third objective of the research was addressed through consideration of the following items:

1. Search for the real measurements of working transformers to use as a basis for the study.
2. Use of artificial intelligence (AI) techniques and other techniques to find the health index of any transformer and corresponding health condition.
3. Testing of the accuracy of the developed health index and health condition.

1.3 Motivation

The most significant motivation that has encouraged this work in the area of transformer end of life and replacement assessments is the crucial role of a transformer in the efficient and reliable operation of a power system. Expecting end of life and making an appropriate replacement decision is critical for avoiding catastrophes caused by unexpected loss of transformers. The following were additional motivating factors:

1. The installation of transformer assets in any power system or distribution system costs millions of dollars. Sudden breakdowns of power transformers can be assumed to be catastrophic due to the high cost of transformers coupled with the cost of interruptions to production lines, blackouts and accompanying robberies of commercial stores, and damage to raw materials. Deaths resulting from blackouts are an additional important issue. An accurate estimation of the time to the end of life of a transformer can reduce all of these costs and alleviate the negative social effects.

2. Existing methods for assessing the end of life of transformers do not estimate the remaining lifetime of the transformer; rather, they give only a general indication of health of a transformer based on a test of part of its solid insulation. Existing end of life techniques are also based

mainly on a paper specimen of the solid insulation of the transformer. The very act of taking a paper specimen can seriously damage the transformer's insulation system so that the transformer will then be damaged even if the test showed that health is outstanding. A goal of this research was to overcome these problems by avoiding the testing of paper specimens from transformer insulation.

3. To the best of the author's knowledge, no existing research estimates the remaining lifetime of a transformer based on a thermal model that takes into consideration all of the uncertainties associated with transformer loading and ambient temperatures. Considering these uncertainties during the modeling of the life of a transformer is very important for ensuring that the model is very close to reality.

4. Many transformers that are working during their wear-out stage cost more because of repetitive outages and the repetitive maintenance and repairs they require. It is therefore economically beneficial in many cases to avoid extra costs by retiring these aged transformers and replacing them with newer versions. if the operator has large numbers of aged transformers, such extra costs can be assumed to be very high.

5. No existing work on the economic evaluation of transformer end of life includes the consideration of effect of the technical issues on the operation of a transformer, such as mechanical, electrical, and thermal stresses. Because these stresses ultimately lead to transformer failure, the bathtub failure model can perfectly demonstrate their combined effect on the transformer. This issue has not been previously addressed in any research related to the economic end of life of any asset. For power systems, the author believes that ignoring technical issues in an economic evaluation of transformer end of life will result in inaccurate and misrepresentative model.

6. No existing research papers related to modeling the lifetime of transformer have simulated its lifetime with a variety of failure rates. Moreover, they have failed to factor in the randomness of failure and repair rates in the calculation of the end of life point. Using Monte Carlo simulation, this research has developed a techno-economic model of a transformer that simulates the physical lifetime of the asset and that takes into consideration its physical lifetime pattern. Different lifetime regions were simulated based on the pattern selected. The Monte Carlo technique simulated increases, decreases, and consistencies of the failure rate for all

lifetime regions along with the associated uncertainties. The result will lead to accurate economic decision based on the technical aspects of the transformer.

7. No research reported in the literature that covers the physical or economic assessment of transformer lifetime, taking into consideration the effects on the end of life decision of the surrounding networks or the loads served by the transformer. In the techno-economic technique developed in this study, the effect of the surrounding network was taken into consideration as follows:

    a. The cost of interruptions caused by transformer failure.

    b. The type of the load served by the transformer.

8. Studies related to a transformer health index or health condition are rare, and most need modification. Many require review of the importance allocated to the parameters measured, some need to include more measurements of additional parameters, and others should use real measurements.

1.4 Thesis Organization

This thesis consists of eight chapters and four appendices. The remaining seven chapters are organized as follows:

- Chapter 2 highlights transformer asset management topics and techniques, such as maintenance, condition monitoring, and health assessment.

- Chapter 3 focuses on the state of the art of the assessment of transformer end of life, reinforcing the motivation for performing the current research as presented in chapter 1. Special emphasis is on the classification methods and modeling techniques for determining the end of life with illustrations provided for each method.

- Chapter 4 provides a detailed explanation of the use of a Monte Carlo simulation technique for building a thermal model of the solid insulation of a transformer as a method of accurately estimating its remaining lifetime. A case study is presented to demonstrate the developed technique. A comparison with existing work shows the superiority of the new technique.

- Chapter 5 offers a complete explanation of all the steps in the developed techno-economic replacement technique of a transformer.

- Chapter 6 describes the testing of the performance of the new techno-economic replacement technique through two case studies. The chapter also presents sensitivity analysis study that was performed with respect to the input variables.
- Chapter 7 introduces three systematic methods of providing information about the health condition (good, moderate, bad) of a transformer.
- Chapter 8 discusses the main contributions and the conclusions of the research along with suggestions for future work.

Appendix A shows the steps used to calculate a transformer hot spot temperature. Appendices B and C present the data used for two case studies of Chapter 6. Appendix D shows the matrices of the weights of the artificial neural network used in Chapter 7.

1.5 Summary

This chapter has provided a general overview of the assessment of transformer end of life and a description of the problems that were tackled in this research. The motivations for, and the objectives of, the research has also been presented, along with the layout of the thesis and the organization of the remaining chapters.

Chapter 2
Transformer Asset Management

2.1 Introduction

Transformer asset management activities are numerous and researchers tackle these issues from different points of view. A detailed explanation of all transformer asset management activities and techniques can be found in [1]. Maintenance plans and condition monitoring techniques are examples of the general asset management activities that can be applied to any equipment, such as transformers, circuit breakers, high voltage capacitors, etc. However, each asset management activity is different from one type of equipment to another. For example, condition monitoring techniques applied to transformers are different from those applied to circuit breakers or high voltage capacitors, although some of these techniques may have some similarities. Moreover, one quantity can be tackled from different asset management points of view. For example, transformer Hot Spot Temperature (HST) can be tackled from a transformer condition monitoring point of view, because it may represent an overloading or serious problem inside the transformer, and it can also be approached from the end of life point of view - because the higher the hot spot temperature over the normal value, the shorter the lifetime of the asset.

This Chapter focuses on transformer asset management as one of the important power system assets. Fig. 2-1 shows the transformer main asset management activities. Transformer asset management can be classified into the following activities:

1. Condition Monitoring (CM) and Condition Assessment (CA) techniques.
2. Performing maintenance plans.
3. Aging, health, and end of life assessments.

In the following sections, each activity (save the third) is discussed in detail. A general overview for the third activity will be given in this Chapter, while a complete review of the current health and end of life assessments will be presented in the next Chapter.

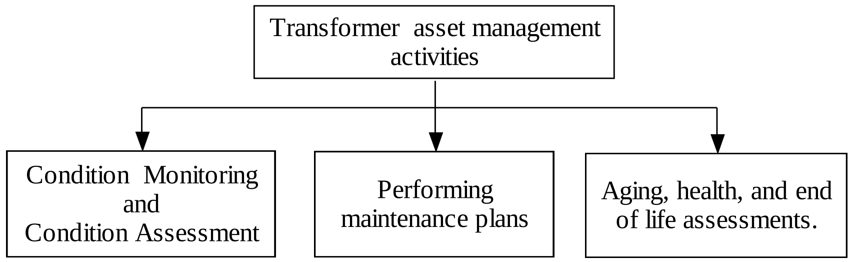

Fig. 2-1 Transformer asset management activities.

2.2 Condition Monitoring (CM) and Condition Assessment (CA) Techniques

Transformer CM is concerned with the application and development of special purpose equipment/methods for monitoring a condition of a parameter in a transformer, and with data acquisition, while CA means the development of new techniques for analyzing this data to both predict the trends of the monitored transformer and evaluate its current performance [1]. CM focuses mainly on the detection of incipient faults inside the transformer that arise from gradual deterioration. Some of these incipient faults may be detected during routine maintenance, while other faults may cause numerous problems before the routine maintenance cycle. As a result, the ability to have detailed information on the state-of-health of the transformer prior to carrying out maintenance work was unavailable. Furthermore, the diagnosis of many incipient faults in the transformer was, in many cases, unavailable, especially with those faults occurring after the routine maintenance cycle [6, 7].

CM has multiple benefits [8]: it reduces maintenance costs due to its ability to detect faults early, limits the probability of complete failures, and identifies the root causes of the failure. On the other hand, there are some obstacles which arise during the realization of CM techniques, such as extra added cost to the system due to the added monitoring and communication equipment, increase in the complexity of the control and communication system, a need for high speed processing systems for data processing, and a need for suitable memory storage for data base knowledge.

In order to have information about the state-of-health of the transformer, the monitored data and the incipient faults detected by the CM system must be analyzed to assess the transformer condition. This assessment is done using the CA of the transformer. Transformer CM can be divided into five main categories [8]: monitoring the Hot Spot Temperature (HST); monitoring the vibration of the transformer wall and winding, monitoring the dissolved gases in the transformer oil; monitoring the Partial Discharges (PDs) in the solid and liquid insulations of the transformer; and, monitoring the winding movement and deformations. In order for these monitored parameters to have meaning, the monitored data must be analyzed to assess the condition of the transformer. Each CM data category can be assessed using a specific CA technique. Fig. 2-2 shows the main categories of transformer CM and the corresponding CA techniques. In the following sub-sections, each CA technique will be discussed separately.

2.2.1 Condition Assessment by Thermal Analysis

Thermal analysis of a transformer can provide useful information about its condition, and can be used to detect inception of any fault. Most faults cause change in the thermal behavior of the transformer. Abnormal conditions, such as transformer overload, can be detected by analyzing the HST. Transformer life is affected greatly by a continuous HST of more than 110°C [3]. Predicting the HST can be done by two techniques. The first technique uses artificial intelligence techniques such as the Artificial Neural Network (ANN) [9]. The second technique develops a thermal model to predict the thermal behavior of the transformer [10-12].

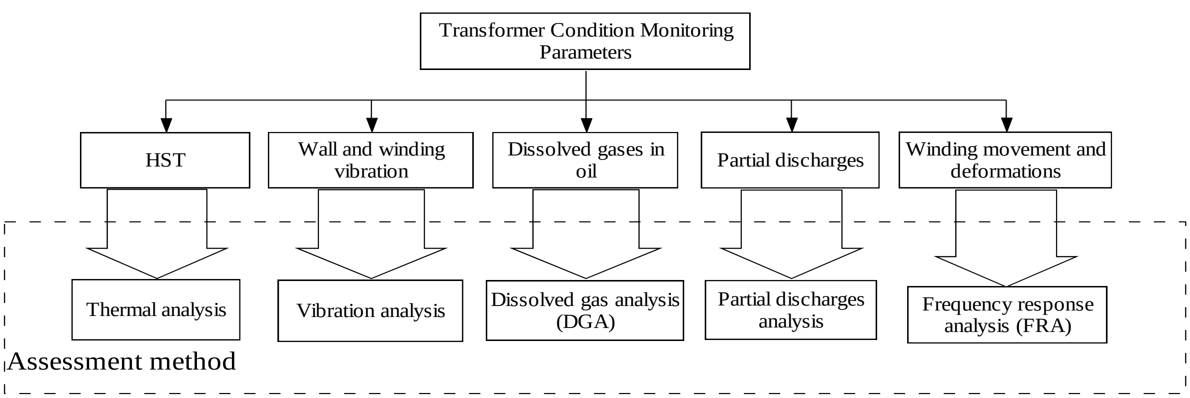

Fig. 2-2 Transformer condition monitoring and assessment techniques.

2.2.2 Condition Assessment by Vibration Analysis

The usage of vibration signals in assessing the transformer health is a relatively new technique compared with other methods of transformer CA. Transformer vibration consists of core vibrations, winding vibrations, and on-load tap changer vibrations [13, 14]. These generated vibrations propagate through the transformer oil until they reach the transformer walls, at which they can be collected via vibration sensors. The health condition of the core and windings can be assessed using the vibration signature of the transformer tank [13]. Vibration analysis is effective for assessing the health of on-load tap changers [14, 15].

2.2.3 Condition Assessment by Partial Discharge Analysis

PDs occur when the electric field strength exceeds the dielectric breakdown strength in a certain localized area, in which electrical discharges partially bridge the insulation between conductors. The dielectric properties of the insulation may be severely affected if subjected to consistent PD activity over a long time. This may lead to complete failure if the PD activity remains untreated [16]. PD can be detected and measured using piezo-electric sensors, optical fiber sensors [17], and Ultra High Frequency (UHF) sensors [16, 18, 19]. On-site PD measurement is often affected by strong coupled electromagnetic interference, which increases the difficulty of extracting PD signals without noise. The most common methods for PD de-noising are the gating method, and the directional sensing method [20]. Wavelet transform is a very powerful tool in signal processing [21, 22]. The usage of the Wavelet Transform for PD de-noising was successfully achieved in [23, 24]. PD measurement is used extensively for the condition assessment of the transformer insulation, because large numbers of insulation problems start with PD activity [18, 20, 25].

2.2.4 Condition Assessment by Dissolved Gas Analysis (DGA)

All transformers generate different gases at normal operating temperatures. Nevertheless, the concentration of these gases increases in the presence of an abnormality. During internal faults, oil produces gases such as hydrogen (H_2), methane (CH_4), acetylene (C_2H_2), ethylene (C_2H_4), and ethane (C_2H_6), while cellulose produces methane (CH_4), hydrogen (H_2), carbon monoxide (CO), and carbon dioxide (CO_2). Each fault type produces certain combinations of the abovementioned gases [26]. Analyzing transformer oil for these key gases by chromatography helps to know the fault type and location [26, 27]. Laboratories rely upon defined critical levels of gases, rates of increase in gas level (on a year by year basis), or one of the ratio methodologies such as Rogers or Dornenberg ratios [26, 28, 29] to assess the condition of oil. However, interpretation of the individual gases can become difficult when there is more than one fault in the transformer.

Low temperature decomposition of mineral oil produces relatively large quantities of H_2 and CH_4, and trace quantities of C_2H_4 and C_2H_6. At medium temperatures, the H_2 concentration exceeds that of CH_4, and the amount of C_2H_4 increases but is still less than the amount of C_2H_6. At the upper end of the thermal fault range, H_2 and C_2H_4 quantities increase and traces of C_2H_2 may be produced [26]. The solid insulation begins to degrade at lower temperatures than the oil, therefore its products are found at normal operating temperatures in the transformer. The thermal decomposition of cellulose produces CO, CO_2, and water vapor. The ratio of CO_2/CO is sometimes used as an indicator of the thermal decomposition of cellulose. Low-intensity discharges such as partial discharges produce mainly hydrogen, with decreasing quantities of methane and trace quantities of acetylene. The acetylene and ethylene concentrations increase as the intensity of the discharge increases [26].

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

2.2.5 Condition Assessment by Frequency Response Analysis

When a transformer is subjected to high through fault currents, the windings are subjected to severe mechanical stresses, causing winding movement, deformations, and in some cases severe damage. Deformation results in relative changes to the internal inductance and capacitance of the winding, which can be detected externally by the Frequency Response Analysis (FRA) method [30]. Winding damage detection can be accomplished by comparing the fingerprints of a healthy winding (or the calculated response using a transformer equivalent circuit) with the fingerprints of a damaged winding. Changes in fingerprints can be used to estimate the degree of winding damage and its location [31, 32].

2.2.6 New Developments in Condition Monitoring and Condition Assessment

With the development of sensor technology and communication systems, more than one parameter can be monitored at the same time [33]. New online CM and CA systems that monitor more than one parameter in the transformer are commercially available. Many parameters can be monitored online using these new systems, such as HST, dissolved gases, and oil temperature. Advanced technology sensors are used for parameter measurements in these new CM systems. All data measured are then collected using a data acquisition subsystem to be analysed and to provide interpretation for the operator. Recently, intelligent systems are used for data analysis and interpretation, such as multi agent systems [34, 35]. These new CM systems provide fast and accurate interpretation of any problem in the transformer.

2.3 Performing Maintenance Plans

Carrying out maintenance plans is the second transformer asset management activity. Transformer outage has harmful effects on the system, and can be assumed as one of the most catastrophic outages, especially for high rating power transformers. Accordingly, maintenance of the transformers must be planned carefully to avoid harmful outages. As shown in Fig. 2-3, the maintenance types can be classified into corrective maintenance, preventive maintenance, and reliability centered maintenance. The definitions, together with the advantages and disadvantages of each maintenance type, will be discussed in the next sub-sections.

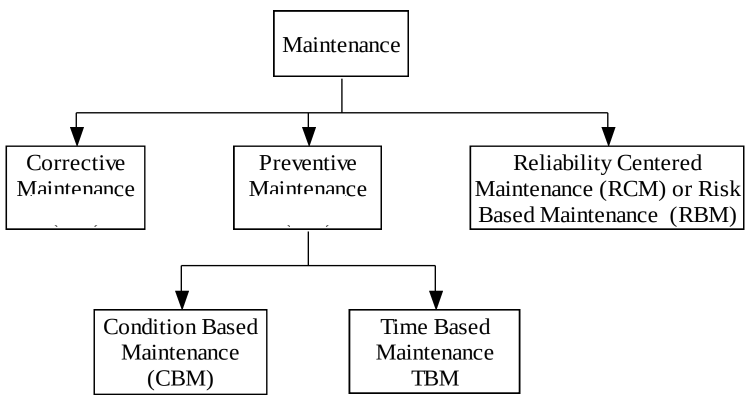

Fig. 2-3 Classification of maintenance activities.

2.3.1 Corrective Maintenance

Corrective maintenance is designed to perform maintenance activity upon occurrence of a failure. This type of maintenance is not in a wide-spread use. Corrective maintenance may lead to repeated failures that cannot be maintained and, finally, to losing the asset. corrective maintenance was the main maintenance activity a long time ago. This type of maintenance, if used, has been reserved for defects that are not serious and have no great consequences, such as failure of some accessories. As a conclusion, the general meaning of corrective maintenance is performing maintenance upon failure occurrence. The advantages and disadvantages of the corrective maintenance are listed below.

Advantages:

1. It is the least expensive type of maintenance.
2. It saves manpower.
3. It spares the system from un-necessary shutdowns.
4. It performs the maintenance only when it is needed, saving un-necessary inspections.
5. It is widely understood by maintenance staff.

Disadvantages:

1. Transformer failure becomes costly to repair and may need expensive spare parts.
2. Some transformer failures may be irreparable if not detected early.
3. Some transformer failures may cause complete shutdown of the production line or the power system for long time. This means losing revenue, which in some cases exceeds the cost of regular inspection.

2.3.2 Preventive Maintenance

Preventive maintenance aims to prevent a failure from occurring, and aims to guarantee a long lifetime for the asset. This can be achieved by shutting down the equipment regularly to perform Time Based Maintenance (TBM) or by installing a CM system to perform Condition Based Maintenance (CBM).

2.3.2.1 Time Based Maintenance (TBM)

TBM is based on examining and maintaining the transformers according to a time schedule, i.e., performing the inspection and maintenance activities at regular intervals. TBM is the current maintenance strategy for many industries and utilities. TBM may prevent many failures; however, it may also cause unnecessary outages, wasting manpower, time, and money, if the maintenance interval is too small [36, 37]. In addition, unexpected incidents may still occur in the interval between maintenance tasks if the maintenance interval is too large. The general meaning of TBM maintenance is performing maintenance at regular intervals. The advantages and disadvantages of the TBM are listed below.

Advantages:

1. It is understood by maintenance engineers and technicians.
2. It can detect the inception of faults to some extent, if the inspection interval is reduced.
3. It increases the lifetime of the transformer due to regular inspections and maintenance.

Disadvantages:

1. It is expensive due to regular un-necessary inspections and the large number of the needed maintenance staff.
2. In some cases, TBM is unable to detect faults especially when the inspection interval is large.
3. It needs un-necessary shutdowns which add extra cost to the maintenance activity.

2.3.2.2 Condition Based Maintenance (CBM)

CBM relies on performing maintenance when the CM system detects an incipient fault. This incipient fault will change to be a complete failure if not treated early by the CBM, i.e., suitable maintenance must be performed after detection of the fault by the CA system. By using this technique, the risk of complete failure is reduced. CBM lets operators know more about the condition of a transformer, to know clearly when and what maintenance is needed. A transformer's historical data - such as operation parameters, diagnostic tests, and environmental conditions - will identify which parameter/part should be monitored and the correct method of monitoring [38].

Advanced online monitoring and assessment techniques such as dissolved gas analysis (DGA), partial discharge (PD), furan analysis (FA), frequency response analysis (FRA), and recovery voltage measurement (RVM) play a key role in developing CBM strategies [39]. The condition monitoring and diagnostic techniques discussed in section 2.2 are the main core of CBM. CBM may depend on continuous, scheduled, or on-request CM. The most widely spread CBM is the continuous one. Scheduled or on-request CBM aims to reduce the cost of continuous condition monitoring, which is the largest problem in the application of CBM. CBM depends on monitoring the parameters/parts of the transformer and diagnosing the incipient faults. When an incipient fault is found, the maintenance activity must take place to avoid the complete failure of the equipment. Thus, maintenance is only performed when necessary.

Fig. 2-4 shows a block diagram of a CBM system integrated with CM and CA systems. The first stage of this integrated system is the raw data stage, in which different types of sensors are used to collect the raw data such as thermal data, partial discharges, vibration signals, gases in oil, etc. The second stage is the pre-conditioning of data stage, which aims to adjust the input data, including removal of extreme data levels, normalizing the input data if needed, or removing the noise contained in the raw data. With advances in sensor technology, this stage may be included in the first stage. The next stage is the extraction of useful information, e.g., estimation of the hot spot temperature based on the top oil temperature, ambient temperature, and load current. The pre-conditioned and pre-processed data will be used to assess the condition of the equipment and classify the type of fault (if any) in the CA and fault diagnosis stage. The next stage is the output stage, in which the outputs from the fault diagnosis stage, either by Artificial Intelligent (AI) agents or by derived logics, are interpreted and sent to maintenance staff. The maintenance action is taken in the final stage according to the outputs stage [11, 18].

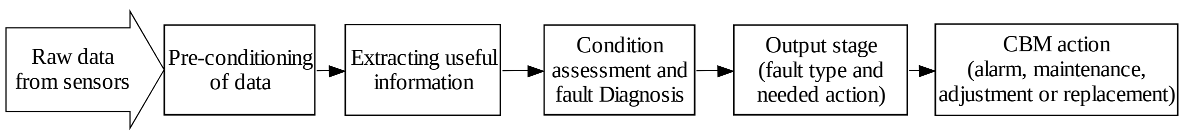

Fig. 2-4 CBM system.

The general meaning of CBM is performing maintenance only upon request from the CM system. The advantages and disadvantages of CBM are listed below.

Advantages:

1. Maintenance is done when it is necessary.
2. Reducing costly unnecessary inspections.
3. Saving manpower.
4. Reducing the unnecessary shutdowns of the system.
5. Low possibility of complete failure.

Disadvantages:

1. Continuous condition monitoring for many parameters is expensive.

2. Less understood by maintenance engineers and technicians.
3. Fast data communication and manipulation facilities are needed for successful online monitoring.
4. It needs experienced people to design the monitoring system, select the suitable parameters to be monitored, and select the suitable frequency of data collection.

2.3.3 Reliability Centered Maintenance (RCM)

The RCM is a technique initially developed by the commercial airline industry. The fundamental goal of RCM is to preserve the function or operation of a system at a reasonable cost [40, 41]. RCM can be defined as a mix of more than one maintenance strategy in an optimized manner in order to reduce the system risk. For a successful RCM plan, the degree of risk of each fault should be identified in order to define the optimum maintenance actions [40, 41]. The risk index can be found as follows:

$$risk\ index = probabilty\ \ of\ \ failure \times consequenc\ \ es\ \ index \tag{2-1}$$

The main items in the implementation of RCM according to (2-1) are the prioritization of the failure modes according to their consequences on the system, and modeling the probability of failure modes [42, 43]. The consequences index of each failure mode can be determined by the analysis of the history of failures or by experience. RCM starts with collecting data about transformer failures, to model the failure modes in a probabilistic form. The information about the consequences of each failure can be collected from the past experience of skilled engineers. The information collected about the consequences of failures, together with the probability of each failure, are used to calculate the risk index of each failure mode. The failure modes that have low risk index are separated, and treated by low cost maintenance methods, such as corrective maintenance. The failure modes that have a high risk index can be treated by preventive maintenance such as CBM or TBM, with optimum maintenance interval based on the maintenance cost [44, 45]. The possibility of failures still exists in the system with RCM; however, the risks are minimized as high risk failures are not likely to occur.

The general meaning of RCM maintenance is optimizing the maintenance plan based on risk analysis. The advantages and disadvantages of RCM are listed below.

Advantages:

1. The cost of the maintenance operation is optimized based on risk.
2. It reduces the unnecessary shutdowns for low risk failures.
3. It saves money paid for unnecessary short interval inspections in case of TBM.
4. It guarantees a low possibility of high risk failures.

Disadvantages**:**

1. Less understood by maintenance engineers and technicians.
2. Complexity of building the maintenance model.
3. Need for large amount of data about failures rates, modes, and consequences.

RCM can be assumed to be the most recent maintenance strategy. More industries are converting from regular TBM to RCM. According to [46], routine preventive maintenance is reduced by 50% on 11kV transformers after using RCM. Moreover, the overall maintenance cost is reduced by 30%-40% after converting to RCM. The challenges facing RCM are the data needed about the failure modes and their consequences, on both the transformer itself and the system as a whole. This data includes recorded information from many operating transformers, about their failure modes and failure consequences. Furthermore, very experienced persons are needed to prioritize the consequences of the failure modes on the system, and to set the consequences indices to be able to calculate the risk.

The main aim of any asset management is to maximize the benefits of the asset. The benefits are maximized from the asset by performing suitable CM techniques and/or performing good maintenance plan to maximize the usage, reducing the outage time, and increase the lifetime of the asset. The lifetime issue will be discussed in the next section.

2.4 Aging, Health, and End of Life Assessments

Equipment aging is a fact of life in power system components. As a piece of equipment ages, it fails more frequently and needs more repair time until the equipment reaches its end of life [47]. Maintenance activities can extend the life of equipment but become very costly for equipment near their end of life. There are three different concepts of lifetime for power transformers: physical lifetime, technological lifetime, and economic lifetime [47].

1. Physical lifetime: A piece of equipment starts to operate from its brand-new condition until it cannot be used in its normal operating state and must be retired.
2. Technological lifetime: A piece of equipment may need to be replaced for technological reasons, even though it may have not reached its physical end of lifetime. For example, a new technology is developed for a type of equipment and manufacturers no longer produce spare parts.
3. Economic lifetime: A piece of equipment is no longer economically valuable, although it may still be physically used. The capital value of any equipment is depreciated every year. Once the asset value approaches zero, it reaches the end of its economic lifetime.

The end of life decision in most of the cases can be divided into the physical and the economic decision. In the next Chapter, the existing end of life criteria for transformers will be presented and the economic and physical lifetime models for transformers will be discussed in detail. Furthermore, the existing methods that provide a health index for transformers will be highlighted.

2.5 Summary

An overview of transformer asset management was presented in this Chapter; the general classification of the asset management activities was illustrated. The three major activities of the transformer asset management are the application of CM techniques in the transformer operation, performing maintenance plans and investigating new less-cost maintenance methods, and assessing the health and end of life of the transformer. A detailed explanation of the first two activities of transformer asset management activities was provided in this Chapter. The various CM and CA techniques used to monitor and assess the condition of the transformer were discussed in detail. Transformer maintenance techniques were highlighted, including the advantages and disadvantages of each type. A brief introduction to the transformer lifetime types were presented. The different end of life criteria from the economic and physical perspectives will be illustrated and reviewed in detail in Chapter 3, as well as current methods that calculate transformer health index and health condition.

Chapter 3
Transformer Health and End of Life Assessments

3.1 Introduction

Transformer life management has gained recognition in recent years for both economic and technical reasons [39, 48]. Due to the importance of physical and economic lifetimes over the technological lifetime as noted in Chapter 2, physical and economic lifetimes are discussed in some detail in the next subsections. The existing end of life and replacement models are reviewed and the disadvantages of the models are presented. Further, the current few techniques that calculate the health index of working transformers are reviewed, and their drawbacks highlighted. Overcoming these drawbacks in the existing models of transformer physical and economic end of life, and transformer health indexing, are the main goals of the research in the thesis. The rest of this Chapter is a survey of current research on transformer physical and economic end of life assessments, and on determination of the transformer health index and health condition.

3.2 Physical End of Life Assessment

Most transformer solid insulation is based on cellulose in the form of paper. In the presence of heat, oxygen, water, and other chemicals, the cellulose molecules undergo chemical changes cause electrical and mechanical degradation of the insulation paper [49], which can be considered as the main reason for transformer physical end of life [2, 50]. Aging can be defined as the ability of the solid insulating material to withstand the designed stresses - such as electrical, mechanical, and thermal - with the passage of time [2, 49]. The ability of insulating material to withstand the abovementioned stresses remains constant or decreases slightly with the passage of time until the wear-out of the asset, at which time this ability degrades rapidly. Abnormal operating conditions, such as repetitive overloading for long periods and non-sinusoidal loads, can affect transformer aging. Transformer physical aging assessment methods can be divided into two main categories: diagnostic tests and thermal evaluation. Fig. 3-1 shows a complete classification of the transformer physical aging assessment techniques. Next, the existing work done to assess the aging and the end of life of the transformer will be presented.

3.2.1 Physical End of Life Assessment by Diagnostic Tests

3.2.1.1 Degree of Polymerization (DP)

DP is the main indication of paper health. Paper fibers are composed of cellulose. Glucose monomer molecules are bonded together by glycosidic bonds to form cellulose. The average length of the cellulose polymer, measured as the average number of glucose monomers in the polymer chins, is referred to as DP. It has been proven, based on the experience of previously retired transformers and experimental work, that a DP of 200 or less means the end of life of the solid insulation has been reached [50-52].

DP is accepted measure of the degradation of solid insulation; however, the measurement of DP for any working transformer needs a specimen of the transformer insulation paper to perform measurements. The paper sample taken from any operating transformer may cause local damage in the winding system or may lead to complete failure of the transformer. Also, DP measurement is usually done by the viscometry method, which is not accurate because it is affected by the ambient temperature and exposure to air [53].

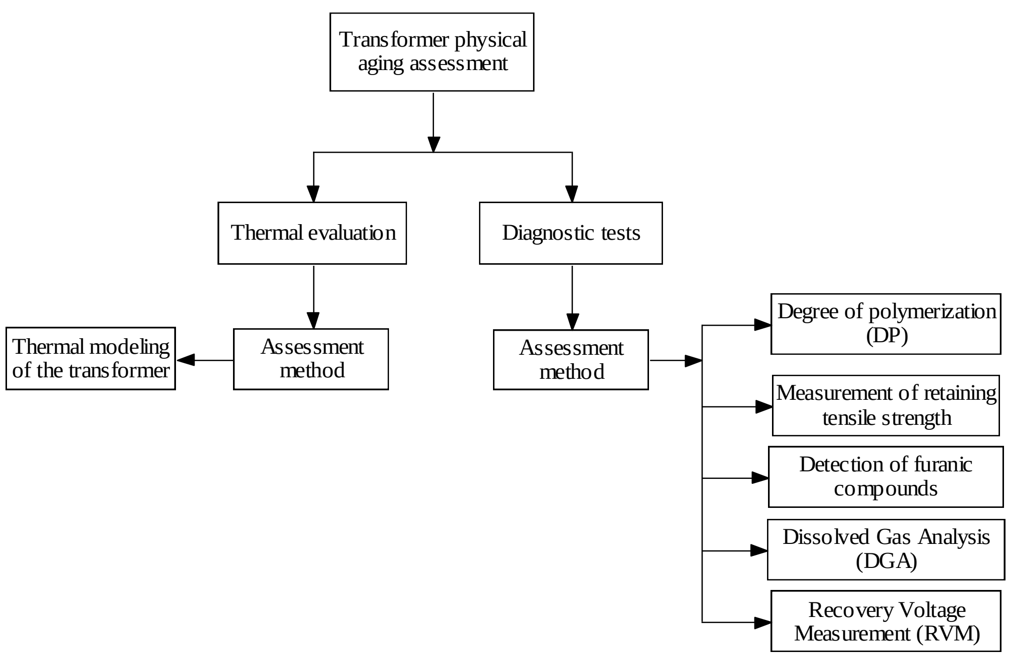

Fig. 3-1 A complete classification of the transformer physical aging mechanisms.

3.2.1.2 Retained Tensile Strength

One of the main mechanical parameters for insulation paper in transformers is tensile strength. As the paper ages, its strength against mechanical forces decreases especially against those arising from inrush current or short circuits [54, 55]. According to [4], insulation paper reaches its end of life when it reaches 50% retention of tensile strength, and it can be left working until it reaches 40% retention of tensile strength, according to [56], or it can be left working until it reaches 25% retention of tensile strength, according to [3]. The problem of insulation damage still exists in the measurements of tensile strength because the measurement of the tensile strength needs a specimen of the insulating paper, which may damage the solid insulation system of the transformer.

3.2.1.3 Furanic Compounds

The paper specimen required for DP and the retained tensile strength tests limit their usage practically. Also, the DP is associated with many errors during measurement. These difficulties, and errors in measuring the DP and retained tensile strength, limit their usage for assessing the health of the transformer, despite their reliability in assessing the age of the solid insulation and the transformer.

As the paper insulation ages, the polymer chains starts breaking and generating glucose monomer units that undergo further chemical reaction and become one of a family of derivatives of 2-furaldehyde (2FAL) [55], or what are called furanic compounds, that increase in the transformer oil with the decrease of the DP of the insulating paper [28, 53, 55, 57, 58]. These furanic compounds dissolve in the insulating oil and can be detected by oil analysis. It is possible to analyze the oil for a number of these furanic compounds as parts per billion by weight. Chendong et al [59] introduced a relationship between the total furfural content and DP. The relation holds for non-thermally upgraded paper but it does not apply correctly for thermally upgraded paper [55]. The amount of the furanic compounds corresponding to a DP of 200 units is modified in [55], in which two formulas are proposed to relate the DP to the amount of furanic compounds in ppb by weight (µg/kg). The first formula is proposed for thermally upgraded paper, in which the total furans in ppb by weight (µg/kg) are used to calculate the DP, is as follows:

$$DP = \frac{\log_{10}(total \quad furans) - 4.0355}{-0.002908} \tag{3-1}$$

According to (3-1), 2844 ppb by weight (μg/kg), total furans concentration corresponds to a DP of 200 units. The second formula is a modification to the Chendong formula. It relates the 2FAL, measured in ppb by weight (μg/kg), with the DP for non-thermally upgraded paper as given below:

$$DP = \frac{\log_{10}(2FAL \times 0.88) - 4.51}{-0.0035} \tag{3-2}$$

According to (3-2), 2FAL concentration corresponds to a DP of 200 at 6457 ppb by weight (μg/kg).

Assessment of transformer aging using furanic compounds analysis is gaining more attention, because this method gives an acceptable indication of the solid insulation age without using any paper specimen. However, the absolute correlation of furanic compounds to DP varies from one transformer to another, and is dependent on humidity, operating temperature, type of oil and paper, and design. Further research on the dependency of furanic compounds on moisture and temperature is necessary.

3.2.1.4 Dissolved Gas Analysis (DGA)

As a transformer ages, the cellulose and oil degrade. The rate of cellulose and oil degradation is significantly increased in the presence of a fault inside the transformer. Low temperature thermal degradation of cellulose produces CO_2, and high temperature produces CO [57]. A high rate of paper degradation is estimated when the ethylene concentration increases and the CO_2/CO ratio decreases below a ratio of about 6 [57, 59]. At a CO_2/CO ratio less than 2, the probability of failure increases significantly [57, 60]. However, the scatter of measurements made on service transformers is so large that no reliable values were found to assess the transformer end of life. Transformer service lives can only be estimated to within +/- 10 years using the phenomenon of generation of CO and CO_2 [60].

3.2.1.5 Recovery Voltage Measurement (RVM)

The rate of paper degradation depends on several parameters such as pulp composition, thermal upgrading, moisture content, and temperature. The higher the water content of the paper, the higher the degradation rate [2, 57]. The RVM technique uses the dielectric response to evaluate its condition with respect to moisture content [2].

To perform RVM, first a sample is charged from a high voltage source for a charging time (t_c). Then, the sample is isolated from the HV source and short-circuited for a discharging time (t_d), where

$t_c > t_d$. At the end of the discharging time, the short-circuit is removed and the return voltage appearing at the electrodes is measured as shown in Fig. 3-2, where V_r is the maximum value of the return voltage, t_{peak} is the time at which the maximum return voltage is occurred , and S_r is the initial slope of the return voltage.

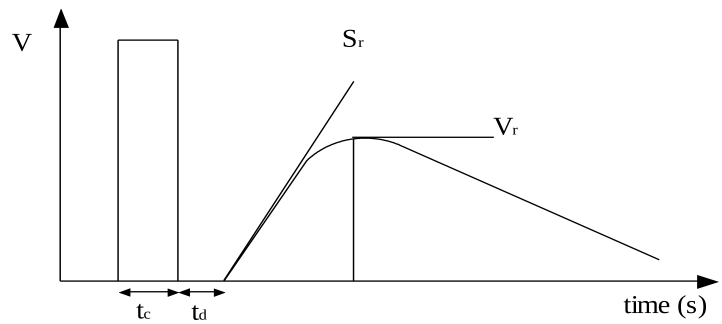

Fig. 3-2 Charging and return voltage during RVM test [57].

A polarization spectrum can be obtained by plotting the value of V_r for different values of the t_c. The time at maximum V_r in that polarization spectrum is called the dominant time constant. If the condition of the oil–paper insulation is homogeneous, and the distribution of the temperature, moisture, and aging in the insulation is uniform, the resulting curves will have one dominant time constant, otherwise; there will be many dominant time constants [57].

3.2.1.6 Weakness of the Transformer Aging Assessment by Diagnostic Tests

Many tests in subsection 3.2.1 that are commonly conducted to assess transformer aging have some difficulties in implementation. The specimen needed in the DP and the retained tensile strength is an example of these difficulties. Moreover, although the aforementioned tests can detect the end of life of the transformer at the time of testing, they do not yield any quantitative information concerning its life expectancy. They can provide a general assessment of the condition and the health of the transformer.

Striking examples are transformers that have provided years of service and yet are found to contain appreciable amounts of furans in the oil. In the case of furans in oil-filled transformers, it is not possible to estimate their life expectancy in terms of furans amounts. Thus, although diagnostic tests provide useful information with respect to the state of transformers and can reveal problems, they do not yield any type of definitive quantitative information concerning life expectancy that is required for the future planning of power systems.

3.2.2 Physical End of Life Assessment by Thermal Evaluation

3.2.2.1 Introduction to Thermal Evaluation of the Transformer Age

Transformer aging can be evaluated using the hot spot temperature (HST) test. The increase in HST has the effect of reducing insulation life [2, 5, 49]. Abnormal conditions, such as overloading, supplying non-sinusoidal loads, or exposure to higher ambient temperature than normal, can accelerate transformer aging and accordingly accelerate the time to end of life.

According to [3], the HST can be calculated as follows

$$\theta_{HS} = \theta_A + \Delta\theta_{TO} + \Delta\theta_H \tag{3-3}$$

where

Θ_{HS}: temperature of hot spot in ^{o}C;

Θ_A: ambient temperature in ^{o}C;

$\Delta\Theta_{TO}$: top oil temperature rise over ambient in ^{o}C;

$\Delta\Theta_H$: winding HST rise over top oil in ^{o}C.

More details on HST calculation can be found in Appendix A. The increase of the transformer HST accelerates the end of the transformer lifetime, and vice versa. The average lifetime of oil-immersed transformers based on the lifetime of the solid insulation is well defined in [3], in which the average lifetimes based on different end of life criteria are summarized. The standard normal lifetimes for oil-immersed power transformer for a continuous HST of 110^{o}C based on [3] and other IEEE standards are summarized in table (3-1). The deviation of the transformer's HST from 110^{o}C will cause the lifetime of the transformer to deviate from those values mentioned in table (3-1). The increase of the HST will reduce the expected physical lifetime, while a reduction of the transformer HST will increase its lifetime.

Table 3-1 The standard normal lifetime for oil immersed power transformers for continuous HST of 110^{o}C

Expected end of life criterion	Expexted lifetime in hrs
50% retained tensile strength according to IEEE std. C57.92-1981 [4]	65000
25% retained tensile strength according to IEEE std. C57.91-1995 [3]	135000
200 retained degree of polymerization according to IEEE std. C57.91-1995 [3]	150000
Distribution transformer functional life test data according to IEEE std. C57.91-1981 [61]	180000

The relationship between the HST and the transformer life consumption is governed by the Arrhenius reaction rate theory which states that [3, 4, 61-64]:

$$per\ \ unit\ \ life = Ae^{\frac{B}{\theta_{HS}+273}} \tag{3-4}$$

where A and B are empirical constants.

The constants A and B are based on material characteristics of the insulation, and are determined such that per unit life is unity at HST of 110^{o}C. The values of A and B are ($9.8*10^{-18}$) and (15000) respectively [3, 4, 61-64]. The reciprocal of (3-4) is the aging acceleration factor (F_{AA}) which can be used to calculate the consumed life for a given HST over a given period. F_{AA} has a value greater than unity for winding hottest-spot temperatures greater than 110°C and vice versa.

The equivalent life (in hours or days) that will be consumed in a given time period for the given temperature cycle can be calculated as shown below [3, 62, 64]:

$$F_{eq} = \frac{\sum_{j=1}^{TI} F_{AA_j}\Delta t_j}{\sum_{j=1}^{TI}\Delta t_j} \tag{3-5}$$

where

F_{eq} : the equivalent aging factor for the total time period;

TI : the total number of time intervals (usually 24 hrs for one day or 8760 hrs for one year);

F_{AA_j} : aging acceleration factor for the temperature which exists during the time interval Δt_j;

Δt_j : time interval, hours.

The value of F_{eq} is higher than unity if HST for the day is higher than 110°C and vice versa. Finally, (3-6) is used to calculate the percentage consumed, or lost life from the total lifetime of the transformer, according to the following equation [3, 62, 64]:

$$\%\ loss\ \ of\ \ life = \frac{F_{eq} \times t \times 100}{normal\ \ \ insulation\ \ \ life} \tag{3-6}$$

where t is the total time period

Using the previously mentioned steps, the lost life of a transformer due to an increase in the HST can be calculated.

3.2.2.2 Current Thermal Evaluation Techniques for Assessment of a Transformer Lifetime

Using the aforementioned steps, the correct loss in life of a transformer can be calculated. It is clear that calculating transformer aging based on the HST is well understood. However, the real challenge in applying this insulation end of life model lies in determining the correct treatment of the transformer load and the ambient temperature, including the associated uncertainties, in order to achieve reliable values of the HST and accordingly reliable values of transformer loss of life.

In [65], measured or estimated daily load profiles and a one-day average ambient temperature are used to determine the equivalent aging factor and the expected end of life of the insulation. Eleven curves were used to represent the daily temperature and load as well as their standard deviations. The main drawback of this method is that it requires a large amount of data. Furthermore, the loading of the transformer during its entire lifetime was assumed to follow eleven similar load curves with no changes in peak time or in the shape of the curve, which does not represent the actual case. In addition, the same pattern of temperature variation was assumed over the entire lifetime of the transformer.

In [62], the estimation of loss of life for a generator step-up transformer was calculated using simulated load values and daily ambient temperatures. Reference [62] assumed that the variation in the daily ambient temperature is sinusoidal. However, a sinusoidal curve cannot represent a typical temperature range over the course of a day. Assuming a sinusoidal temperature variation also implies that the difference between the highest and lowest temperatures is always 12 hours, which is not the actual case. Furthermore, the hourly load values used in [62] were selected randomly without conformance to any load curve pattern.

Although the authors in [62] were determining the lifetime of the insulation in a generator step-up transformer, the benchmark value of the normal thermal lifetime of the insulation was used as a benchmark value for a distribution transformer. The load of a distribution transformer is governed by the end user, which therefore makes it an uncontrollable load. On the other hand, the power of a generator step-up transformer is controlled by the operator through the control of the generator power. Accordingly, the operation of a distribution transformer is completely different from that of a generator step-up transformer. The benchmark value for the normal insulation lifetime of the distribution transformer that the author used in [3] can thus not be used as a benchmark for the study of the transformer presented in [62].

3.2.2.3 Drawbacks of Current Thermal Evaluation Assessment Techniques

As mentioned in the above subsection, existing methods for assessing transformer lifetime, which are based on thermal evaluation, do not provide the correct treatment of the inputs of the thermal lifetime model in [3]. The estimation of the transformer load is not accurate enough to give reliable lifetime estimation. The estimated ambient temperature, which is a very important factor in the correct estimation of transformer lifetime based on thermal analysis, does not reflect the actual ambient temperature and the associated uncertainties.

3.3 Economic End of Life Assessment

As the asset is purchased, it losses part of its value every year until reaching zero value or its salvage value, where the salvage value is an estimate of the value of the asset at the time it will be disposed of; it may be zero. The yearly lost part of the asset cost is called the depreciation cost. The lifetime of the asset ends when it depreciates to zero or the salvage value [66]. The depreciation concept is discussed extensively in the literature [66-68]. The main two categories of time-based depreciation are straight line depreciation and accelerated depreciation, with only one depreciation model being used throughout the lifetime. The main purpose of depreciation used by accountants is for the income tax purposes, because the depreciated value of the asset is deducted from taxable income. In this regard, accounting professionals prefer to use one of the accelerated depreciation methods to guarantee savings in income taxes in the early years of operation.

It is sometimes more economical to retire and replace the equipment before its capital value reaches zero, and before the end of physical lifetime, rather than continue to face high operating and maintenance costs. This concept, together with the depreciation concepts, are discussed in the next subsections.

3.3.1 Straight Line Depreciation

Straight-line depreciation is the simplest and most often used technique, in which the asset is assumed to lose equal amounts of its capital cost throughout its lifetime. In other words, the annual depreciation cost equals the capital cost of the asset minus its salvage value divided by number of years of its useful lifetime (useful lifetime is the average lifetime for such an asset) [66-68]. Straight line depreciation can be defined as follows [66-68]:

$$d(j) = \frac{C - SV}{lifetime} \tag{3-7}$$

where

d(j): depreciation charge for year j;

SV: the transformer salvage value;

C: the capital cost of the asset;

lifetime: the asset lifetime in years.

For example, a transformer that depreciates over 20 years, is purchased at a cost of $100,000, and will have a "salvage value" of $3000, will depreciate at $4,850 per year: ($100,000 - $3,000)/ 20 years = $4,850 per year.

The present worth of the transformer at any point in its useful lifetime can be calculated according to the following formula:

$$PW\ (k) = C - \sum_{j=1}^{t} d\,(\,j\,) \tag{3-8}$$

where

PW (k) : the transformer's present worth at the end of year (k);

$\sum_{j=1}^{k} d\,(\,j\,)$: the accumulated depreciation charges from the first year until year (k).

The present worth of a transformer under straight line depreciation is shown in Fig. 3-3(a)

3.3.2 Accelerated Depreciation

Accelerated depreciation assumes the asset to lose a larger proportion of its value during the initial years, and a lesser proportion in the later years. It includes the reducing balance depreciation and sum of years digits depreciation (SOYD). The present worth of a transformer under the accelerated depreciation is shown in Fig. 3-3(b,c)

3.3.2.1 The Reducing Balance Depreciation

The reducing balance depreciation provides a steady declining balance of the depreciation cost over the estimated lifetime of the asset. The most common ways to calculate the reducing balance deprecation are 200% and 150% reducing balance depreciation [66-68]. The annual depreciation cost for year (k) can be calculated as follows

$$d\,(\,j\,) = \frac{p}{lifetime} \times PW\ (\,j-1) \tag{3-9}$$

where p is the reducing balance value (1.5 for 150% and 2 for 200% reducing balance depreciation).

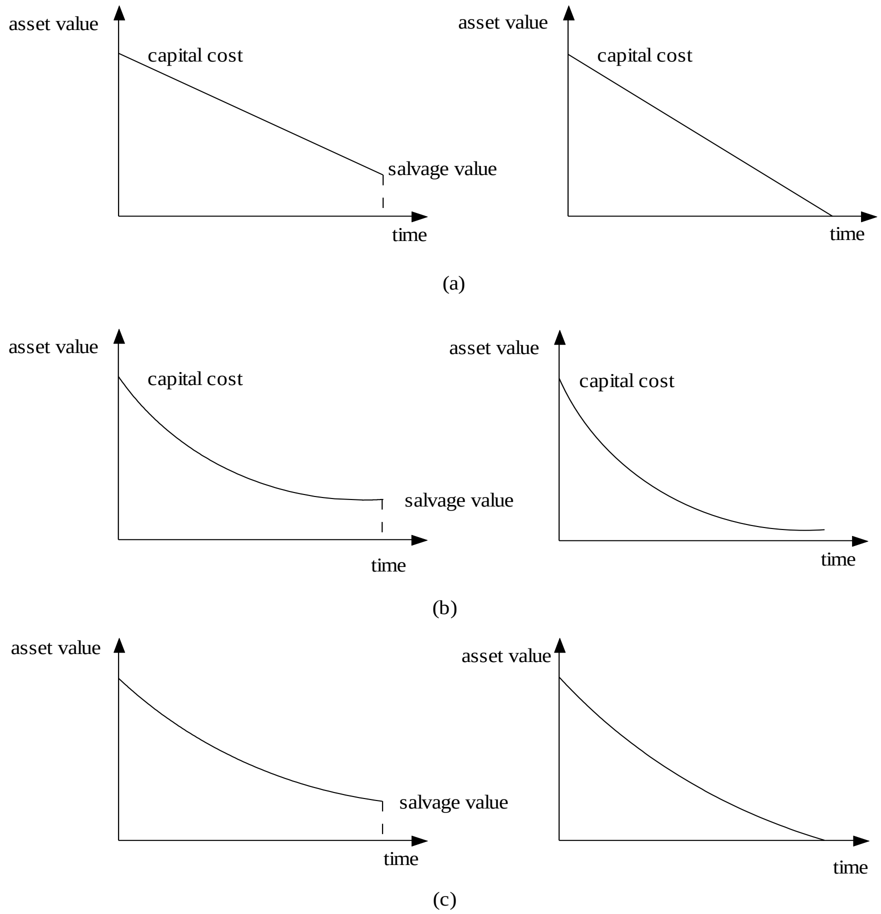

Fig. 3-3 Asset present worth under different depreciation models with and without salvage value (a) linear deprecation (b) reducing balance depreciation (c) sum of years digits depreciation.

3.3.2.2 The Sum of Years Digits (SOYD) Depreciation

Like the reducing balance depreciation, SOYD depreciation also uses steadily declining periodic amounts. SOYD is performed by applying successively smaller depreciation amounts each year to the asset value at the beginning of the calculation year. The annual depreciation for year *k* using the SOYD method can be calculated as follows [66-68]:

$$d(j) = \frac{lifetime - j + 1}{SUM} \times (C - SV) \qquad (3\text{-}10)$$

where SUM is the sum of the years digits of the lifetime, for example, If the expected lifetime is 4 years, then, SUM=1+2+3+4= 10.

3.3.3 Other Economic End of Life Assessment Methods

It is sometimes economical to retire a transformer before its capital value reaches the salvage value (accounting end of life) and before the end of physical lifetime, rather than continue to face high operating costs. In this regard, the operating and maintenance costs are taken into the economic end of life decision by calculating the minimum Equivalent Uniform Annual Cost (EUAC) of the transformer [67, 68]. EUAC relies on converting all unequal annual costs of the transformer into equivalent equal annual costs starting from the decision year and ending at each year of the remaining years of the transformer's useful lifetime. The result is a curve that represents the equivalent equal annual cost of maintaining the transformer in service until each year of the expected remaining lifetime. The curve is like the one shown in Fig. 3-4.

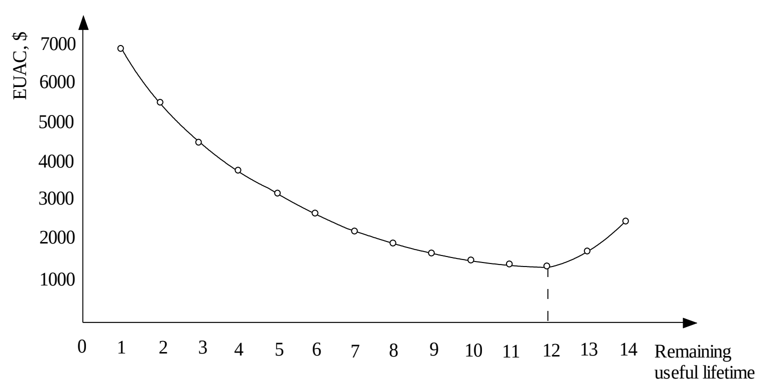

Fig. 3-4 Example EUAC curve shape for a given transformer.

According to Fig. 3-4, a transformer owner pays around $7000 for leaving the transformer in service for one year after the calculation date, and he pays around $5500 each year for leaving the transformer in service two years after the calculation date and so on. For the case shown in Fig. 3-4, the minimum EUAC is $1300, which represents the amount of money paid by the transformer owner every year for leaving the transformer in service twelve years after the calculation date. According to the minimum EUAC, the most economic end of life is 12 years after the decision date. Note that the numbers shown in Fig. 3-4 do not represent any real values or any results of any study on any transformer, and are for illustrative purposes only.

3.3.4 Drawbacks of Assessment Methods for Transformer Economic Aging

The models presented in subsections 3.3.1 and 3.3.2 are end of life assessments made on purely an accounting basis. No physical or technical aspects are taken into consideration in these models. Neither the effects of the thermal, mechanical, and electrical stresses, nor the effect of maintenance and operating costs, are taken into consideration in those models. Moreover, there is no evidence that when the present value of a transformer reaches zero, the transformer can no longer operate, or that its operating and maintenance cost will be higher than those of a new transformer.

The model presented in subsection 3.3.3 tries to cover the weak points of the aforementioned methods [66-68]. It takes maintenance and operating costs into consideration, in order to arrive at a decision about the most economic lifetime of the transformer. However, this type of economic replacement method, as presented in [66-68], is not based on realistic parameters for this type of equipment (transformers). For example, the effect of transformer failure rate on operating and maintenance costs is not taken into consideration. As well, the economic replacement methods described in [66-68] do not take into account the uncertainties inherent in failure and repair rates. These uncertainties affect the annual unavailability of the asset (the expected annual outage time), the cost of interruptions, and the cost of repairs. The cost of interruptions is itself not considered, and the annual present worth calculated for the transformer is based on a depreciation method that does not incorporate the different stages in the life of a transformer (infant, normal, and wear-out).

3.4 Transformer Health Condition

After assessing a transformer's end of life, the transformer may not reach the end of its lifetime. If the transformer does not reach its end of life, the next logical question is what the health condition of the transformer is. The concept of health index can answer this question. Giving the transformer a health index from zero to ten can provide clear information about its health condition. Insufficient research work has been presented as yet to evaluate the health condition of a transformer. In [69, 70], clear steps are given to calculate the health index of a power transformer; however, the methods presented in [69, 70] ignored an important measurement in assessing the health index, which is the amount of total solids in the transformer oil. The amount of total solids is a good indication about the condition of the insulation system of the transformer. Further, they give the measurements of total furans less weight than other less important factors such as the winding resistance and oil quality. It is known that the amount of furans is an important indicator of the degree of polymerization of the solid insulation [28, 53, 55, 57, 58]. The degradation of solid insulation (paper) can be considered the primary reason for a transformer end of life [2, 50, 51, 71, 72]. The work done in [73] includes all parameters affecting the health of the transformer; however, the paper did not reveal the method used in the calculation of the health index. The total furan in the transformer oil is ignored in the method presented in [74]. Further, no case studies are given to illustrate the method.

3.5 Summary

An overview of transformer end of life assessment methods are presented in this Chapter. Current techniques used to calculate the health condition of a transformer are also presented. The transformer end of life can be divided into physical end of life and economic end of life. Each category was highlighted. The weaknesses of each category were introduced and discussed. The weaknesses of the existing methods used to calculate transformer health condition were also presented. The drawbacks of existing end of life and replacement techniques, together with the importance of accurate estimation of transformer end of life, were the main motivations of the author of this thesis to present new transformer end of life and replacement methods as will be discussed in Chapters 4 to 6. Furthermore, the drawbacks of the existing methods that calculate the transformer health index and health condition were the reason to introduce three methods to assess the transformer health condition in Chapter 7.

Chapter 4

A Monte Carlo Approach for Calculating the Thermal Lifetime of Transformer Insulation

4.1 Introduction

The degradation of solid insulation can be considered as the main reason for transformer physical end of life [2, 50]. This Chapter presents an accurate method for estimating the thermal lifetime of solid insulation in an oil-immersed transformer [75]. The method estimates the ambient temperature using the monthly average ambient temperature and the monthly solar clearness index, taking into consideration the associated uncertainties for both of them. The average daily load curve and the standard deviation for each hour in the daily load curve are used to model the transformer load. A Monte Carlo simulation is used to generate two separate artificial histories for the loading and for the ambient temperature by using their inherent uncertainties. The annual equivalent aging factors for each year are used in the Monte Carlo simulation in order to find the corresponding estimated thermal lifetime. The probability distribution for the estimated thermal lifetimes for all simulation years is then used to calculate the average lifetime of the transformer.

The new presented method uses the model presented in [3] to estimate the lifetime of transformer insulation; however, the uncertainty with respect to the transformer load is batter modeled. The ambient temperature is more accurately estimated using the solar clearness index, and the uncertainty with respect to the ambient temperature is considered in the treatment of the end of life model input. These temperature and loading models are used to simulate the transformer lifetime, from which the lifetime of the transformer insulation is calculated.

4.2 Proposed End-of-Life Estimation Technique

The proposed approach for estimating the lifetime of transformer insulation is based on the simulation of transformer loss of life using a Monte Carlo technique. The approach consists of three steps: building an artificial history of the ambient temperature, building an artificial history of the transformer loading, and simulating the transformer loss of life based on the model presented in [3]. The Monte Carlo simulation is used in order to account for the uncertainty inherent in both the daily temperature and the transformer loading.

4.2.1 Building the Artificial History of the Ambient Temperature

The HST value depends on the ambient temperature, the rise in the top oil temperature over the ambient temperature, and the rise in the winding HST over the top oil temperature [3]. The latter two terms can be calculated using the top oil temperature rise over the ambient at the rated load, the winding HST rise over the top oil at the rated load, and the load value. The first term is found by employing the historical ambient temperature data to calculate the equivalent past loss in transformer life. The ambient temperature should, however, also be estimated in order to project the future equivalent loss of life of the transformer. The correct estimation of the ambient temperature can be used to obtain a correct estimation of the transformer HST, from which a correct estimation of the equivalent future transformer loss of life and the remaining lifetime can be determined.

For the purposes of this research, the estimation of the ambient temperature is based on the monthly average ambient temperature and the monthly solar clearness index (K_{Tm}). It was found that monthly average temperatures have lower standard deviations than average temperatures for the same day over several years [76, 77].

The average ambient temperature for a specific hour (h) for a month (m) can be calculated as follows [77]:

$$T_{m,h} = \overline{T}_m + A_m \begin{bmatrix} 0.4632 \cos(HOD - 3.805) + \\ 0.0984 \cos(2HOD - 0.36) + \\ 0.0168 \cos(3HOD - 0.822) + \\ 0.0138 \cos(4HOD - 3.513) \end{bmatrix} \tag{4-1}$$

where

$\overline{T}_m$: the mean value of the average ambient temperature for month (m) in ^{o}C;

A_m: the diurnal temperature swing (peak to peak) for month (m) in ^{o}C;

HOD: a dimensionless expression for the hour of the day.

A_m and HOD can be calculated as follows [77]:

$$A_m = 25.8\overline{K}_{Tm} - 5.21 \tag{4-2}$$

$$HOD = \frac{2\pi(h-1)}{24} \tag{4-3}$$

where

$\overline{K}_{Tm}$: the average solar index for month m;

h: an index for the hour of the day, starting from zero at midnight.

K_{Tm} is the ratio of the monthly average daily radiation on a horizontal surface (H_m) to the monthly average daily extraterrestrial radiation ($H_{o,m}$). Solar radiation data is commonly available in the form of hourly total radiation on a horizontal surface (I) for each hour for extended periods of one or more years [78]. The hourly total radiation on a horizontal surface (I) is used to calculate (H_m).

The average solar index for month m, ($\overline{K}_{Tm}$), is calculated by

$$\overline{K}_{Tm} = \frac{\overline{H}_m}{H_{o,m}} \tag{4-4}$$

where $\overline{H}_m$ is the mean value of the monthly average daily global solar radiation on a horizontal surface for the data years.

The monthly average daily extraterrestrial radiation for month (m), ($H_{o,m}$), in J/m^2 is calculated as follows [76, 78]:

$$H_{o,m} = \frac{24 \times 3600}{\pi} \times \left(1 + 0.033 \cos \frac{(360 \times midday_m)}{365}\right) \times G_{sc} \times \begin{pmatrix} \cos(\phi)\cos(\delta)\sin(\omega_s) \\ + \dfrac{\pi}{180}\omega_s \sin(\varphi)\sin(\delta) \end{pmatrix} \tag{4-5}$$

where

G_{sc}: the solar constant (=1367 W/m^2);

φ : the latitude of the site (weather station);

δ : the solar declination;

ω_s: the main sunshine hour angle for the month;

$midday_m$: the middle day of month m.

The solar declination and the main sunshine hour angle in degrees for a given month are as follows [78]:

$$\delta = 23.45 \sin\left(\frac{360}{365}(284 + midday_m)\right) \tag{4-6}$$

$$\omega_s = \cos^{-1}(-\tan(\varphi)\tan(\delta)) \tag{4-7}$$

The monthly average daily global solar radiation on a horizontal surface for any year (i), ($H_{m,i}$), can be calculated as follows:

$$H_{m,i} = \frac{\sum_{d=1}^{e}\sum_{h=1}^{24} I_{d,h} \times 3600}{e} \tag{4-8}$$

where

$H_{m,i}$: the monthly average daily global solar radiation on a horizontal surface for month m in year i in J/m^2;

$I_{d,h}$: the hourly radiation on a horizontal service for day d at hour h for month m in W/m^2;

d: an index for the day of the month;

e: an index for the end day of the month, e.g., e = 31 for Jan.

After ($H_{m,i}$) is calculated for each month of the year, the mean value of the monthly average daily global solar radiation on a horizontal surface ($\overline{H}_m$) for multiple data years can be calculated as follows:

$$\overline{H}_m = \frac{\sum_{i=1}^{n} H_{m,i}}{n} \tag{4-9}$$

where *n* is the total number of data years.

The average ambient temperature for hour h in month m can be calculated using (4-1). However, (4-1) calculates the mean average daily ambient temperature for a month. The average daily global solar radiation on a horizontal surface (H_m) for any month m is not constant for every year. The value of (H_m) has a mean value ($\overline{H}_m$) and a standard deviation (SD_{Hm}).

To account for the uncertainty in the average daily global solar radiation on a horizontal surface for any month and for the uncertainty in the average daily temperature for any month, a Monte Carlo simulation is performed in order to generate an artificial history of the ambient temperature. To generate the artificial history of the ambient temperature, the value of H_m is assumed in this research to be a normally distributed random variable with a mean value equal to ($\overline{H}_m$) and a standard deviation equal to SD_{Hm}. A set of random numbers between zero and one [0,1] is generated for each month, with the size of each set being equal to the number of days in each month (e.g., 31 random numbers for January, 28 random numbers for February, and so on). Using the random numbers generated for each month, a normally distributed random variable is generated with an average equal to $\overline{H}_m$ and a standard deviation equal to SD_{Hm}. The result is 12 normally distributed random variables that represent the whole year. The mean and standard deviation values of these random variables are the mean and standard deviation values of the monthly average daily global solar radiation on a horizontal surface for each respective month.

Using these random variables for each month provides as many values of (H_m) as the number of days for each month. As a result, as many values of (K_{Tm}) as the number of days in each month can be calculated, and accordingly, as many values of the diurnal temperature swing (peak-to-peak) for each month as the number of days in the month can also be determined. Using (4-1), the number of daily temperatures equal to the number of the days in the respective month is generated. In this way, the changes in the diurnal temperature swing (peak to peak) during the month are accounted for.

To account for the changes in the average monthly temperature, 12 normally distributed random variables (T_1-T_{12}) are generated. Each random variable represents the respective mean value and standard deviation for the average monthly temperatures for each month in the available data years. The length of each of these random variables equals the number of days in its respective month. Thus, using the elements of K_{Tm} generated from the random variables of H_m and the monthly temperature random variables, different daily temperatures for each month can be generated.

Typical data shows that the daily temperature increases from February 15^{th} to July 15^{th} and decreases from August 15th to January 15th. Moreover, the average temperatures seem nearly constant in the periods from January 15th to February 15th and from July 15th to August 15th. In the developed temperature model, the elements of the 12 random variables (T_1-T_{12}) are therefore sorted in ascending order from element 16 of T_2 (February) to element 15 of T_7 (July) and in descending order from element 16 of T_8 (August) to element 31 of T_{12} (December) and from element 1 of T_1 (January) to element 15 of T_1. The other elements, from 16 of T_1 to 15 of T_2 and from 16 of T_7 to 15 of T_8, are kept without sorting. This sorting algorithm prevents unrealistic jumps in temperature from month to month.

The values of the random variables (T_1-T_{12}) are then merged with the generated values for the diurnal temperature swings, which permit temperatures for the entire 365 days of the year to be generated, taking into consideration the uncertainty present in the temperatures.

4.2.2 Building the Artificial History of the Transformer Loading

Typical daily load data for the whole lifetime of a transformer is not easy to find. No utility collects load data for 24 hours, 365 days for the whole lifetime of the transformer. Even if this data was available, it would be past data, and a method for projecting the future load of the transformer would still be required. The developed approach for calculating the thermal lifetime of transformer insulation can be used for transformers either with or without a complete load history. It can also be used for transformers that have recently been put into service.

An alternative solution for modeling transformer load is to simulate the load, or to build what is called an “artificial history” of the transformer load. To model the artificial history of the transformer load, the average transformer daily load curve is used; a typical curve is shown in Fig. 4-1 [79]. The average load curve may differ from one transformer to another. The uncertainty with respect to the hourly load is used to generate multiple daily load curves (artificial history) for the transformer.

A normal distributed random variable is constructed so that its mean value is the loading at a specific hour on the average daily load curve, as shown in Fig. 4-1. A set of these normally distributed random variables is generated thereafter for every hour on the average daily load curve using the above approach. The standard deviations of these generated random variables are δ_{load}% of the rated transformer load. This technique allows the generation of different daily load curves with different shapes. In this approach, the uncertainty of the average daily load curve is utilized in order to represent different modes of transformer operation, such as normal loading, planned loading beyond nameplate, and short-time emergency loading [3].

The next step is to construct the daily load curves for every day of the year. For any daily load curve, the load for each hour is selected randomly from the corresponding normally distributed random variable constructed for that hour. This process is repeated thereafter for the remaining days and years. Fig. 4-1 shows three randomly selected daily load curves generated according to this approach. It is clear that the three curves are different in shape. As shown in Fig. 4-1, three hours have been selected (hours 4, 11, and 21) in order to show the generation of the hourly load for the daily load curves that represent the artificial history. From the mean load curve, the probability distributions of the hourly loads are used to generate each hourly load for the artificial history daily load curves. The loads during these hours may be larger than, less than, or equal to the mean load at these hours. The artificial history of the loading is then generated as follows:

1. Find the average daily load curve for the transformer.
2. Generate 24 vectors of random numbers between zero and one (corresponding to the 24 hours in a day). The length of the vector equals the number of days in a year.
3. Generate 24 normally distributed random variables with mean values equal to their hourly mean values and with standard deviations equal to δ_{load}% of the normal load.
4. Use these 24 random variables to generate different daily load curves as previously explained.

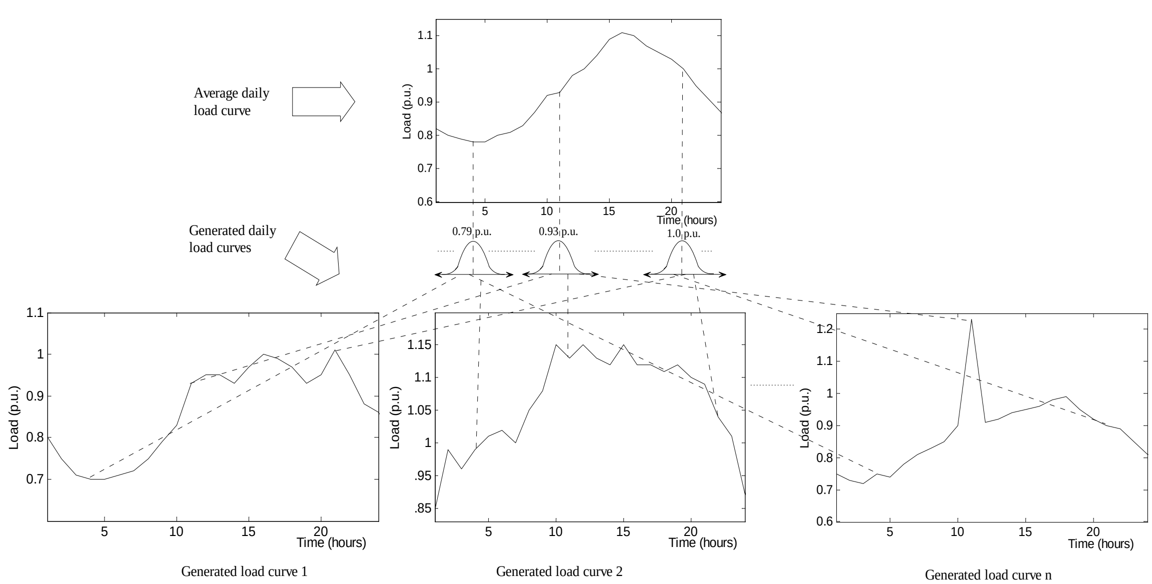

Fig. 4-1 Generation of daily load curves.

4.2.3 Simulating the Transformer Lifetime

The artificial histories of the loading and the ambient temperature are used in the Monte Carlo simulation in order to find the annual equivalent aging factors. To complete the artificial histories, the steps explained in subsections 4.1.1 and 4.1.2 are repeated in order to generate more annual data for the load and ambient temperature. The loading and ambient temperature artificial histories are used year over year in order to calculate the hourly HST, from which the hourly acceleration factor (F_{AA}) [3] can then be determined.

$$F_{AA} = \exp^{\left[\frac{1500}{383} - \frac{1500}{HST + 273}\right]} \tag{4-10}$$

The annual equivalent aging factor is thus calculated as follows:

$$F_{eq} = \frac{\sum_{j=1}^{TI} F_{AA_j} \Delta t_j}{\sum_{j=1}^{TI} \Delta t_j} \tag{4-11}$$

where

F_{eq} : the equivalent aging factor for the total time period;

TI : the total number of time intervals (usually 24 hrs for one day or 8760 hrs for one year);

F_{AA_j} : aging acceleration factor for the temperature which exists during the time interval Δt_j;

Δt_j : time interval, hours

The expected lifetime is then

$$EL_j = \frac{NIL}{F_{eq\ j}} \tag{4-12}$$

where

EL_j: the expected lifetime using the equivalent aging factor for simulation year j;

NIL: the normal solid insulation lifetime based on 50% retained tensile strength and a continuous HST of 110^{o}C according to [10] (7.42 years);

F_{eqj}: the equivalent aging factor [3] for the simulation year (j).

It should be noted that the equivalent aging factor is calculated every year and that the expected lifetime is calculated using (4-12), assuming that the equivalent aging factors for the whole transformer lifetime are the same as the equivalent aging factor for the simulation year j.

The average expected lifetime is calculated for every year of the simulation using the following equation:

$$\overline{EL}_c = \frac{\sum_{j=1}^{c} EL_j}{c} \tag{4-13}$$

where

$\overline{EL}_c$: the average expected lifetime until year c of the simulation;

j: the index for the simulation year;

c: the number of simulation years until year c.

The simulation continues until the stopping criterion is reached. The stopping criterion used in the Monte Carlo simulation depends on the coefficient of variation ε(c) [3, 80], where ε(c) can be calculated as follows:

$$\varepsilon(c) = \frac{\sqrt{V(c)}}{\sqrt{c} \times E(c)} \tag{4-14}$$

where

ε(c): the coefficient of variation at year c of the simulation;

E(c): the expectation of the estimate function at year c;

V(c): the variance in the estimate function at year c.

E(c) and V(c) can be calculated as follows:

$$E(c) = \frac{1}{c}\sum_{j=1}^{c} F(j) \tag{4-15}$$

$$V(c) = \frac{1}{c-1}\sum_{j=1}^{c} (F(j) - E(c))^2 \tag{4-16}$$

where F is the estimate function ($\overline{EL}_c$ here).

The simulation stops when ε(c) falls below a very small tolerance level (TL). The coefficient ε(c) becomes very small when the annual estimated average lifetimes ($\overline{EL}_c$) become very close in magnitude. The use of this technique enables the probability distribution of the expected age to be built. The most probable age (mode) and the average age can also be found from the probability distribution.

4.3 Case Study

A 2 MVA transformer is assumed for the case study. The thermal characteristics according to [4] are as follows:

1) rise in top oil temperature over ambient at the rated load: $\Delta\Theta_{TO,R}$= 50 °C;
2) rise in hottest spot conductor temperature over top oil temperature, at the rated load: $\Delta\Theta_{HS,R}$ = 30 °C;
3) ratio of load loss at the rated load to no-load loss: R = 3.2;
4) thermal time constant of the oil for the rated load: $\tau_{TO,R}$= 3.5 h.

The average daily load served by the transformer in per unit notation is shown in Fig. 4-1 [79]. A 10% standard deviation is assumed for the hourly load. Ten years of data about the hourly ambient temperature and hourly incident radiation on a horizontal surface (I) were collected from the weather station at the University of Waterloo (latitude: 43.4738 N; longitude: 80.5576 W; elevation: 334.4 m above sea level). Some data was missing; they were estimated using linear interpolation. The monthly mean values for the temperature and their standard deviations for the 10 recorded data years are shown in Table 4-1. The hourly total radiation on a horizontal surface (I) for each hour in W/m^2 is used in order to find the monthly average daily global solar radiation on a horizontal surface ($H_{m,j}$) for month (m) in year (j) using (4-8). The mean values of the monthly average global daily radiation ($\overline{H}_m$) for the available data years are calculated using (4-9). ($\overline{H}_m$) values with their standard deviations for the 10 recorded data years are shown in Table 4-1. When (4-6) and (4-7) are applied, the solar declination (δ) and the main sunshine hour angle for the month (ω_s) can be calculated for each month of the year. Because (δ) and (ω_s) have been determined, the monthly average daily extraterrestrial radiation ($H_{o,m}$) can then be calculated using (4-5). The values of ($H_{o,m}$) are shown in Fig. 4-2.

As discussed in subsection 4.1.1, the 12 monthly average global daily radiation values (H_1-H_{12}) are assumed to be normally distributed random variables with the mean values and standard deviations shown in Table 4-1. The normally distributed random variables can be built by generating 12 uniformly distributed vectors of random numbers (U_1-U_{12}) between zero and one (0,1) that correspond to the 12 months of the year. The length of each vector equals the number of days in the respective month. The 12 normally distributed random variables can be generated using the Box-Muller method [81]. When each element of the 12 random variables (H_1-H_{12}) is divided by its respective monthly average daily extraterrestrial radiation value ($H_{o,1}$-$H_{o,12}$), a number of solar indices are produced for each month. The number of solar indices equals the number of days in the respective month. The values of the solar indices for each month are substituted for $\overline{K}_{Tm}$ in (4-2) in order to generate a number of diurnal temperature swings (peak-to-peak) for each month equal to the number of days in the month.

To account for the changes in the average daily temperature for each month, the average monthly temperatures are assumed to be normally distributed random variables with the means and standard deviations shown in Table 4-1. The mean value of the average ambient temperatures ($\overline{T}_m$) for month (m) in (4-1) is replaced with (T_m) in order to account for the daily changes in the average temperature, where (T_m) represents (T_1-T_{12}). The simulated ambient temperature for one month (30 days) is shown in Fig. 4-3, while the simulated ambient temperatures for one complete year are shown in Fig. 4-4.

Table 4-1 Monthly average temperature and monthly average daily global solar radiation data

month	$\overline{T}_m$ (°C)	SD_{tem}	$\overline{H}_m$ (MJ/m^2day)	SD_{Hm}
Jan.	-5.73	3.09	5.18	0.53
Feb.	-5.49	2.32	8.65	0.62
Mar.	-0.92	1.95	12.6	1.76
Apr.	6.55	1.16	16.0	1.70
May	12.8	1.7	18.8	1.79
Jun.	18.7	1.3	20.8	1.60
Jul.	20.6	1.33	20.8	1.46
Aug.	19.6	1.2	18.5	1.24
Sep.	16.0	1.28	14.7	1.54
Oct.	9.15	1.67	8.7	0.80
Nov.	3.41	1.55	5.05	0.49
Dec.	-3.15	2.58	4.12	0.48

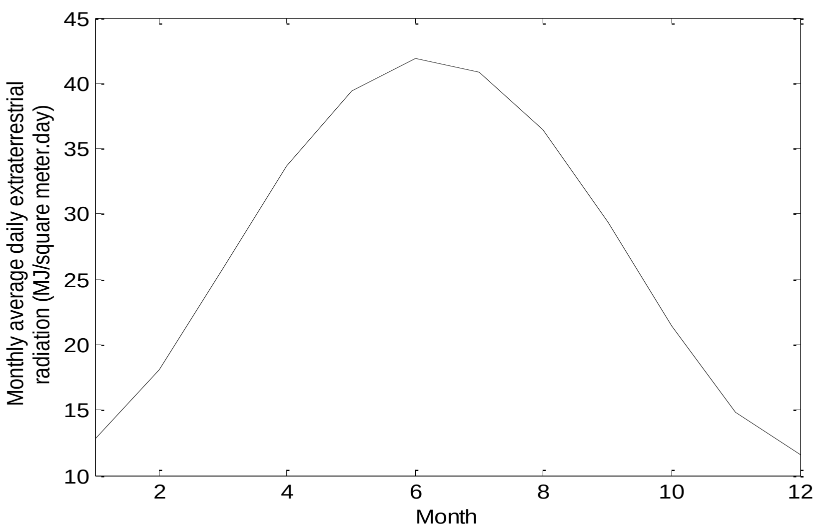

Fig. 4-2 Monthly average daily extraterrestrial radiation (MJ/m^2.day).

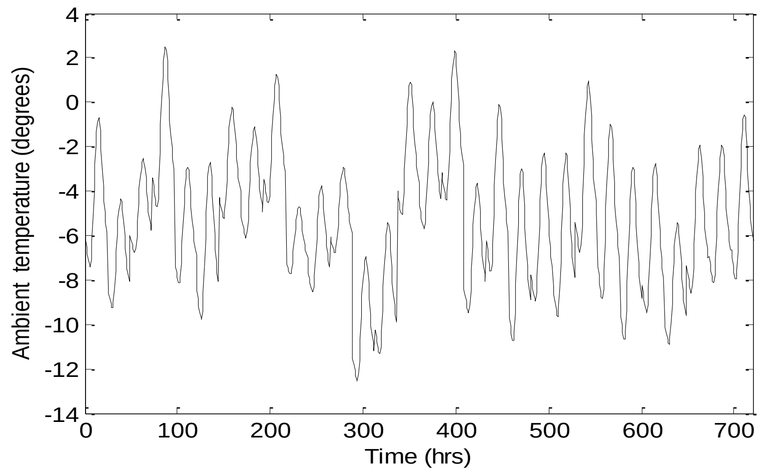

Fig. 4-3 Simulated ambient temperature for one month (30 days).

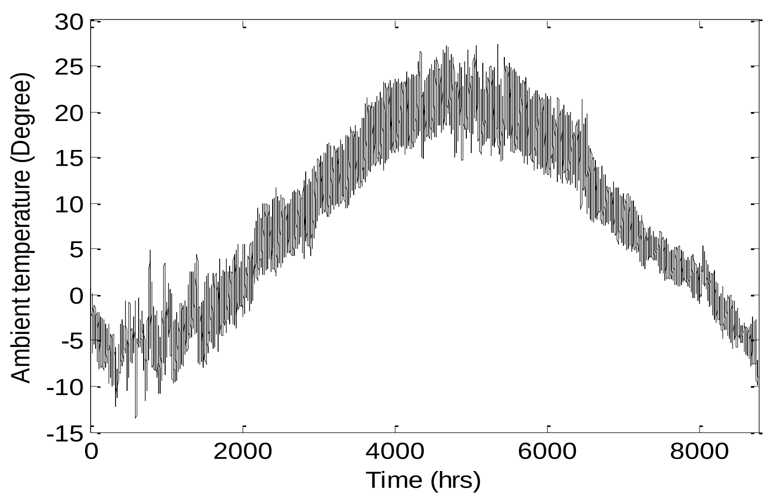

Fig. 4-4 Simulated ambient temperature for one year.

The artificial history of the transformer loading is modeled as discussed in subsection 4.1.2. Twenty-four random variables are generated. The mean values and the standard deviations of each random variable are the mean values and the standard deviations of the 24 hours of the daily load curve. The mean values are shown in Fig. 4-1, and the standard deviation is taken as 10% of the normal load. The length of each random variable is the number of hours in one year (8760 hr) multiplied by the number of simulation years (s). The simulated load for one month is shown in Fig. 4-5.

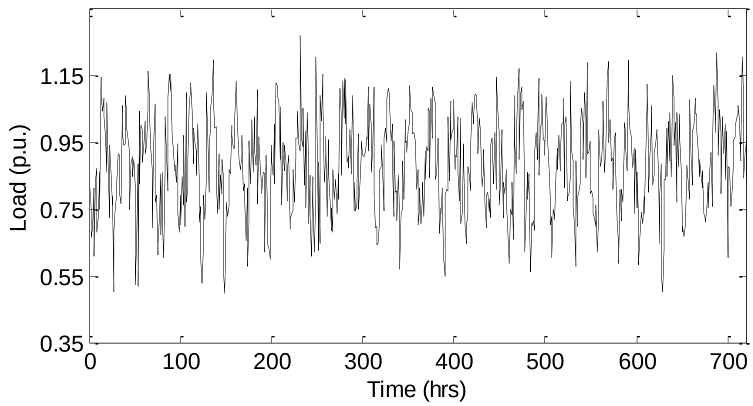

Fig. 4-5 Simulated load for one month (30 days).

A Monte Carlo simulation is then performed for the transformer using the artificial histories of the loading and ambient temperature. The simulation begins with the artificial histories of year one. The HST is calculated for every hour according to [3], using the thermal data given in this study and the artificial load and ambient temperature data generated. The aging acceleration factor (F_{AA}) is calculated for every hour, from which the equivalent aging factor (F_{eq}) for the total year is calculated. The simulation continues year over year. (F_{eq}) is calculated for each year of the simulation, and $\overline{EL}_c$ is calculated according to (4-13).

The simulation continues until the stopping criterion is reached, as shown in (4-12). The simulation stops when the coefficient of variation ε(c) falls below the tolerance level (TL). The TL should be a low value; in this case it was set to 0.0005. Because the coefficient of variation oscillates and may fall below the TL and then rise again for the next sample, the simulation stops if the coefficient of variation falls below the TL for five successive years. When the criterion was applied, the simulation stopped after 72 years. The mean expected age at the end of the simulation was found to be 43.48 years. The fluctuation in the expected age of the transformer along the simulation time is shown in Fig. 4-6. Fig. 4-7 shows the coefficient of variation from the start of the simulation until the stopping criterion is reached.

Fig. 4-8 shows the histogram of the expected age according to the annual aging acceleration factor and a fitted beta distribution using Easyfit 5.0. The boundary parameters for the beta distribution are a minimum value a = 40.6 and a maximum value b = 46.009. The shaping parameters are α = 2.66 and β = 2.3332. The distribution mean is 43.48 years, and the mode of the distribution is calculated as follows [82]:

$$Mode = a + \frac{\alpha}{\alpha + \beta}(b - a) \tag{4-17}$$

$$Mode = 40.6 + \frac{2.66}{2.66 + 2.3332}(46.009 - 40.6)$$
$$= 43.48 \ years$$

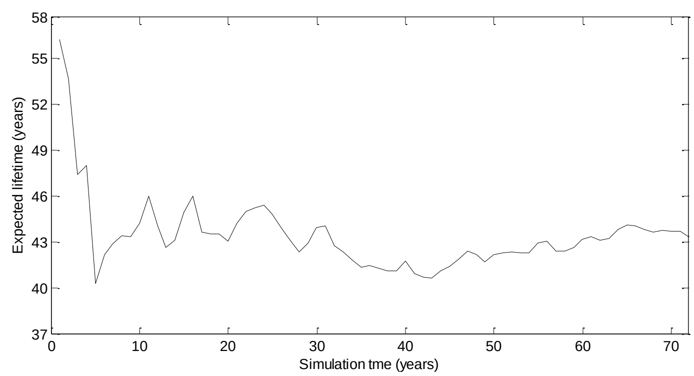

Fig. 4-6 Convergence of the expected lifetime.

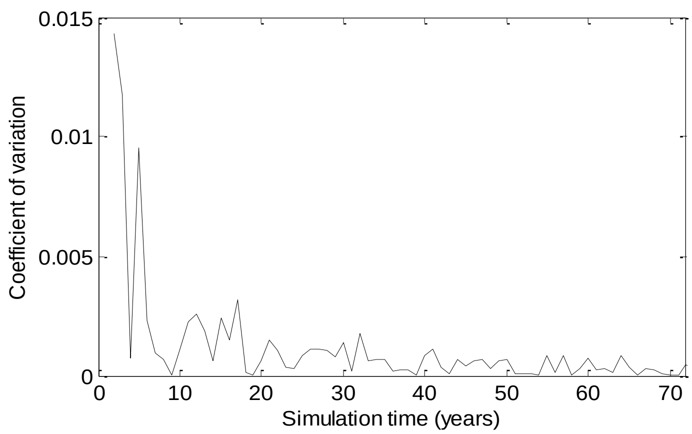

Fig. 4-7 Coefficient of variation.

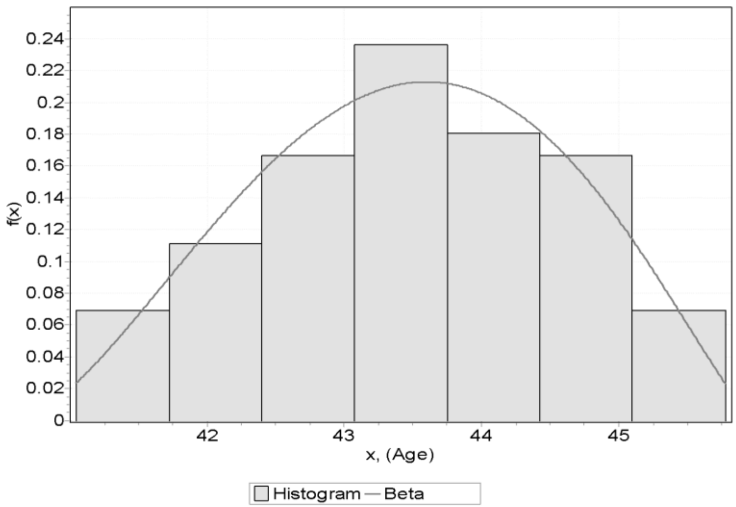

Fig.4-8 Fitted beta distribution for the expected lifetime.

The mode of 43.48 years is the same as the mean. The beta distribution representing the expected lifetime is symmetrical so that the mean is the same as the mode (most probable event). The most probable value of the transformer life as calculated by the proposed analysis is close to the recorded retirement ages of power transformers [58, 83, 84]. Although there are other parameters that can affect the lifetime of the transformer beside the thermal parameter, the thermal parameter (ambient temperature and loading) is a major contributor in determining the lifetime of the transformer. However, due to the fact that these parameters are not included in this study, there is a degree of uncertainty in this analysis.

4.4 Comparison with Previous Work

In [62], an attempt was made to establish the time to failure for the insulation of a transformer. The method relied on the use of an equivalent aging factor in order to find the lifetime of the insulation. An artificial model based on probability was used to model the load. More information about the method can found in [62]. The data from section 4.2 was used to test this technique.

Fig. 4-9 shows the life consumption simulation curves that result after the transformer insulation lifetime is simulated 50 times, as stated in [62]. The fitted Weibull distribution of the simulation results is shown in Fig. 4-10. Fig. 4-9 shows that the average actual usage time in days to reach the insulation end of life (7500 days as stated in [62]), is 41,631 days, or 114.1 years, which is not a practical insulation lifetime. All recorded transformer lifetimes, which depend mainly on the lifetime of the insulation, are very much shorter [58, 83, 84].

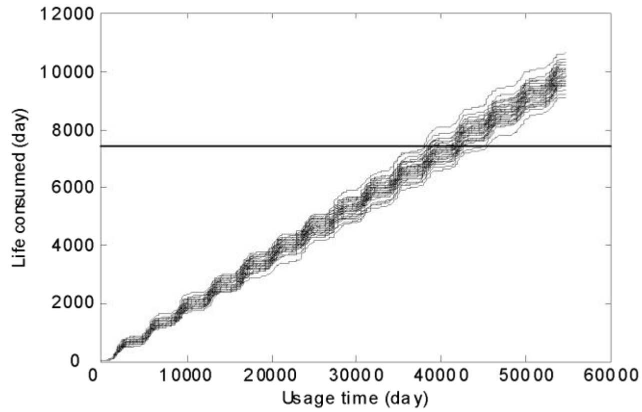

Fig. 4-9 The resultant life consumption simulation curves for the technique presented in [62].

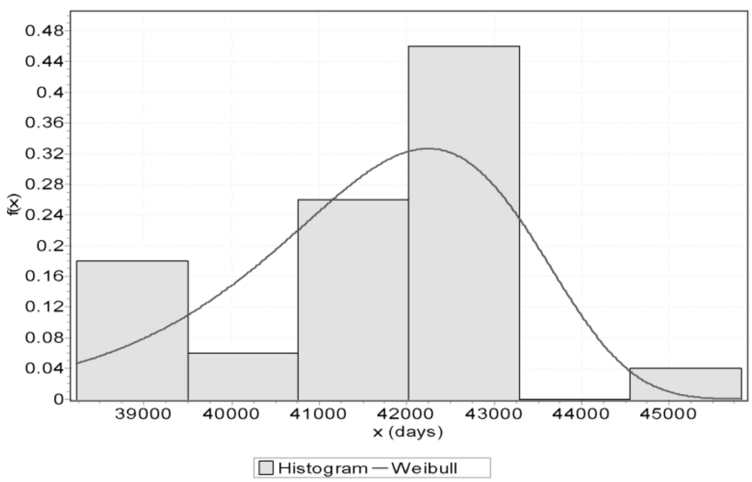

Fig. 4-10 Weibull distribution of the simulated life consumption values shown in Fig. 4-9.

In [65], load and temperature were represented by a set of curves that give, for each instant, load and temperature values associated with a probability value. The particular load value at any time (t) can be calculated as follows [65]:

$$L(t) = m(t) + Z \times sd\,(t) \tag{4-18}$$

where

L(t): the load at time (t);

m(t): the mean of the load;

Z: a standard normal random variable.

To find the value of the standard normal random variable (z), the probability of the event should be known. For example, for a probability of 90%, the value of (z) is 1.28. If (z) is used as a parameter, a set of 11 load curves can be obtained. These curves correspond to probabilities from 2.5% to 97.5%. Figs. 4-11 and 4-12 show the set of 11 curves representing all 11 probabilities of the load along with the ambient temperature. If all combinations of the daily load and ambient temperature are applied, 121 possible combinations can be found for every day. Because the daily load is assumed to be constant, 121 possible combinations can thus be found for each year. For each combination, the HST and the corresponding loss of life are calculated. The average loss of life is calculated as follows [65]:

$$LOL_{tot} = \sum_{k,j} F_{eq\,k,j} \times Q_k \times Q_j \tag{4-19}$$

where

LOL_{ave}: the average loss of life;

$F_{eq\,k,j}$: the equivalent loss of life for load curve (k) and temperature curve (j);

Q_k, Q_j: the corresponding probability values.

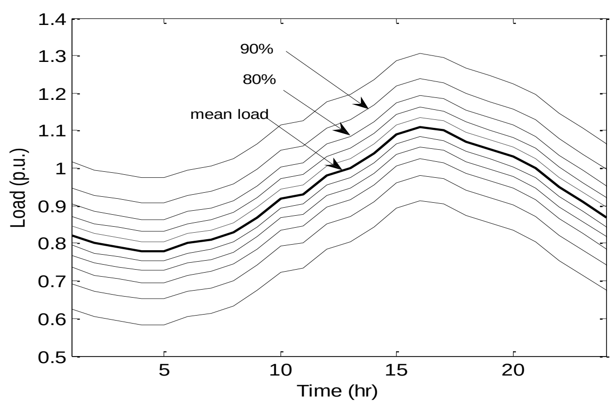

Fig. 4-11 Set of load curves.

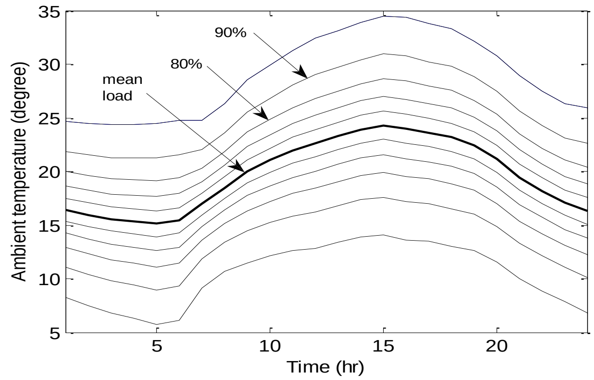

Fig. 4-12 Set of ambient temperature curves.

When this technique is implemented and the transformer parameters from the case study in section 4.2 are used, the loss of life values for the 121 possible combinations are shown in Fig. 4-13. It is clear from Fig. 4-13 that the loss of life for the first combination is too small and the loss of life for the last combination is too high. The reason is that the first combination combines the lowest curves in Figs. 4-11 and 4-12. The resultant HST is low, and as a result, the loss of life is small. On the other hand, the two curves in Figs. 4-11 and 4-12 are combined in combination 121. The HST for combination 121 is too high, and as a result, the loss of life is too high.

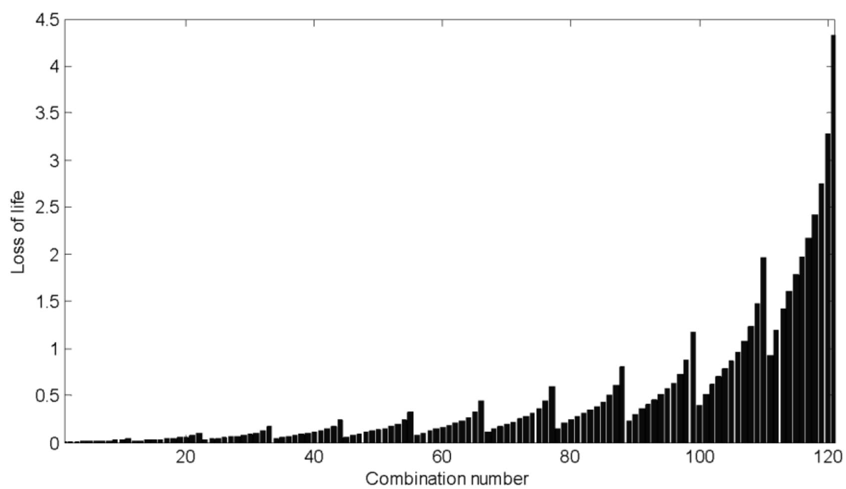

Fig. 4-13 Loss of life for the 121 combinations in (4-17).

The average annual loss of life is found to be 0.379. Applying the benchmark value for insulation life according to [4], which is 65,000 hr, the transformer insulation would be expected to last 19.58 years: less than the common lifetime of distribution transformers [58, 83, 84]. This outcome occurs because of the shortcomings of the method of reference [65], as explained in the introduction of this Chapter.

4.5 Conclusion

The technique presented in this Chapter estimates the lifetime of transformer insulation based on the specific loading and location of the transformer. The new approach incorporates the generation of two artificial histories for a transformer: one for the ambient temperature and one for the load. The solar clearness index and average monthly temperatures are used to generate the artificial history of the ambient temperature. The uncertainties inherent in both the solar clearness index and the average monthly temperatures are considered when the ambient temperature is determined, and variations in the load are taken into account when the artificial history of the load is modeled. Both artificial histories are used as inputs to a Monte Carlo simulation technique in order to find the average lifetime of a given transformer. The proposed method is compared with existing methods used to determine the thermal lifetime of transformer insulation. The lifetime estimated by the proposed method is significantly closer to the recorded statistical end of life data for power transformers than are the results produced by the previous methods. Further, the presented method gives quantitative information about the transformer estimated lifetime. This quantitative information does not exist in the existing aging assessment by diagnostic test. Moreover, the advantage of the results of the presented method over the existing aging assessment by thermal modeling methods is clear from the comparison subsection. The reason behind this advantage is the accurate modeling of the load and ambient temperature uncertainties.

Chapter 5
A Techno-Economic Method for Replacing Transformers: Method Concepts

5.1 Introduction

Determining the expected replacement date of a working transformer represents a highly important asset management activity, especially in view of the current aging condition of the overall power system infrastructure.

As mentioned earlier in Chapter 3, a number of tests can be performed in order to obtain information about the technical performance of a transformer, such as tests for moisture content, oil gassing tendency, and furanic compounds. Other tests, such as the degree of polymerization and the retained tensile strength of the paper insulation, cannot be performed because they require access to the insulating paper within the transformer. However, even if complete test results were available, while they would provide a general assessment of the condition of the transformer, they would not yield any quantitative information concerning its life expectancy.

A transformer near the end of its physical lifetime costs more to maintain because of the aging of its components, and the likelihood of its failure is also increased, resulting in increased costs for power interruptions and repairs. Replacing a transformer before it reaches its physical end of life is therefore frequently a wise option from an economic perspective.

The main aim of the investigation presented in this Chapter is to develop a more systematic approach to determining the life expectancy of transformers [85]. The approach is based on an economic analysis of the operational characteristics of transformers in conjunction with the technical issues involved in the decision process. Enhanced use of the well-known bathtub failure model, including repairs and scheduled maintenance, is made in order to arrive at a more economically oriented replacement decision [85]. This goal is achieved in part by taking into account the uncertainty inherent in transformer failures and the corresponding interruptions in power. In essence, this technique constitutes a decision support system for determining the life expectancy of a transformer.

The main challenge was to develop an approach that would address the lack of correlation between a diagnostic test performed on a transformer specimen and the expected life of the transformer. A transformer aging due to physical and chemical degradation is caused by the simultaneous actions of thermal, electrical, and mechanical stresses. All of these stresses ultimately lead to transformer failure, which is depicted as the bathtub reliability curve [86-88]. In essence, the bathtub curve delineates the synergistic effects of the stresses applied to the transformer as well as the resistance of the transformer to these stresses. The bathtub failure model is therefore used to represent the technical aspects of the decision to replace a transformer based on economic reasons. The effect of the use of the bathtub failure model on the time and cost required for repairs, the cost of interruptions, the uncertainty in the time-to-failure and time-to-repair, and the change in the failure rate throughout the expected useful lifetime, is also considered in the presented method. The uncertainty in the time-to-failure and time-to-repair is modeled using a Monte Carlo simulation technique, from which a probability distribution for transformer outage time is generated and is subsequently used in order to calculate the repair time and cost of interruptions. The repair and interruption costs together with the operating costs are then used to generate the equivalent uniform annual cost (EUAC) [86-88] for the existing transformer (defender) and for a new transformer (challenger). The EUACs for the defender and the challenger are compared in order to determine the most economical year in which to replace the defender.

5.2 Replacement Model Concepts

Fig. 5-1 is a flow chart that represents the steps in the proposed replacement method. The new method consists of five main stages: the data initialization stage, the calculation of the transformer's present worth stage, the calculation of the annual costs stage, the calculation of the EUAC stage, and the decision stage. The main objective is to determine the total annual costs and the present worth for each year for both the challenger (new transformer) and the defender (existing transformer). This data is then utilized to plot the EUAC curves for the challenger and the defender, which then establish the replacement year, as discussed in subsequent subsections.

5.2.1 Data Initialization Stage

The first stage of the replacement method is to acquire the data for both the new and the existing transformers. This data includes the capital cost of the transformer, the failure rate in the normal region, the average repair time, the average switching time, the frequency and average duration of scheduled maintenance (assuming time-based maintenance), the transformer rating, the losses, and the expected useful lifetime. The next step is to enter the load data. This data includes the size of the load served by the transformer and its load factor, the load type or types, and the percentage of each load type if it comprises several types. The next step is to input the financial data, which include the energy charge, the demand charge, the interest rate, and the sector customer damage function (SCDF) for each of the load sectors. The SCDF is explained in subsection (5.2.3.3).

For the purposes of this study, the transformer failure rate is considered to follow the bathtub curve, which is considered the most acceptable failure rate model [86-88]. A bathtub curve that represents a transformer failure rate is shown in Fig. 5-2(a). Next, the starting point (year) of the wear-out stage and the end point (year) of the infant stage in the bathtub curve must be determined for both the new and the existing transformers. These steps are important in the calculation of the present worth of the transformer for each year of its remaining lifetime and in the calculation of the repair and interruption costs for each year of the remaining useful lifetime. This information can be determined from surveys of transformer failures, or through engineering experience with populations of similar transformers [81, 89, 90]. All of these data are used in order to calculate the transformer's annual costs and present worth, and these values are then used in order to obtain the transformer EUAC curves.

5.2.2 Calculation of the Transformer's Present Worth Stage

The next stage involves the calculation of the present worth at each year of the useful lifetime of both the new and the existing transformers. A transformer's present worth is calculated using a proposed depreciation method, which is different from the concept used by accounting specialists, which is discussed in depth in [66, 68, 91]. The two usual main types of time-based depreciation are straight line depreciation and accelerated depreciation, with only one depreciation method being used throughout a lifetime. The presented technique for calculating an asset's present worth is based on using the depreciation rules in a new way. A different depreciation method is used for each stage of the lifetime in order to account for the changes that occur during the three different lifetime stages: infant, normal, and wear-out. Therefore, the present worth of the transformer for each year of its lifetime can be assumed to be the real market value of the transformer.

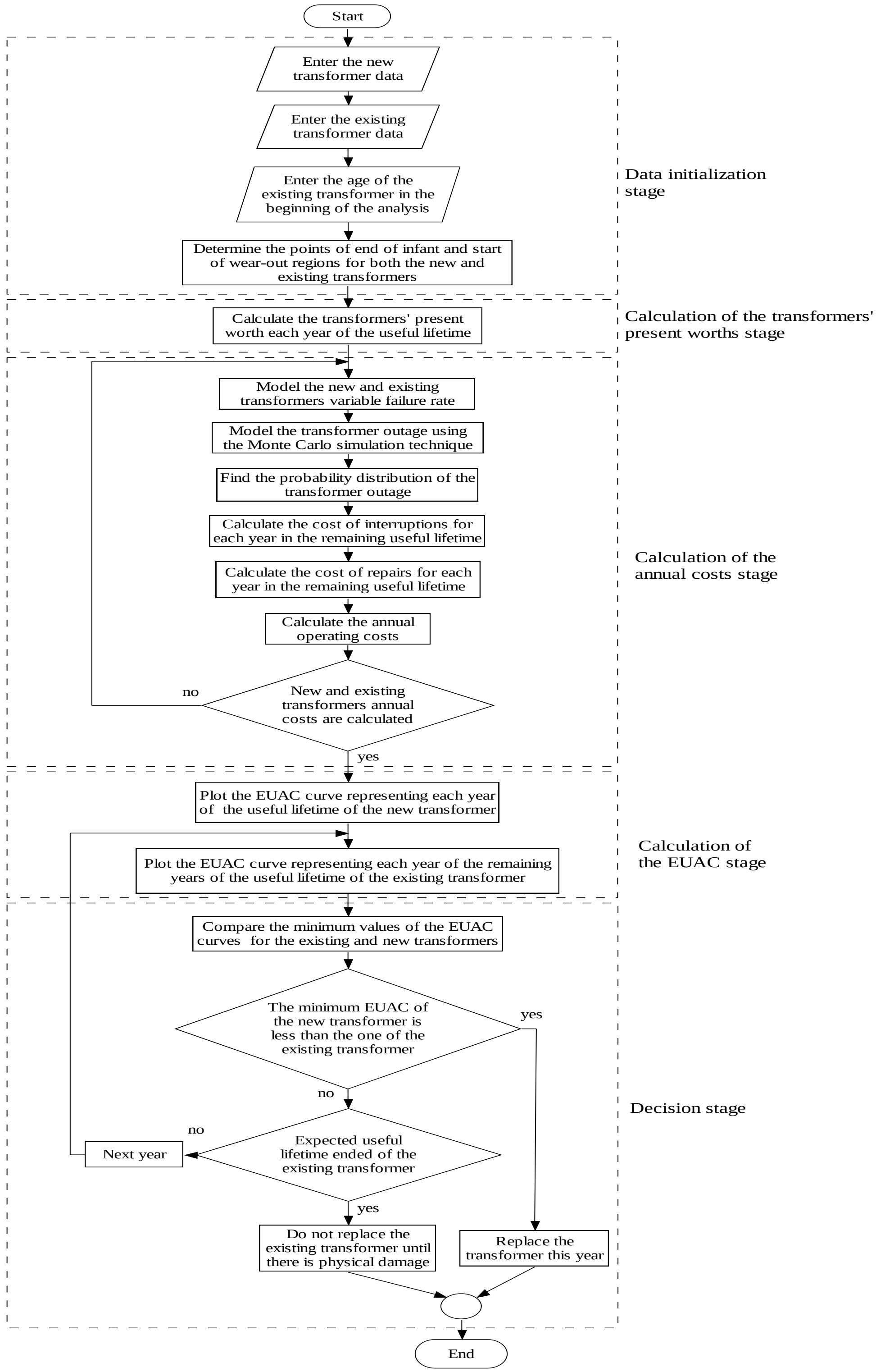

Fig. 5-1 Flow chart for the proposed replacement method.

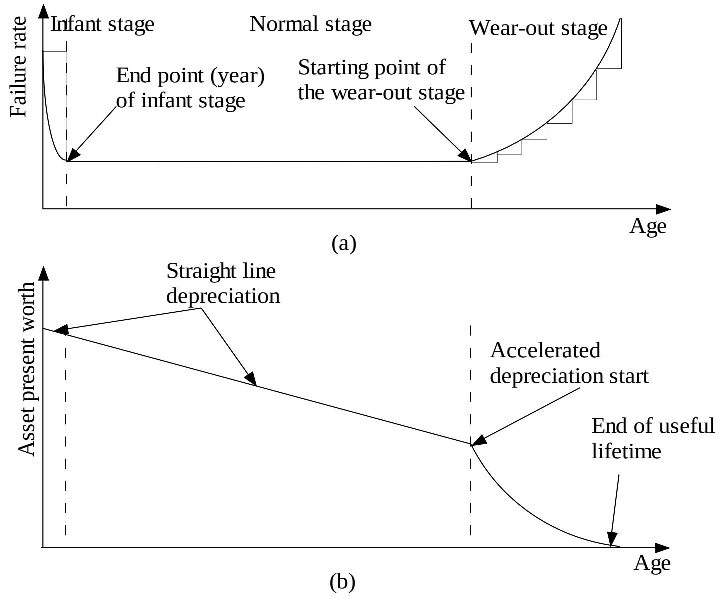

Fig. 5-2 The proposed depreciation technique (a) Transformer failure rate model (b) Present worth of the asset based on the stages of the physical lifetime.

According to the bathtub pattern, the lifetime is segmented into the infant, normal, and wear-out stages, so the suggested depreciation model is likewise divided into three stages. The depreciation method for each stage depends on the properties of the failure rate (constant, increasing, or decreasing) in the corresponding stage. Straight line depreciation is thus suitable for the normal region because the failure rate is constant, and the depreciation of the transformer is therefore constant in this stage. In the wear-out stage, the depreciation of the transformer increases due to wear and tear. In the later years of the wear-out region, the value of the transformer is nearly equal to its salvage value; i.e., the transformer operator can no longer resell the transformer. The depreciation charges in the later years of the wear-out region are thus less than those in the early years. Therefore, an accelerated depreciation method such as the sum-of-years-digits (SOYD) method is more appropriate for the wear-out region. For the infant region, straight line depreciation is suggested. The infant region is very short compared to the other stages. It normally ends in one year or sometimes in even less than one year, so which depreciation method is used is unimportant because the difference is very small.

Fig. 5-2(a) depicts the bathtub failure model [86-88]. Fig. 5-2(b) represents a transformer's present worth (market value) throughout its useful lifetime, calculated using the proposed depreciation technique. After the depreciation of the transformer is modeled according to the above method, the present worth of the transformer at any point in its useful lifetime can be calculated according to formula (3-8).

According to the proposed depreciation model, the depreciation charges d(j) in the early years of operation, i.e., until the starting point of the wear-out stage, are calculated according to the straight line depreciation method. After the starting point of the wear-out region, the sum of years digits depreciation (SOYD) method is used. To calculate the depreciation charges using the SOYD method, a value for the capital cost must be included as part of the calculation equation [66-68]. The actual capital cost of the transformer cannot be used because the SOYD depreciation method is used only in the wear-out region, not from the beginning of the transformer's lifetime. To solve this problem, in the equation used to calculate the depreciation charges using the SOYD method in the wear-out stage, the present worth of the transformer at the end of the normal region is used in place of the actual capital cost. These depreciation charges are used in (3-8) to calculate the present worth of the transformer at the end of any year. Details about the straight line and accelerated depreciation methods can be found in [66, 68, 91].

5.2.3 Calculation of the Annual Costs Stage

The purpose of this stage is to calculate the annual cost of interruptions, the cost of repairs, and the operating cost for both the new and existing transformers in conjunction with their present worth in order to calculate the EUAC value for both the new and existing transformers. The bathtub model for the failure rate and the uncertainty associated with the failure rate of the transformer are both taken into account when the annual costs are calculated. The next subsections explain the steps involved in calculating the annual costs of the new and existing transformers.

5.2.3.1 Modeling the Transformer Failure Rate

The first step in determining the annual costs is to model the changes in the failure rate throughout the useful life of the transformer. The calculated failure rate values for each year of the transformer's lifetime are then used to calculate the annual cost of repairs. They are also required in the Monte Carlo modeling of the transformer outages that is utilized in the calculation of the annual cost of interruptions.

To model the changes in the failure rate during the transformer's lifetime, a time-varying scaling factor is used [88]. The scaling factor is constant in the normal stage, increases in the wear-out stage, and decreases in the infant stage, as shown in Fig. 5-3. The time-varying failure rate is calculated as follows:

$$\lambda(t) = \alpha(t) \times \lambda_n \tag{5-1}$$

where

λ(t): the failure rate at year (t);

λ_n : the failure rate of the normal region of the bathtub curve;

α(t): the exponential time-varying scaling factor.

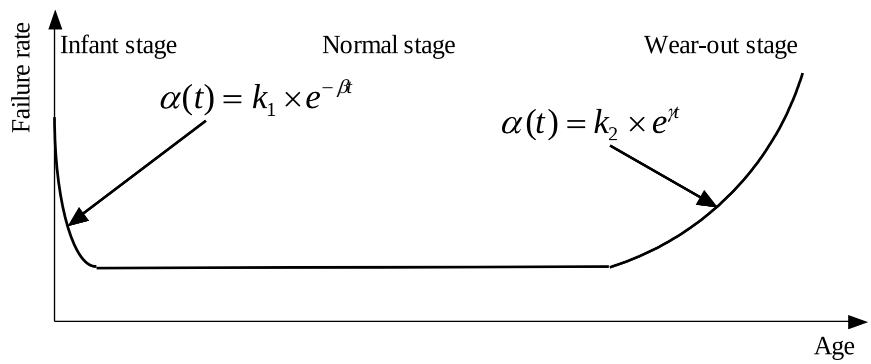

Fig. 5-3 Time-varying scaling factor.

The variable (λ_n) represents the constant failure rate normally used for the transformer; (λ_n) is thus an input in (5-1). The scaling factor decreases exponentially towards the end of the infant region, where it diminishes to a scaling factor of unity in the normal region; it subsequently increases exponentially in the wear-out region.

The scaling factor during the infant region is given by [88]

$$\alpha(t) = k_1 \times e^{-\beta t} \tag{5-2}$$

where

k_1: the maximum value of the scaling factor at the beginning of the infant period;

β: a factor that is calculated by substituting unity for α(t) at the end of the infant region.

$$\beta = \frac{\ln(k_1)}{t_{\inf ant}} \tag{5-3}$$

where t_{infant} denotes the infant period in years.

During the wear-out period, the scaling factor begins to increase exponentially [88]:

$$\alpha(t) = k_2 \times e^{\gamma t} \tag{5-4}$$

where the k_2 and γ factors represent the rate of exponential increase.

(k_2) is determined by substituting unity for $\alpha(t)$ at the starting point of the wear-out region.

$$k_2 = e^{-\gamma(lifetime - t_{wo})} \tag{5-5}$$

where
lifetime: the expected useful lifetime of the transformer;
$t_{wo:}$ the duration of the wear-out region in years.

γ is the calculated scaling factor at the end of the expected useful lifetime given by

$$\gamma = \frac{\ln(\alpha_{\max})}{t_{wo}} \tag{5-6}$$

where α_{max} represents the maximum value of the scaling factor at the end of the wear-out region.

The values of k_1, t_{infant}, t_{wo}, and α_{max} should be provided as data that are complementary to the initial data. By substituting for t_{infant} in (5-3), lifetime and t_{wo} in (5-5), and t_{wo} and α_{max} in (5-6), the scaling factor can be calculated for the infant and the wear-out regions of the transformer's lifetime using (5-2) and (5-4). The failure rate at any year (t) can then be calculated using (5-1).

5.2.3.2 Modeling the Transformer Outage Probability Distribution

The next step is to calculate the transformer outage probability distribution using the Monte Carlo technique. This probability distribution is used in the next step in order to calculate the annual cost of interruptions. The transformer failure rate is modeled year by year as mentioned before. According to Fig. 5-2(a), each year of the transformer's lifetime has an average failure rate value, which can be calculated according to the previous step. The output of the Monte Carlo simulation is the probability distribution of the transformer outage time. The transformer outage is modeled using the four-state outage model shown in Fig. 5-4 [81, 92]. In this model, the transformer is typically in one of the following four states:

(i) State (1) is the normal operating state (in service), in which the transformer is operating and feeding its loads.

(ii) State (2) is the switching state (out of service), in which the transformer is transferred from the up state to the switching state in the case of a forced outage (failure) in order to be ready for repair.

(iii) State (3) is the repair state (out of service), in which the transformer is switched out after the failure in order to start the repair process.

(iv) State (4) is the scheduled maintenance state (out of service), in which the transformer is shut down in order to perform scheduled maintenance.

According to Fig. 5-4, the transformer outage is either a forced outage or an outage due to scheduled maintenance. The time to failure (TTF), time to switch (TTS), and time to repair (TTR) are all random variables governed by specific probability distributions. The time during scheduled maintenance, which is called here the scheduled repair time (SRT), is also a random variable governed by a specific probability distribution. The Monte Carlo simulation technique is used to account for uncertainties in the failure rate, the TTF, the TTS, the TTR, and the SRT. The sequential Monte Carlo simulation is used to evaluate the transformer outage time and its probability distribution. A transformer is typically either in service (up state) or out of service (down state). A transformer is considered to be in its up state when it is operating and feeding its loads and to be out of service (down state) during switching, repairs, or scheduled maintenance. The parameters 1 and 0 are assigned for the up and down states of the transformer, respectively.

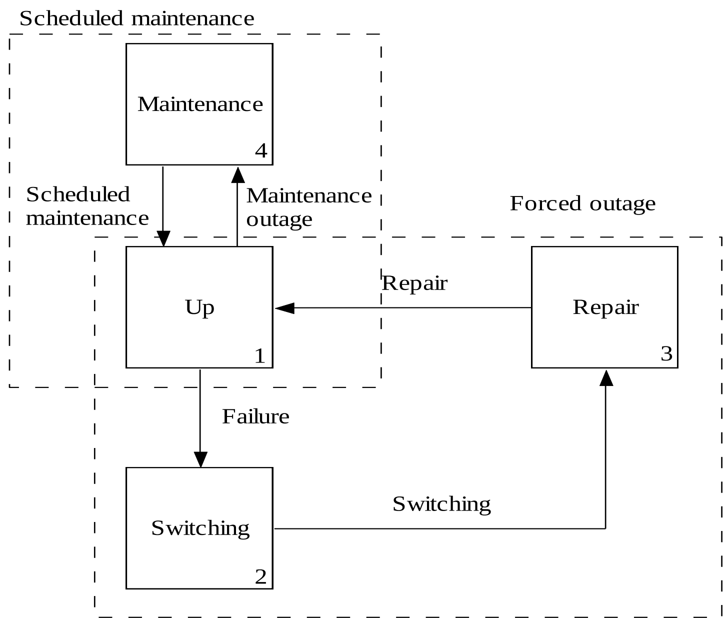

Fig. 5-4 Transformer four-state outage model.

Two artificial histories are generated for the transformer in order to simulate the forced and scheduled outages using the Monte Carlo simulation. The sampling technique is the state duration sampling (sequential sampling) [81]. The state duration sampling is based on sampling the probability distribution of the component state duration (up or down). In this approach, chronological component state transition processes for all system components are first simulated (artificial history). The chronological state transition process for the total system is then created by combining all of the chronological component state transition processes (total system artificial history) [81].

In the present case, the total transformer artificial history is generated from the forced outage artificial history and the scheduled outage artificial history based on Fig. 5-4. These two artificial histories are combined (multiplied) to generate the total transformer artificial history, which is then used in order to determine the probability distribution of the outage time per failure.

In the scheduled maintenance process, time-based maintenance (TBM) is assumed to be the maintenance strategy, implying that maintenance is performed at predetermined intervals: i.e., the time to scheduled maintenance (TTSM) is constant. As a result, the SRT is the only random variable in the scheduled maintenance artificial history. The scheduled maintenance artificial history has the form shown in Fig. 5-5(a). The steps taken to generate the scheduled maintenance artificial history are as follows [81, 92]:

Step 1: Let the initial state of the transformer be the up state, i.e., the transformer is operating.

Step 2: Generate a random number sequence (U_1) between (0, 1) with minimal correlation.

Step 3: Find the durations of the SRT using the following formula:

$$SRT = F^{-1}(U_1) \tag{5-7}$$

where

SRT: the scheduled repair time random variable;

$F^{-1}(U_1)$: the inverse of a selected cumulative probability distribution function.

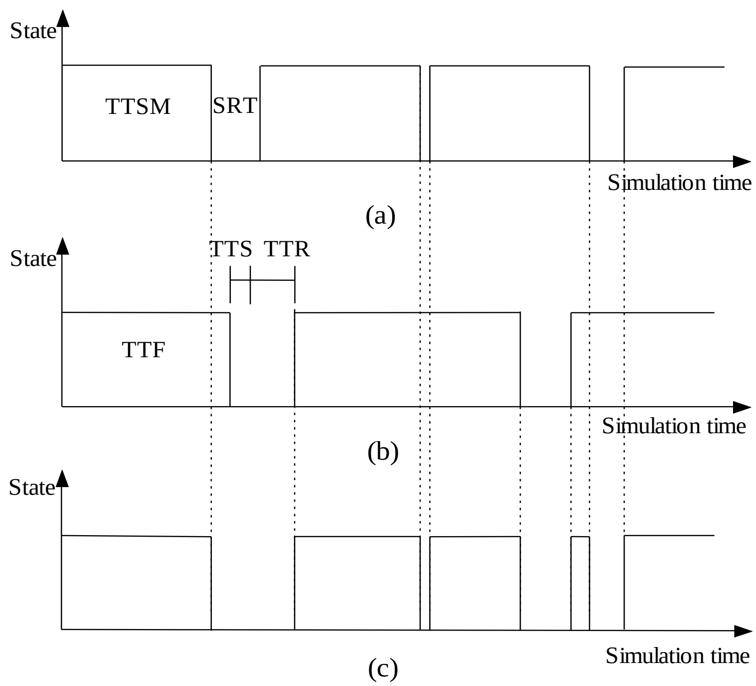

Fig. 5-5 The transformer artificial history (a) scheduled maintenance artificial history (b) forced outage artificial history (c) total transformer artificial history.

The resulting SRT variable is a random variable that is randomly distributed according to the selected probability distribution. The artificial history is built by starting the history with the TTSM and then inserting the first element of the SRT calculated in step (3). The TTSM is then inserted again into the artificial history followed by another value of the SRT, and so on, until the end of the artificial history is reached.

In the forced outage artificial history, three variables exist: TTF, TTR, and TTS. The steps for generating the artificial history of the forced outage are as follows [81, 92]:

Step 1: Let the initial state of the transformer be the up state, i.e., the transformer is operating.

Step 2: Generate three sequences of random numbers, (U_2, U_3 U_4), between (0, 1) with the same specifications as previously mentioned.

Step 3: Similarly, sample the duration of the TTF as explained above using the following formula:

$$TTF = F^{-1}(U_2) \tag{5-8}$$

Step 4: Repeat step 3 for the TTS and TTR using the random number sequences U_3 and U_4.

The resulting variables TTF, TTS, and TTR are random variables, which are randomly distributed according to the selected distribution types. The artificial history is built by starting the history with the first element of the TTF calculated from step 3 and then inserting the first element of the TTS calculated in step 4. The first element of the TTR calculated in step 4 is then inserted to complete one cycle. The next cycle starts with the insertion of the second values of the TTF, TTS, and TTR random variables, following the same approach illustrated above, and so on, until the end of the artificial history is reached. The artificial history is then as shown in Fig. 5-5(b).

The total artificial history of the transformer looks like the one shown in Fig. 5-5(c). The total transformer chronological artificial history can be used for any type of reliability analysis required, such as calculating the outage time per year and its probability distribution, or the outage time per failure and its probability distribution [81]. The smallest time unit taken in this simulation is one half-hour because smaller time units take considerable simulation time without much effect on the final results. The simulation continues year after year, and the average outage time per failure is calculated during the simulation time using the following formula:

$$r_a = \frac{\sum_{j=1}^{TO} r_j}{j} \tag{5-9}$$

where

r_a: the average outage time per failure;

r_j: the outage time for failure (j);

T : the total number of transformer outages during the simulation period (artificial history).

The simulation of the artificial history continues until the stopping criterion is reached. The stopping criterion of the Monte Carlo simulation depends on the coefficient of variation (ε) [80]. The same equations (4-12) to (4-14) can be used here. The simulation stops when (ε) goes below a specific small tolerance level (TL). The estimate function is (r_a)

To obtain the probability distribution of the outage time per failure (or duration), the probability of outage events must be calculated for each probable duration. The probability of (x)-hour transformer outages is calculated using

$$P_x = \frac{TO_x}{TO} \tag{5-10}$$

where

P_x: the probability of transformer outage occurring for x hours;

TO_x: the total number of transformer outages of x hours during the simulation (artificial history).

These procedures for calculating the outage time per failure probability distribution are performed on a year-by-year basis, i.e., they are repeated each year of the useful lifetime of the transformer because the failure rate varies during the different life stages. The result is a number of probability distributions for the outage time per failure equal to the number of useful lifetime years of the transformer. The next subsection describes how these probability distributions are used to calculate the annual cost of interruptions.

5.2.3.3 Calculation of the Annual Cost of Interruptions

The next step is to calculate the annual cost of interruptions using the probability distributions of the outage time per failure calculated in the previous step. Customer surveys provide interruption cost estimates by sector or by what is termed the sector customer damage function (SCDF) [81, 93]. A cost of interruption survey was conducted in Canada to establish the SCDF for a variety of customers [81, 94-96]. Interruption cost data are normalized by dividing the cost of the interruption by the annual peak load in kW ($/kW). The SCDF represents a function of the cost of the interruption per unit of power and the duration of the outage in each sector. The SCDF is a curve that relates the cost of a power interruption in ($/kW) to outage durations of 0.33, 1, 4, and 8 hours. If the loads supplied by the transformer are composed of different types (sectors), a group customer damage function (GCDF) should be calculated in order to determine the total cost of interruptions due to the transformer outage [81, 94-96]. The GCDF is also a curve that relates the cost of a power interruption in ($/kW) to outage durations of 0.33, 1, 4, and 8 hours. To determine the GCDF, weighting factors are calculated (w_k) for all sectors. The weighting factor for a sector is the annual energy consumption of that sector expressed as a percentage of the total annual energy consumption. Equation (5-14) illustrates the method for calculating the GCDF [81, 95]:

$$GCDF_j = \sum_{k=1}^{S} SCDF_{jk} \times w_k \tag{5-11}$$

where

$SCDF_{jk}$: the sector customer damage function for load type (k) and duration index (j);

w_k: the weighting factor for load type (k);

S: the number of load sectors.

Equation (5-14) is applied on a point-by-point basis; e.g., the $GCDF_1$ represents the value of the GCDF for a 0.33 hr outage duration, and GCDF1 denotes the value of the GCDF for a 1 hr outage duration, and so on. The resulting total cost of interruption is high if the bulk power supplied by the transformer is directed mainly to a high SCDF, and vice versa.

The classic method for calculating the annual cost of transformer interruptions is based on the multiplication of three terms: the failure rate times the average load served by the transformer times the value of the GCDF that corresponds to the average outage time per failure [81, 95]. However, this method is not accurate because it assumes that the outage time per failure is certain, but in fact, it has an inherent uncertainty. In addition, the failure rate of the transformer is not constant because it is governed by the bathtub curve.

In the proposed technique, the probability distributions of the outage time per failure determined in subsection (5.2.3.2) are used as a means of finding the cost of interruption distribution. For any year, the cost of interruptions in the current year is calculated using the probability distribution of the outage time per failure for that particular year. The cost of interruption is calculated for each probable outage event by multiplying the failure rate of the year by the average load served by the transformer by the GCDF that corresponds to the outage time of each probable event. The result is a probability distribution for the cost of interruptions based on the probable outage time per failure event determined earlier. The cost of interruptions ($C_p(t)$) of a particular year (t) is the average value of this probability distribution. Due to the non-linearity of the SCDFs, this calculated average cost of interruptions for each year is not equal to the cost of interruptions that corresponds to the average outage per failure.

5.2.3.4 Calculation of the Annual Cost of Repairs

In a manner similar to that used for the annual cost of interruptions, the annual cost of repairs is used to calculate the EUAC. The repair and scheduled maintenance costs are assumed to be governed by a linear relationship. A constant amount of money (b) is assumed to be spent for any repair or scheduled maintenance. A variable amount (a) is assumed to be spent for each hour of the outage duration.

$$C_r(t) = (a \times r_a + b) \times \lambda(t) \tag{5-12}$$

where

$C_r(t)$: the annual repair cost for year (t);

a: the variable repair cost per hour;

r_a: the average outage time per failure for the particular year;

b: the constant repair cost per outage;

$\lambda(t)$: the average failure rate for the particular year (t).

5.2.3.5 Calculation of the Annual Operating Cost

The annual operating cost is also used in the calculation of the EUAC. The operating cost is divided into the energy cost and the demand cost.

$$C_o = (P_{nl} + P_l \times LF^2 + P_{au} \times prob.) \times 8760 \times tariff + (P_{nl} + P_l + P_{au}) \times D_c \times 12 \qquad (5\text{-}13)$$

where

C_o: the annual operating cost;

LF: the load factor;

tariff: the energy tariff ($/kWh);

P_{nl}: the no load power losses (kW);

P_l: the load losses (kW);

P_{au}: the auxiliary losses;

Prob.: the probability of operation of the auxiliary equipment;

D_c: the monthly demand charge ($/kW).

The main auxiliary equipments are the motors used for operating the forced air and the oil pumps. In large units, these motors must operate when the load exceeds a specific value. The probability of the operation of the auxiliary equipment is equal to the number of operating hours of the pumps expressed as a percentage of the number of hours in any given month.

The three main annual costs are then calculated for the new transformer over each year of its useful lifetime. Similarly, the annual costs are also determined for the remaining years of the useful lifetime of the existing transformer. As indicated in Fig. 5-1, the next stage is to determine the EUAC for both the new and existing transformers, which will be utilized for arriving at a replacement decision.

5.2.4 Calculation of the EUACs for the New and Existing Transformers

The next and most important stage is to calculate the EUACs for the new and existing transformers. The cash flow diagram for the whole lifetime of a new transformer is shown in Fig. 5-6. Fig. 5-6 shows that annual costs start with high values due to the high failure rate in the infant region. The costs become steady in the normal region and then begin to increase in the wear-out region due to the increase in the failure rate, which causes the cost of interruptions and repairs to increase as well.

The calculation of the EUAC relies on the conversion of all unequal annual costs of the transformer into equivalent equal annual costs, beginning with the decision year (present age of the existing transformer) and terminating at each year of the remaining years of the transformer's useful lifetime [67, 68, 91, 97]. The result is a curve that represents the equivalent equal annual cost of keeping the transformer in service each year for the duration of the expected remaining physical lifetime (cf. Fig. 5-7). The curve depicted in Fig. 5-7 indicates the minimum uniform annual cost (\$EUAC-$_{min}$,), which represents the amount of funds expended by the transformer's owner every year in order to maintain the transformer in service for a period of 12 years after the decision year (most economical remaining lifetime).

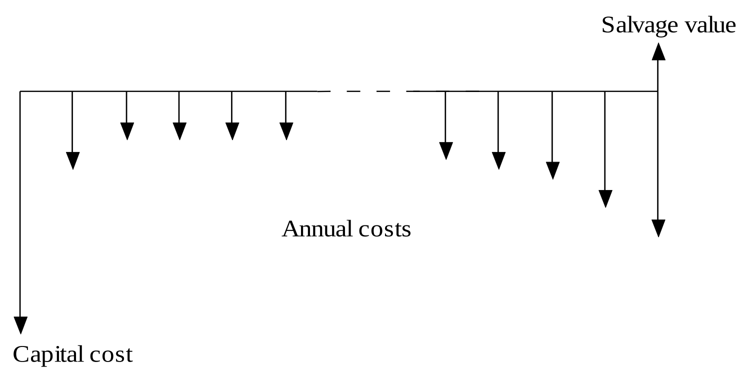

Fig. 5-6 Cash flow diagram for the new transformer.

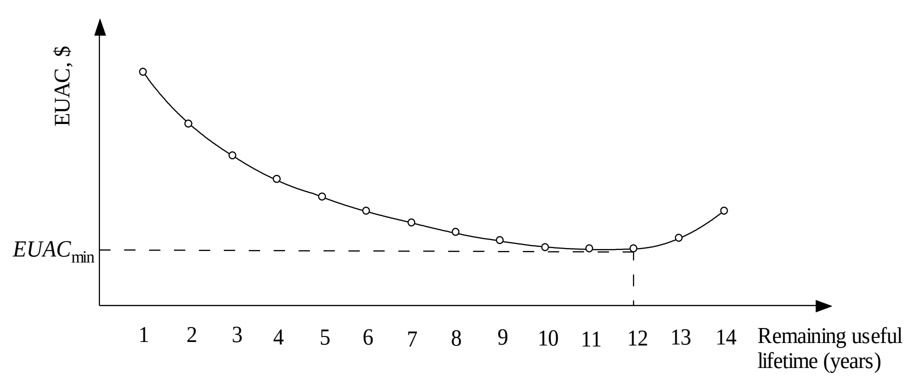

Fig. 5-7 Equivalent uniform annual cost (EUAC) for a transformer.

The EUAC of the new transformer is calculated in the same way as that of the existing transformer except that the calculation starts from the first year of the lifetime of the new transformer. The result is a curve that is nearly the same as the one shown in Fig. 5-7. However, the x-axis represents the total useful lifetime rather than the remaining useful lifetime. The EUAC for a specific year (the calculation year) is determined by calculating the future value of all transformer costs (the capital cost and the annual costs) preceding the calculation year minus the present worth of the transformer at the calculation year. The resultant value is converted into equal annual installments from the first year to the calculation year [66, 68]. The steps in the calculation of the EUAC for the new transformer are as follows.

The first step is to calculate the future value:

$$FV_m = C(F/P,i,m) - PW(m) + \sum_{j=1}^{m}(C_{o_j} + C_{r_j} + C_{p_j})(F/P,i,m-j) \tag{5-14}$$

where

FV_m: the future value of all transformer costs at the calculation year (m) minus the present worth of the transformer at year (m);

(F/P, i, m): the single-payment future-worth factor for interest rate (i) and period equal to (m) years;

PW (m): the transformer's present worth at year (m);

m: the year for which the EUAC is being calculated (the calculation year).

The single-payment future-worth factor can be calculated as follows;

$$(F/P,i,m) = (1+i)^m \tag{5-15}$$

The second step is to convert the net future value into equal annual installments, which are the EUAC from the first year until year m (calculation year).

$$EUAC_m = FV_m(A/F,i,m) \tag{5-16}$$

where

$EUAC_m$: the equivalent uniform annual cost for year m;

(A/F,i,m): the sinking fund factor for interest rate (i) and period equal to (m) in years.

The sinking fund factor is given by

$$(A/F,i,m) = \frac{i}{(1+i)^{m} - 1} \tag{5-17}$$

The EUAC for the new transformer is calculated from the first year until the end of its useful lifetime; i.e., the result is a single curve. For example, the EUAC for year five on the curve is the expected annual cost paid by the transformer owner to keep it in service for five years. For most cases, the most economical lifetime for a new asset is that of the useful lifetime of the asset or very close to it. The minimum point of the EUAC curve for the new transformer represents the economic lifetime of the new transformer.

The steps in calculating the EUAC curve points for the new transformer are repeated for the existing transformer. The EUAC curve in this case is plotted from the year following the present age of the existing transformer up to the end of its useful lifetime. Equations (5-14) to (5-17) are used for the case of the existing transformer except for two changes. The first change is that (m) now represents the calculation year starting from the present age of the existing transformer. For example, if the present age of the existing transformer is 22 years, then the year following the 22nd year is the first calculation year for the existing transformer, and (m) in this case is 1 and not 23. The second change is that the capital cost (C) is replaced by the present worth at the present age of the existing transformer. The minimum point of the EUAC curve for the existing transformer is recorded. This point represents the economic lifetime of the existing transformer.

5.2.5 Decision Stage

After the EUAC is calculated for the new and existing transformers, two curves are generated. The first is the EUAC curve for the new transformer, which runs from the first year of the transformer's lifetime until the end of its useful lifetime. The second curve is the EUAC curve for the existing transformer, which starts from the year following the present age of the existing transformer and ends at the last year of its useful lifetime. The minimum EUAC is recorded for the existing and the new transformers (EUAC for the most economical remaining lifetime). The minimum EUAC for the new transformer is compared to the minimum EUAC for the existing transformer. If the minimum EUAC for the new transformer is less than the minimum EUAC for the existing transformer, then the existing transformer should be replaced with the new transformer in the current year. If this condition is not satisfied, then the existing transformer should not be replaced.

The question now is when the existing transformer should be replaced. To solve this problem, the EUAC curves for the existing transformer should be plotted starting from each year subsequent to the present age of the existing transformer, one year at a time. The result is a family of curves equal to the remaining lifetime years of the existing transformer. None of these curves coincides with the preceding curve, because the cost calculations for each EUAC curve do not take into consideration the past costs of the preceding year, which is termed the non-owner viewpoint [66]. The same approach used in plotting the first EUAC curve for the existing transformer is used to plot the subsequent EUAC curves that begin in each of the years subsequent to the present age of the existing transformer, one year at a time. The EUAC curves for the existing transformer starting from each subsequent year are plotted year after year until the minimum point of the EUAC curve for the new transformer is less than the minimum point of the EUAC curve for the existing transformer, which commences at some year between its present age and its useful lifetime. This is the year during which the transformer should be replaced; otherwise, the operator will incur higher annual costs.

The performance of the presented techno-economic replacement method for transformers is evaluated in the next Chapter. Two case studies are used to test the performance of the proposed method. The effect of changing parameters is also tested in the sensitivity analysis section.

5.3 Conclusion

A new method for determining the life expectancy of transformers, and accordingly the time to replacement, has been proposed. This method has the advantage of being based on both economic constraints and the technical parameters of the transformer. Transformer stresses are indirectly accounted for by the use of the bathtub model of the failure rate. The new method is, in essence, a reliability-based method that is supported by consideration of the economic factors in transformer operation; it yields the likely number of years remaining in the lifetime of a transformer before it is removed from service. The transformer costs used in the economic analysis are calculated based on the bathtub failure model, while a linear repair model is employed in order to calculate the repair costs. A Monte Carlo technique and the failure rate data obtained from the bathtub model are used in order to calculate the annual cost of interruptions. A new depreciation method is introduced for determining the present worth of the transformer throughout its lifetime. This depreciation method is designed to mimic the differences in the failure rate represented by the bathtub model. The transformer's present worth, the cost of interruptions, the cost of repairs, and the cost of operation are used to obtain the EUAC for both the new and the existing transformer. The EUAC concept is utilized in order to determine the most economical replacement year.

In a time of aging power system assets, it is important to plan for the retirement of equipment. The method presented in this Chapter provides an effective tool for estimating the life expectancy of power apparatus assets: a unique advantage not offered by other existing procedures, which can determine only whether the equipment should be replaced at the time of the assessment.

Chapter 6
A Techno-Economic Method for Replacing Transformers: Case Studies

6.1 Introduction

This Chapter presents the performance evaluation of the techno-economic replacement method for a transformer presented in the previous Chapter. Two case studies are used in this Chapter to test the performance of the proposed method. It is found that the proposed method gives reliable results in the two case studies. The effect of changing the parameters is also tested in the sensitivity analysis section. Moreover, a comparison is done with a thermal based technique.

6.2 Case Study I

6.2.1 Data Initialization

In this case study, a 2 MVA power transformer is assumed to feed an industrial plant as shown in Fig. 6-1. At the end of the 21st year of the defender (existing transformer) age, it is required to determine the best year to replace the transformer using the techno-economic replacement method. The transformer load is assumed to be of one type and the challenger (new transformer) capital cost is assumed to be constant, with no annual increase in the cost for the sake of illustration and simplicity. The annual increase in the challenger's capital cost will be considered in case study II. Moreover, different load types with different sector customer damage functions (SCDFs) will be considered in case study II to represent a real situation.

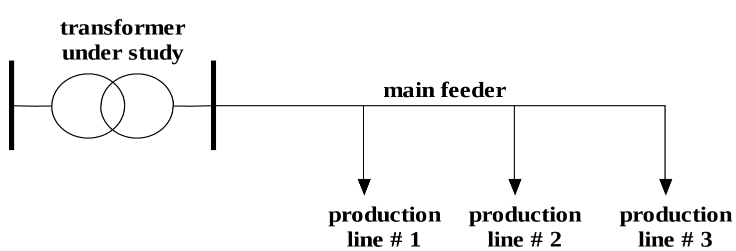

Fig. 6-1 Single line diagram for the system of case study I.

The technical specifications of the new and existing transformers, such as the useful lifetime, the infant and normal regions' durations, the failure rate, repair times, and losses, are assumed to be identical for the defender and the challenger. The new and existing transformers' technical data are documented in Table B-I, the load data are documented in Table B-II, and the financial data are documented in Table B-III in appendix B. The SCDF of the industrial load is shown in Table B-IV in appendix B. In this study, the existing transformer capital cost is assumed to be $150,000 and the new transformer capital cost is $250,000. The useful lifetime of both the challenger and the defender is assumed to be 35 years [83]. The transformers are assumed to start wear-out at the end of year 20 [89, 90]. The infant mortality region is taken as one year for both transformers. The failure rates of the normal region of the new and existing transformers are assumed to be 0.07 failures/year [98]. The average transformer repair time is 24 hour/failure [98]. The mean switching time, the scheduled maintenance rate, and the average scheduled maintenance time are assumed to be 1 hour, 0.2 occurrence/year, and 10 hrs/failure, respectively [81].

According to [89], the failure rate in the wear-out region doubles in ten years. The wear-out region duration in this study is taken from year 21 to year 35, i.e., 15 years; as a result, the failure rate at the end of the transformer lifetime is taken as 0.2 failure/year, which is nearly three times the failure rate in the normal region. The infant region failure rate is higher than the normal region failure rate, but lower than the maximum failure rate in the wear-out region, so, the maximum failure rate in the infant region is taken as 0.105 failure/year (1.5 times the failure rate in the normal region [99]). The SCDF of the industrial plant is taken from [96] and is shown in Table B-IV in appendix B. The transformer depreciation is taken as a straight line in both the infant and the normal regions. The infant region is very short (one year), therefore, it is included in the normal region in the depreciation calculation. The accelerated depreciation method used in the wear-out region is taken as sum of the years digits (SOYD). The present age of the existing transformer is taken as 21 years (end of year 21).

6.2.2 Present Worth of Existing and New Transformers

The present worth of the existing and new transformers are calculated using the proposed algorithm presented in Chapter 5. The present worth of the existing and new transformers across their lifetimes are shown in Fig. 6-2.

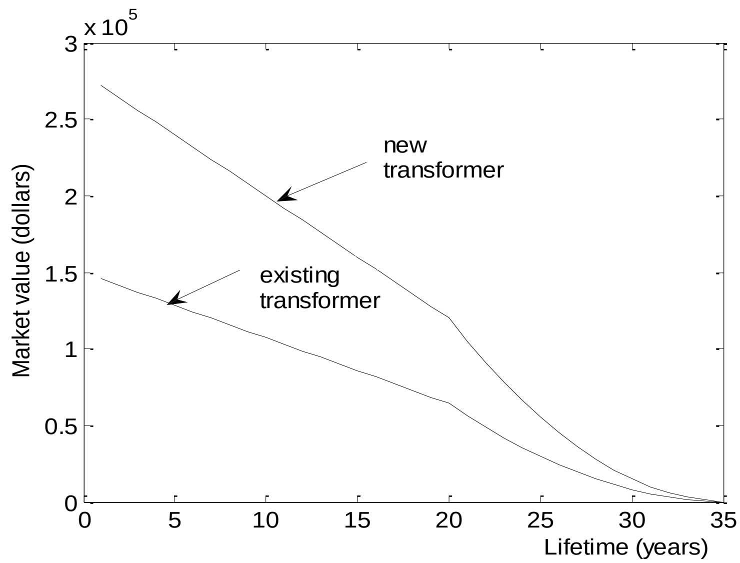

Fig. 6-2 Existing and new transformers' market values along their lifetimes.

6.2.3 Calculation of the Annual costs

6.2.3.1 Annual cost of Interruption

The SCDF is used directly here as the transformer load is of one type; therefore, the calculation of group customer damage function (GCDF), which represents the damage function for a group of different loads, is not needed. The transformer outage is modeled using the Monte Carlo technique. The time to failure (TTF) is modeled as exponentially distributed while the time to repair (TTR), time to switch (TTS), and scheduled repair time (SRT) are modeled as log-normally distributed [81]. Use the time-varying failure rate model to find the average failure rate in all years of the useful lifetime as shown in Fig. 6-3.

The TTS and SRT will have standard deviations (SD) of mean/6 while the SD of the time to repair is mean/2. The log-normally distributed SRT, TTR, and TTS can be generated as follows [81]:

1. Generate four independent uniformly distributed random number sequences U_1, U_2, U_3, and U_{temp} between zero and one (0, 1). U_1 and U_2 are used to generate SRT and TTR, U_3 and U_{temp} are used to generate TTS. U_{temp} is a temporary random number sequence used to help generating the log-normally distributed random variates.
2. Use the independent random numbers U_1 and U_2 to generate two independent normally distributed random variates (Z_1, and Z_2) using the Box-Muller method as follows:

$$Z_1 = \sqrt{-2\ln(U_1)}\cos(2\pi U_2) \quad (6\text{-}1)$$

$$Z_2 = \sqrt{-2\ln(U_1)}\sin(2\pi U_2) \quad (6\text{-}2)$$

3. Use the independent random numbers U_3 and U_{temp} to generate two independent normally distributed random variates (Z_3, and Z_4) using the Box-Muller method as follows:

$$Z_3 = \sqrt{-2\ln(U_3)}\cos(2\pi U_{temp}) \quad (6\text{-}3)$$

$$Z_4 = \sqrt{-2\ln(U_3)}\sin(2\pi U_{temp}) \quad (6\text{-}4)$$

4. Calculate X1,X2, and X3 as follows:

$$X_j = \mu_j + \sigma_j Z_j \quad (6\text{-}5)$$

Where, μ_j and σ_j are the means and standard deviations of the normal distribution corresponding to the log-normal distribution. The parameters μ and σ can be calculated as follows:

$$\mu = \ln\left[\frac{mean^2}{(\text{var}iance + mean^2)^{1/2}}\right] \quad (6\text{-}6)$$

$$\sigma^2 = \ln\left[\frac{\text{var}iance + mean^2}{mean^2}\right] \quad (6\text{-}7)$$

5. SRT, TTR, and TTS are log-normally distributed random variates and are calculated as follows:

$$SRT = e^{X_1} \tag{6-8}$$

$$TTR = e^{X_2} \tag{6-9}$$

$$TTS = e^{X_3} \tag{6-10}$$

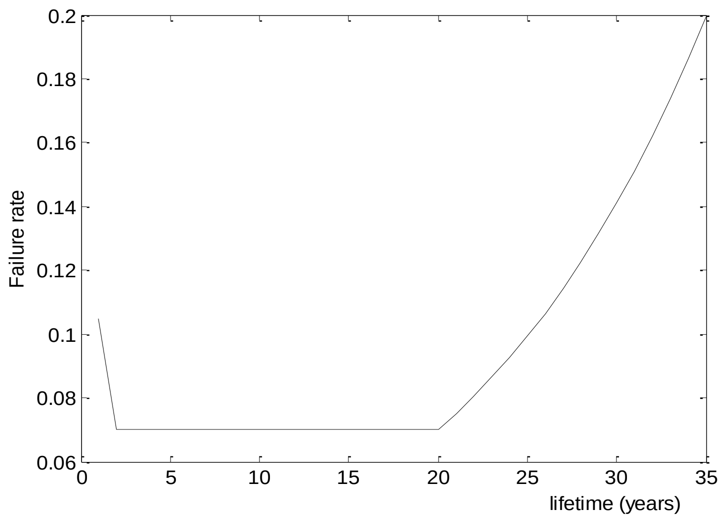

Fig. 6-3 failure rate in the useful lifetime of case study I.

The exponentially distributed can be generated as follows [81]:

1. Generate a uniformly distributed random number sequence U_4 between zero and one (0, 1).
2. Produce the cumulative distribution function for exponential distribution F(t) to produce TTF as follows.

   The probability distribution (density) function for the exponential distribution is

$$f(x) = \lambda e^{-\lambda x} \tag{6-11}$$

   Its cumulative distribution function is

$$F(x) = 1 - e^{-\lambda x} \tag{6-12}$$

Using the inverse transform, then X can be calculated as:

$$X = -\frac{1}{\lambda}\ln(1 - U_4) \tag{6-13}$$

Where U_4 is a uniformly distributed random number between (0,1). Since (1-U_4) distributes uniformly in the interval (0,1) the same way as U_4, as a result:

$$X = -\frac{1}{\lambda}\ln(U_4) \tag{6-14}$$

$$TTF = X \tag{6-15}$$

The transformer artificial history is generated as stated in section (5-2) and the estimate function is calculated throughout the artificial history. The Monte Carlo simulation stops when the coefficient of variation (ε) of the estimate function goes below TL of 0.0005. Samples of the convergence of the estimate function in the Monte Carlo simulation is shown in Figs. 6-4 to 6-7.

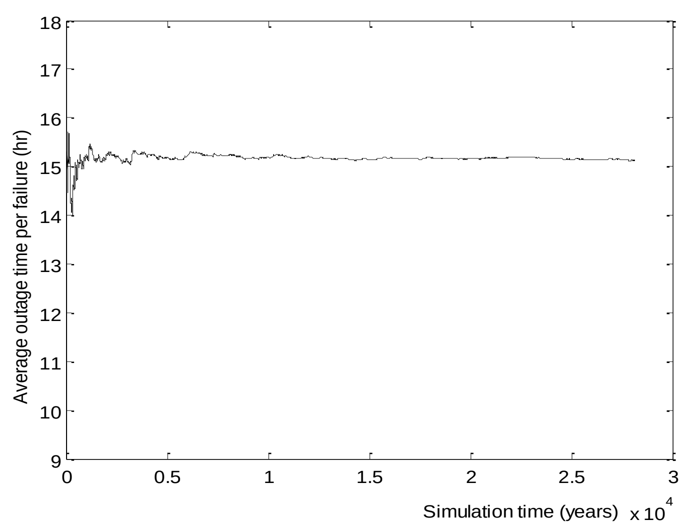

Fig. 6-4 Convergence of the estimate function in Monte Carlo simulation in the first year.

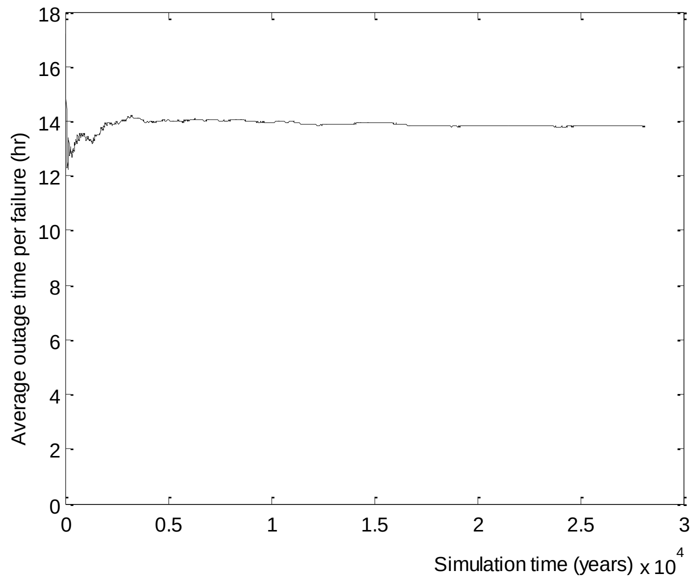

Fig. 6-5 Convergence of the estimate function in Monte Carlo simulation in the normal region (year 2 to year 21).

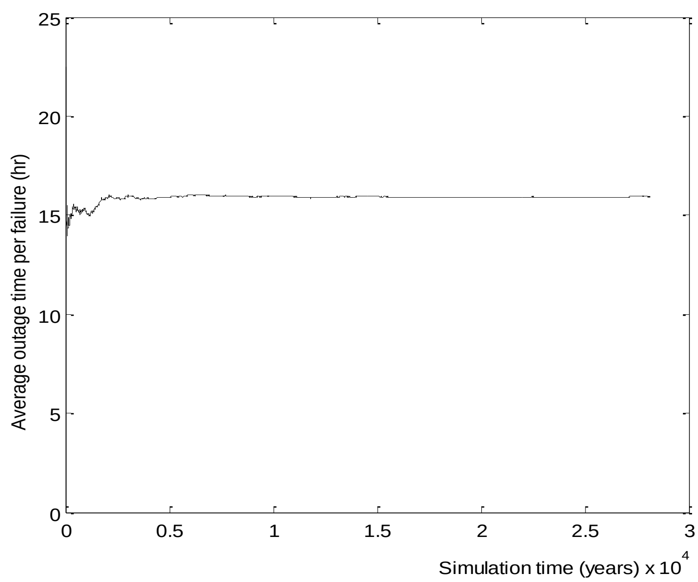

Fig. 6-6 Convergence of the estimate function in Monte Carlo simulation in the year 30.

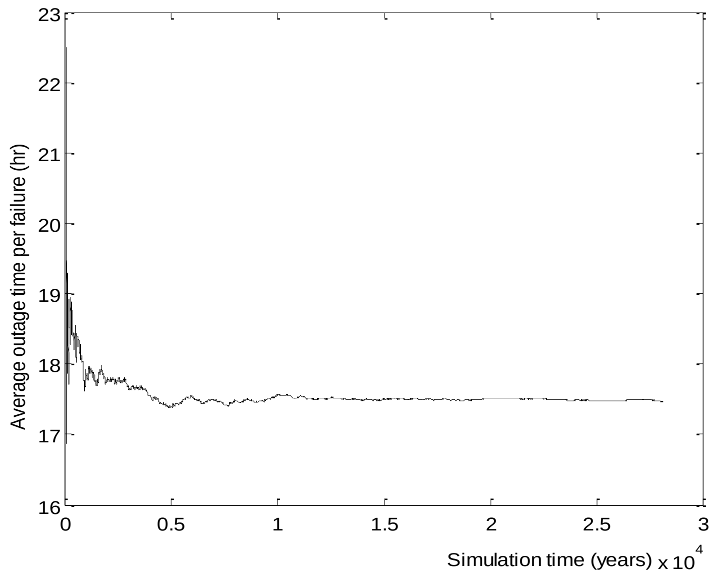

Fig. 6-7 Convergence of the estimate function in Monte Carlo simulation in the year 35.

The time-varying failure rate model is used to find the probability distribution of outage time per failure in each year of the transformer useful lifetime (the probability distributions of outage time per failure for both new and existing transformers are the same because the reliability data is assumed to be the same for both). Figs. 6-8 to 6-11 are samples of the resultant probability distributions in the infant, normal, and wear-out stages of the transformer life. These probability distributions are used to calculate the cost of interruption for each event of the outage events using the SCDF. This can be achieved by performing basic fitting for the SCDF. A quadratic fitting is a suitable choice. The resultant fitted curve is shown in Fig. 6-12. After calculating the cost of interruption for each probable outage event, the resultant is the same probability distribution with the outage durations replaced by their respective costs of interruption. The final cost of interruptions probability distributions are used to find the average cost of interruption for each year as discussed in section (5-3-3). The annual cost of interruption is shown in Fig. 6-13.

6.2.3.2 Repair Cost

The repair cost is calculated according to the presented linear model. To repair a 2MVA transformer, \$250 is used to represent the constant costs such as car rental, etc; \$540 is used for the variable cost per hour. The variable cost is based on a crew of 3 persons, each one with hourly wages of \$60, plus 50% overhead for the contractor. This means that the equivalent is \$270 per hour. The

$270 is multiplied by 2 to represent a rough estimate of any spare parts needed. The total variable cost is $540 per hour. The annual repair cost is shown in Fig. 6-13.

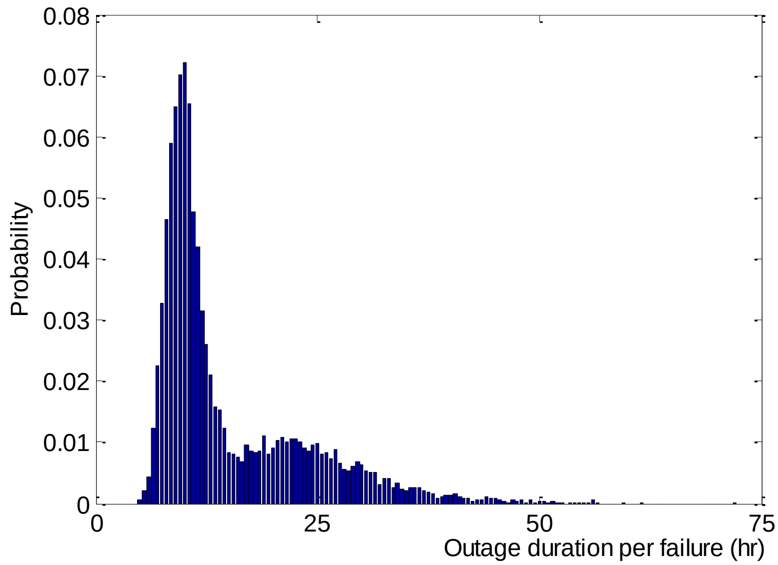

Fig. 6-8 Probability distribution of the outage duration per failure in the first year of the transformer life.

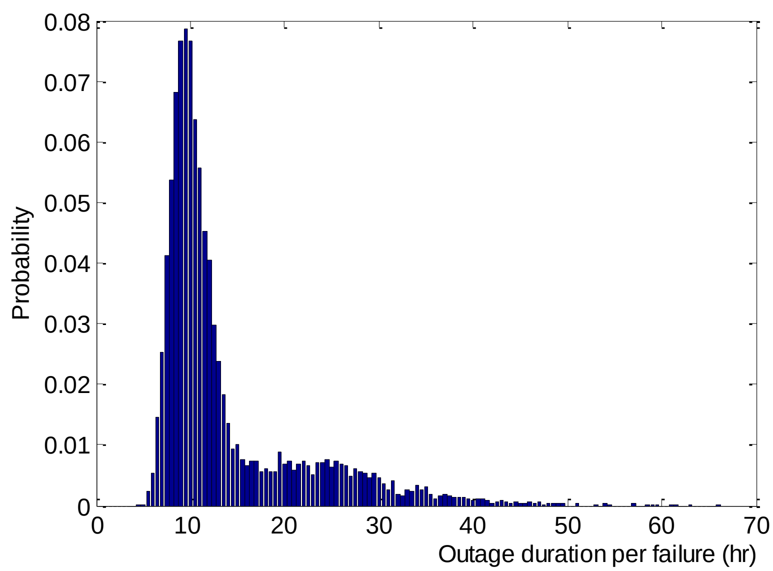

Fig. 6-9 Probability distribution of the outage duration per failure in the normal region (year 2 to year 21) of the transformer life.

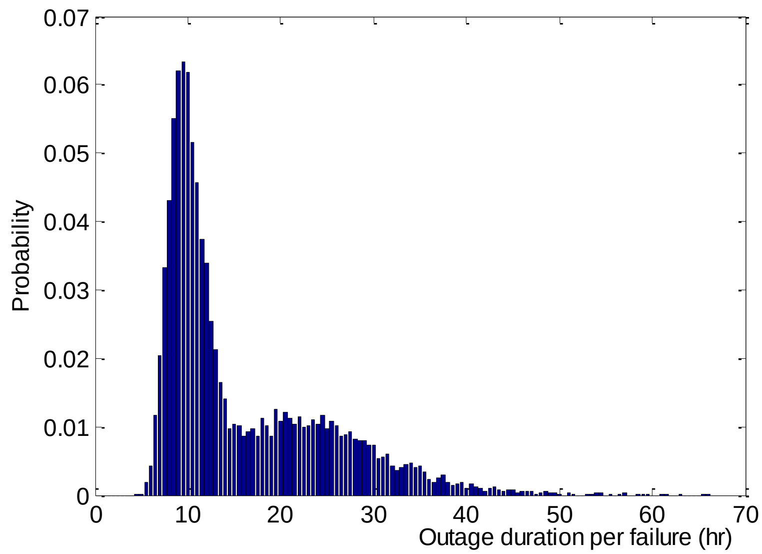

Fig. 6-10 Probability distribution of the outage duration per failure in year 30 of the transformer life.

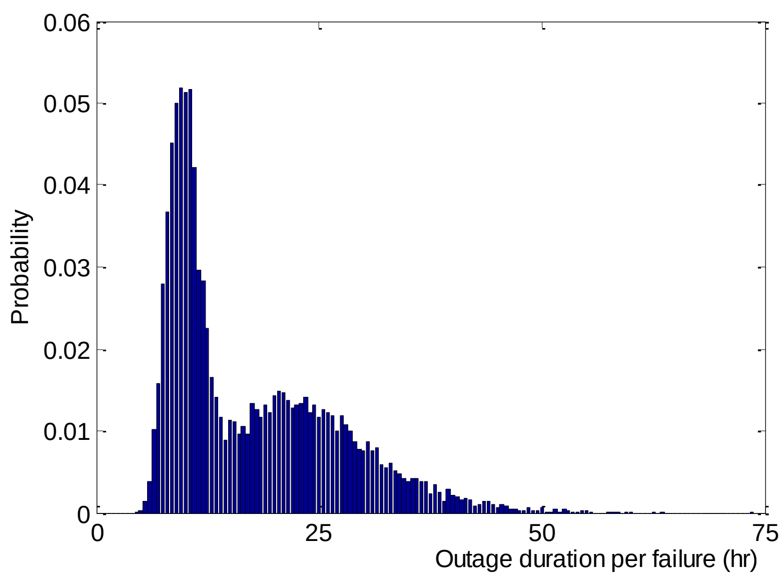

Fig. 6-11 Probability distribution of the outage duration per failure in year 35 of the transformer life.

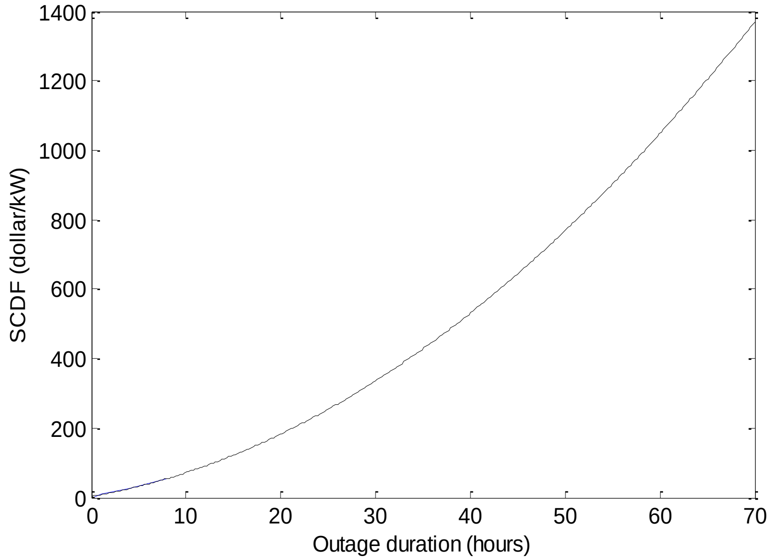

Fig. 6-12 Quadratic curve fitting of industrial SCDF

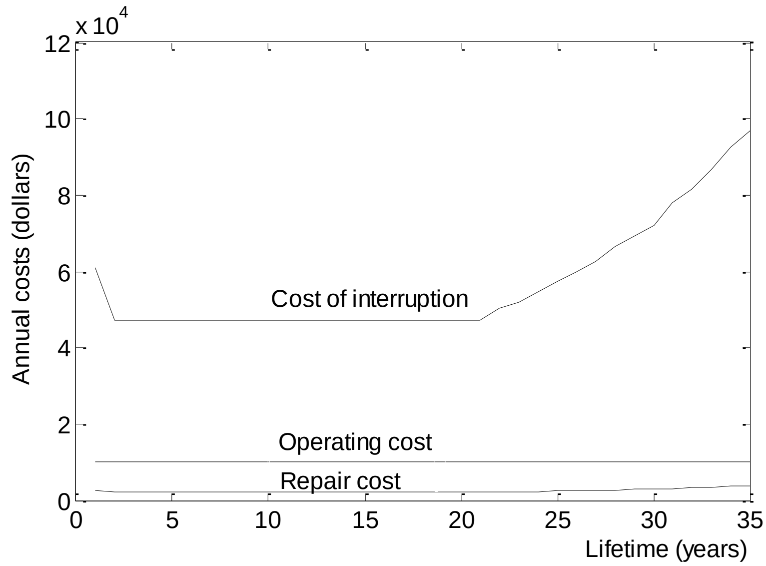

Fig. 6-13 Annual costs of the new and existing transformers for case study I.

6.2.3.3 Operating Cost

The operating cost is divided into the energy cost and the demand cost, which are the costs of the transformer losses. The energy charge is assumed to be 5 Cents/kWh and the monthly demand charge is assumed to be \$5/kW. The auxiliary losses are assumed zero in this case study as the transformer is lower than 3 MVA, therefore, it does not need oil pumps or fans. The calculated annual operating cost according to presented technique is shown in Fig. 6-13.

6.2.4 Calculation of the EUAC and Replacement Decision

EUAC is a financial method to show the most economical lifetime of the equipment. The EUAC technique indicates how much money, spread over equal payments, will be paid annually to keep the equipment in service a certain number of years. EUAC is used in the proposed method to decide the most economical replacement time. The EUAC for the challenger is calculated starting from the first year. The EUAC for the defender is calculated starting from the year following the present age of the existing transformer. Calculation of the EUAC for the defender ignores all past costs and concentrates only on future costs, which is called the non-owner point of view. This is a very important concept for calculating the replacement year.

In the present case study, the present age of the existing transformer is taken as the end of the 21st year of operation. According to the non-owner point of view, all costs paid for the existing transformer from the first year to the 21st year are ignored. In this case study, the challenger and the defender are assumed to have the same useful lifetime, technical properties, and reliability indices. The only difference is the initial cost. The annual costs of the new and existing transformers, including the repair cost, the interruption cost, and the operating cost, are used, together with the present worth of the new and existing transformers, to plot the EUAC curves for the new and existing transformers as shown in Fig. 6-14. The minimum point for the EUAC of the new transformer is at the 33rd year of service (the most economical lifetime). For the existing transformer, the EUAC curve is drawn starting from year 22; it is increasing as shown in Fig. 6-14. The increasing shape of the EUAC for the existing transformer is due to the increase of all transformer costs in the late years of service: the repair cost, cost of interruption, and depreciation cost. Also, this increase is due to ignoring the sunk costs, which are the costs paid prior to the decision year. The minimum point of the EUAC curve for the 22nd year is less than the minimum point of the EUAC curve for the new transformer, which means that this year (the 22nd year of the existing transformer age) is not the most economical year for replacement.

To accurately find the most economical replacement year, the EUAC curves are plotted for the existing transformer starting from the 23rd year until the final year of the useful lifetime. The EUAC curves for all years that succeed, including the decision year, are not coincidental, because the costs for the preceding years are ignored for each curve. For example, for the EUAC curve that starts from year 23, the costs paid in the 22nd year as well as years 1-21 are ignored (non-owner view point), and so on. As shown in Fig. 6-14, the minimum point of the EUAC in the 23rd year is still less than the minimum point of the EUAC of the new transformer, which means that the 23rd year is not the best year for replacement. The operation continues year after year until the minimum point of the EUAC of the existing transformer is higher than the EUAC for the new transformer. At this year, the replacement of the existing transformer by a new one is economically viable, and the new transformer will have an annual cost less than the annual cost of the existing transformer. From Fig. 6-14, the most economic replacement year is the 30th year. At the 30th year, the minimum point of the EUAC for the existing transformer is higher than the minimum point of the EUAC for the new transformer, i.e., the existing transformer should be replaced after 9 years from the decision year (present age of the defender, which is 21 years).

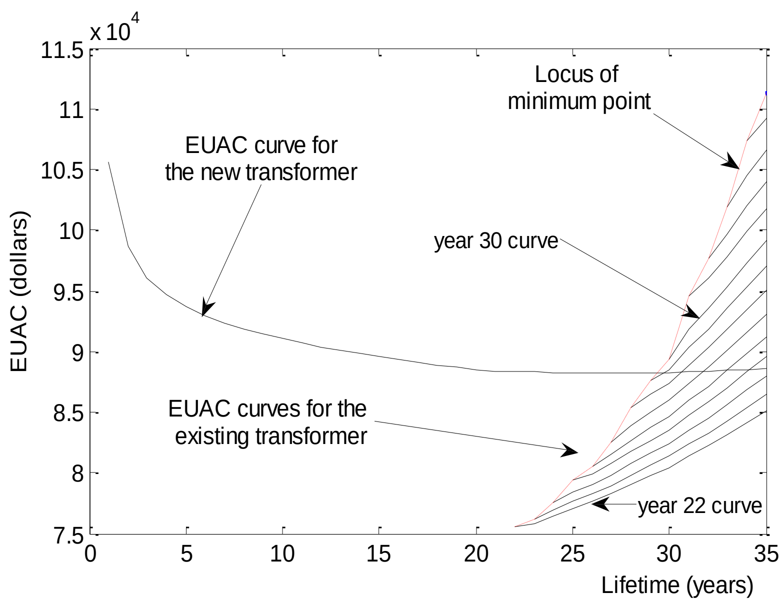

Fig. 6-14 EUACs for the new and the existing transformers for case study 1.

If the replacement is delayed until the end of the 35th year of the transformer age, the operator will face five years of higher costs than the costs paid if the transformer is replaced at the 30th year of operation.

6.3 Case Study II

6.3.1 Data Initialization

In this case study [100], a 3 MVA transformer is assumed to feed a certain region. This region contains a residential load, an industrial load, and a commercial load as shown in Fig. 6-15 [100]. After 23 years of the transformer's service, a techno-economic study is carried out starting from the 24th year to check the replacement time for the transformer. Now we want to decide, using the techno-economic replacement method, the most economical replacement time for the existing transformer.

The main difference between this case study and case study 1 is assuming variable capital cost for the challenger. The challenger cost is assumed to increase by a factor of 3% for each year delay in the replacement process. This increase of capital cost is due to inflation and the increase in cost of raw materials. The manipulation of the problem in this case study is more complicated than the first case study, as will be shown in subsequent sections.

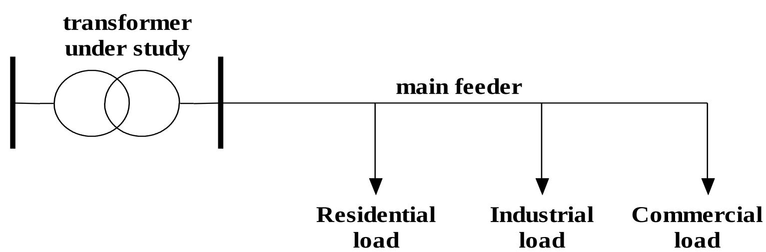

Fig. 6-15 Single line diagram for the system of case study II.

The reliability parameters for the existing transformer and the new transformer, such as the failure rate, repair time, scheduled maintenance time, switching time, and durations of the infant, normal and wear-out regions, are assumed to be identical, and they can be found in Table C-I in appendix C. The failure rates for both the normal regions of the new and existing transformers, and the average repair time, are assumed to be 0.07 failures/year and 24 hours/failure respectively [98]. The mean switching time, the scheduled maintenance rate, and the average scheduled maintenance rate are assumed to be 1 hour, 0.2 occurrences/year, and 10 hours/failure respectively [81]. The failure rate at the end of the wear-out is assumed to be four times the failure rate in the normal region [89]. The failure rate at the beginning of the infant region is taken as 1.5 times the failure rate in the normal region [99]. In this case study, the useful lifetimes for the existing transformer and the new transformer are assumed to be identical. Many transformers can work until 40 years of service. The useful lifetime in this case study is assumed to be 40 years. The infant region duration and normal region duration, are 1 and 19 years respectively. The transformer is assumed to start wearing out after 20 years.

The financial data for the new and the existing transformer are shown in Table C-II in appendix C. In this study the existing transformer capital cost with accessories is assumed to be $200,000. The capital cost of the new transformer with accessories is $390,000, and is assumed to increase by 3% annually due to inflation and the increase in raw materials and labour costs.

The peak load served by the transformer is 2.4 MW with load factor at 0.8 as shown in Table C-III in appendix C. The composition of the area system load is as follows:

1. 25% for the residential load,
2. 35% for the industrial load, and
3. 40% for the commercial load.

The SCDFs for the three load sectors are shown in Table C-IV in appendix C [81, 99].

6.3.2 Existing and New Transformers Present Worth

The existing and new transformers' present worths are calculated using the proposed algorithm. The straight line depreciation is used in the infant and normal regions, while the accelerated depreciation method used in the wear-out region is SOYD. The present worth profiles of the existing and new transformers are shown in Fig. 6-16. The capital cost of the new transformer is assumed to be $390,000 if the replacement takes place immediately, and will increase by 3% for each year of delay in the replacement process. As a result, the new transformer has 17 present worth profiles starting from the 24th year of the existing transformer and ending at the 40th year of the existing transformer. Fig. 6-16 also shows the present worth for the new transformer starting from the 24th year and ending at the 40th year of the existing transformer's lifetime.

6.3.3 Calculation of the Annual costs

6.3.3.1 Annual cost of Interruption

The GCDF is calculated for the group of loads with the weighting factors mentioned in subsection (5.2.3.3). The GCDF is calculated at every time point using the SCDFs for the three loads. For example, the GCDF for a 20 minutes' outage is calculated as follows:

$$GCDF \quad (20 \text{ min}) = 0.093 \times 0.25 + 3.868 \times 0.35 + 2.969 \times 0.4$$
$$= 2.5646 \quad \$ / kW \tag{6-16}$$

The GCDF is calculated at each point of time, i.e., at 20 minutes, 1 hour, 4 hours, and 8 hours using the same approach as (6-16). The calculated GCDF for the group of loads of case study II is shown in Table C-V in appendix C. The transformer outage is modeled using the Monte Carlo technique, as in case study I. The time to failure (TTF) is modeled as exponentially distributed, while the time to repair (TTR), time to switch (TTS), and scheduled repair time (SRT) are modeled as log-normally distributed [81]. Use the time-varying failure rate model to find the average failure rate in all years of the useful lifetime as shown in Fig. 6-17. TTF, TTS, and TTR probability distributions are modeled the same way as explained in case study I.

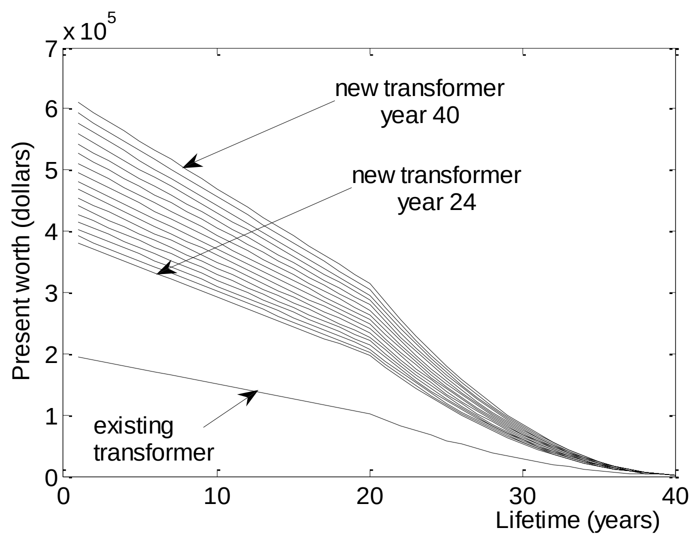

Fig. 6-16 Present worth of the existing and the new transformers for case study II.

The transformer artificial history is generated as stated in section (5-2), and the estimate function is calculated throughout the artificial history. The stopping criterion is when the coefficient of variation (ε) of the estimate function goes below a TL of 0.0005. Convergences of the estimate function in the Monte Carlo simulation for years 1, 2-20, 30, and 40 are shown in Figs. 6-18 to 6-21.

The same steps explained in case study I are used to find the probability distributions of outage time per failure in each year of the transformer useful lifetime (the probability distributions of outage time per failure for both new and existing transformers are the same because the reliability data is assumed the same for both of them). Figs. 6-22 to 6-25 show the probability distribution for the outage time per failure or years 1, 2-20, 30, and 40.

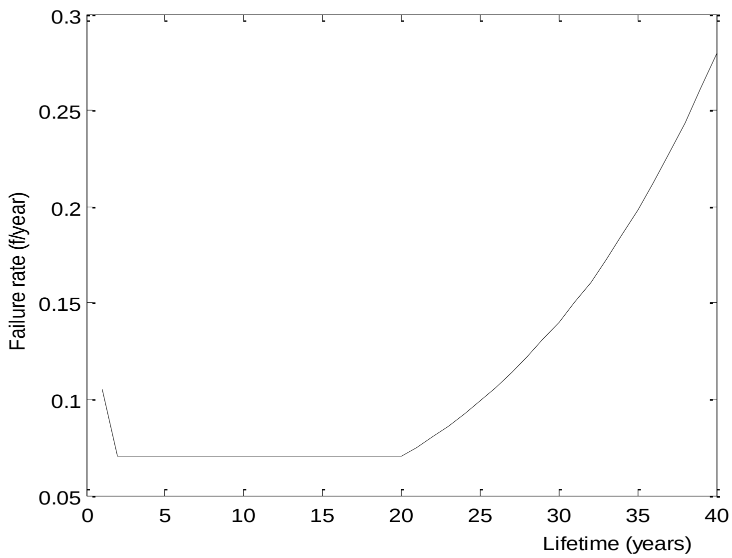

Fig. 6-17 failure rate in the useful lifetime of case study II.

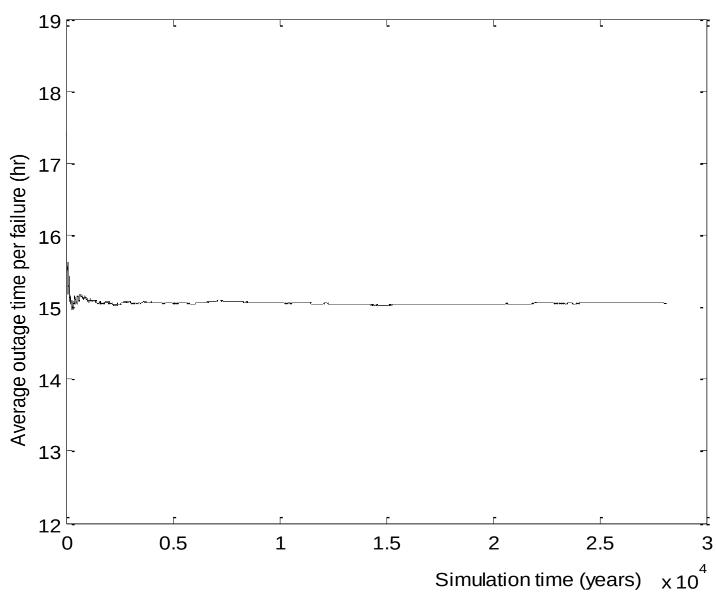

Fig. 6-18 Convergence of the estimate function in Monte Carlo simulation in the first year for case study II.

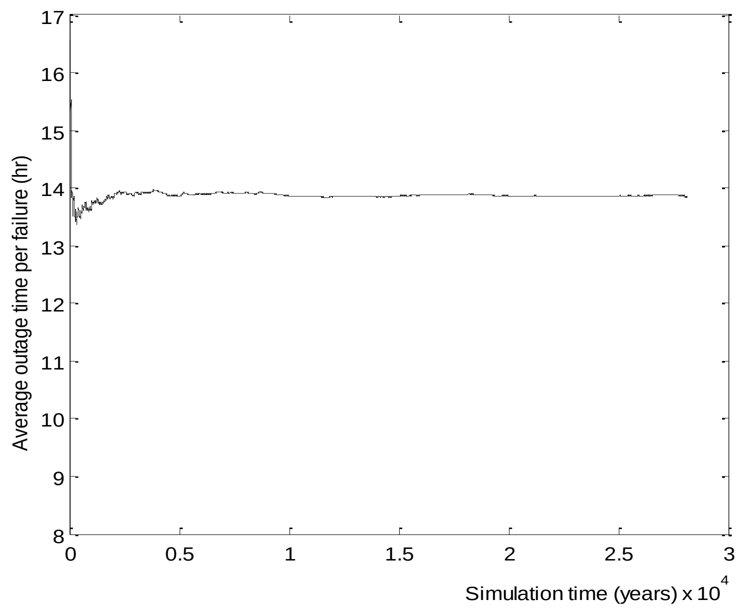

Fig. 6-19 Convergence of the estimate function in Monte Carlo simulation in the normal region (year 2 to year 20) for case study II.

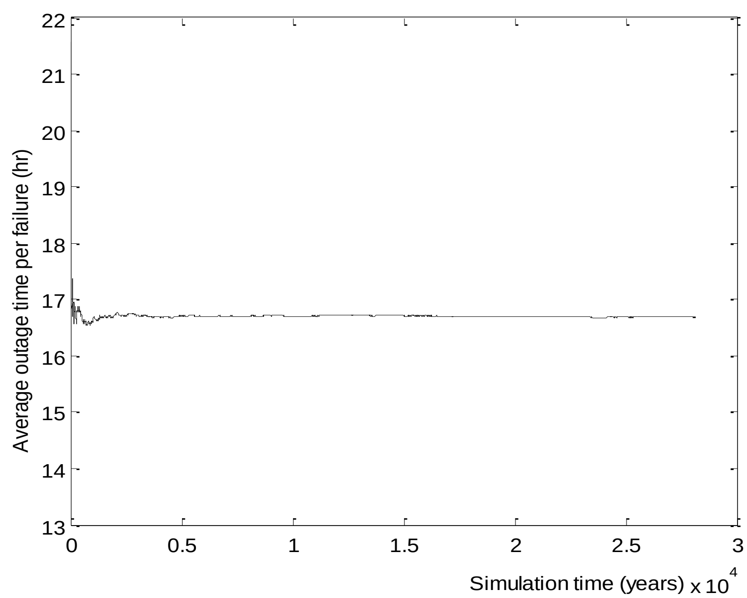

Fig. 6-20 Convergence of the estimate function in Monte Carlo simulation in year 30 for case study II.

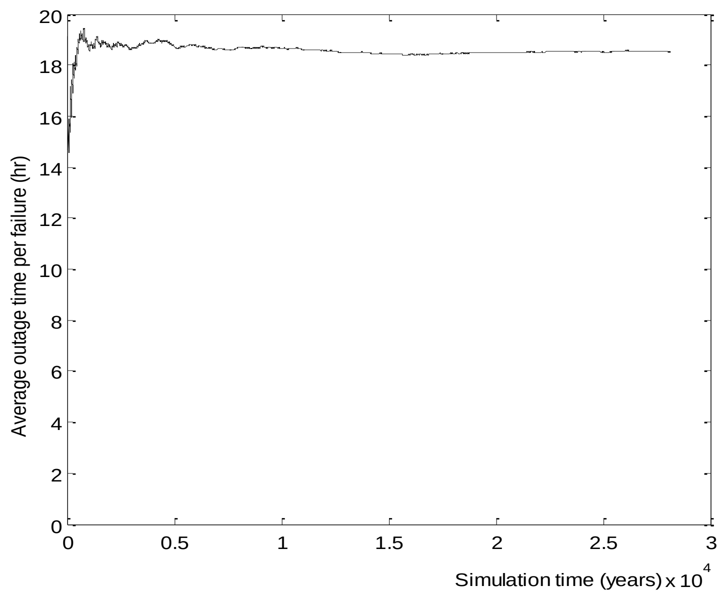

Fig. 6-21 Convergence of the estimate function in Monte Carlo simulation in year 40 for case study II.

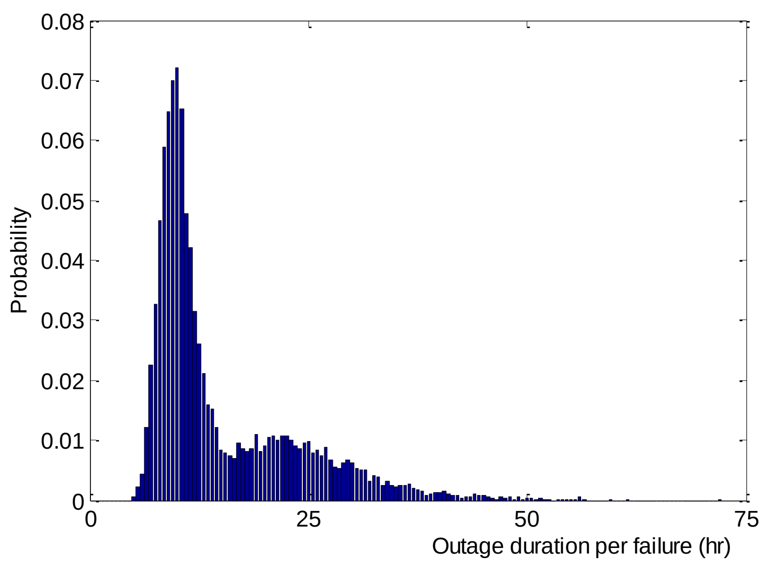

Fig. 6-22 Probability distribution of the outage duration per failure in the first year of the transformer life for case study II.

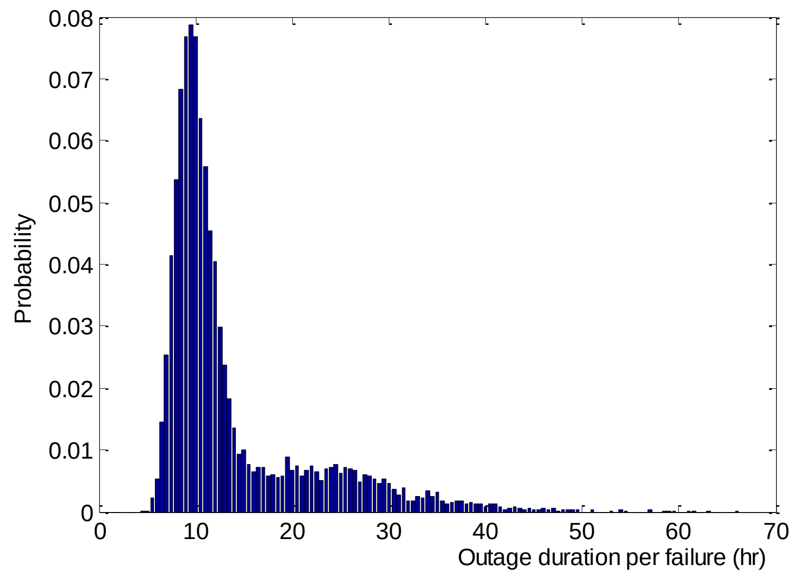

Fig. 6-23 Probability distribution of the outage duration per failure in the normal region (year 2 to year 20) of the transformer life for case study II.

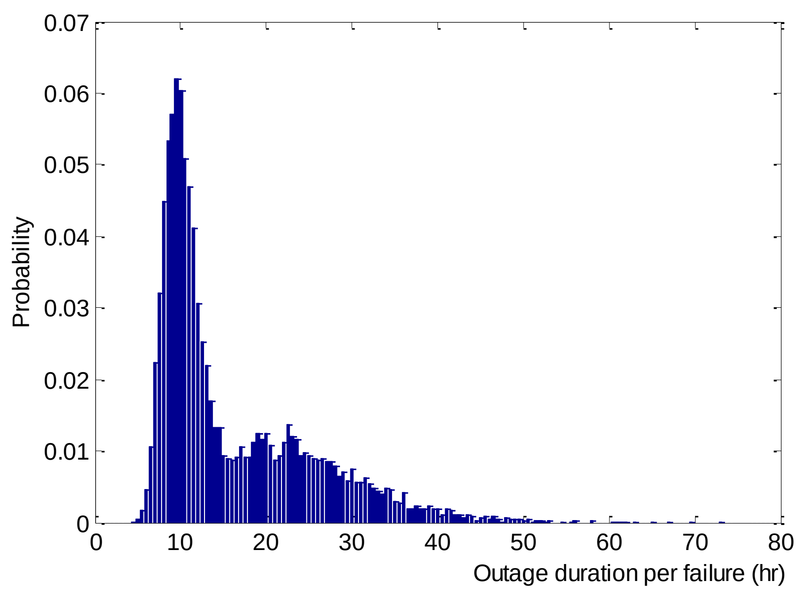

Fig. 6-24 Probability distribution of the outage duration per failure in year 30 of the transformer life for case study II.

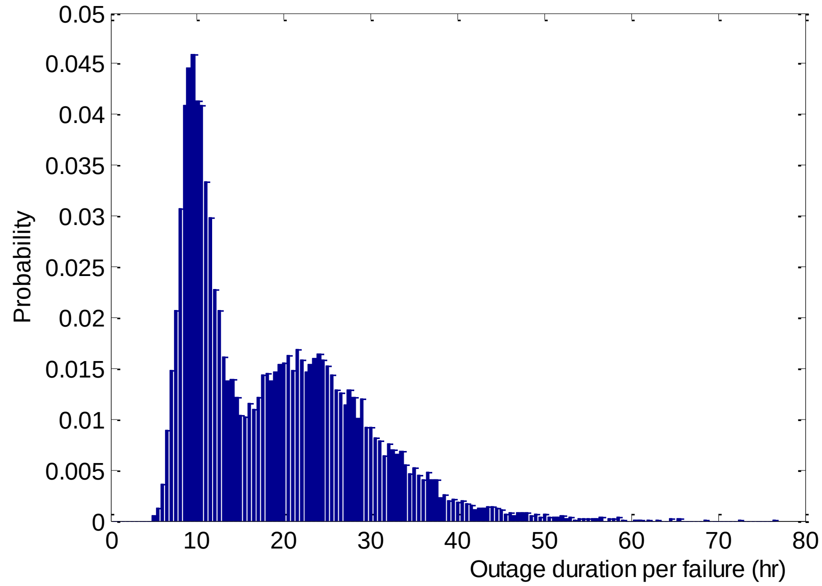

Fig. 6-25 Probability distribution of the outage duration per failure in year 40 of the transformer life for case study II.

The probability distributions are used to find the cost of interruptions of each year in the useful lifetime using the same approach as case study I except for using the GCDF instead of the SCDF because the system is composed from different load sectors. The fitted curve for the GCDF is shown in Fig. 6-26. As the reliability parameters are equal for both the new and existing transformers, the annual cost of interruption is the same for both of them. The annual cost of interruption is shown in Fig. 6-27.

6.3.3.2 Repair Cost

The annual repair costs are the same for the new and existing transformers. The annual repair cost is calculated according to the presented linear model. A constant repair cost of $250 is assumed. The variable cost is based on a crew of 3 persons; each one has hourly wages of $70 plus 50% overhead for the contractor. The equivalent crew and contractor are multiplied by 2 to represent a rough estimate of any spare parts needed. The total variable cost is $630 per hour. The annual repair cost is shown in Fig. 6-27.

6.3.3.3 Operating Cost

The energy charge is assumed to be 4 cents/kWh and the monthly demand charge is assumed to be

$4/kW. The annual operating cost is shown in Fig.6-27.

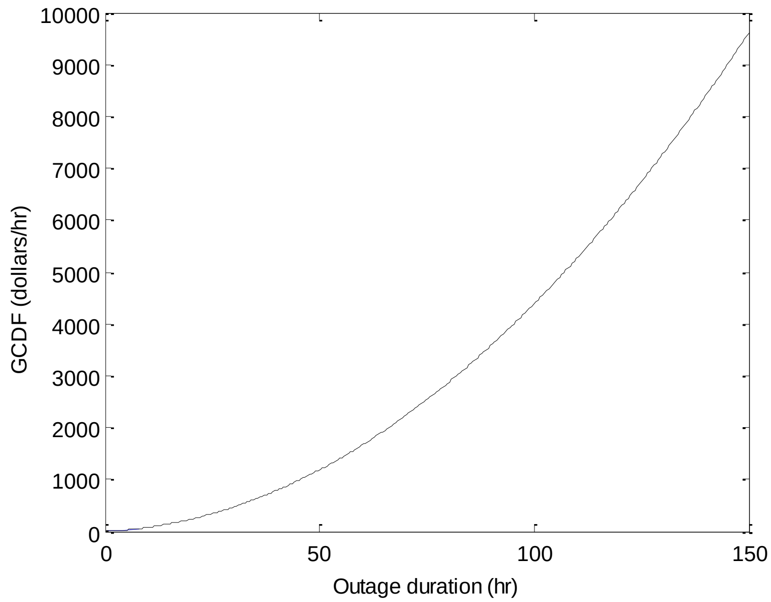

Fig. 6-26 Quadratic curve fitting of industrial GCDF

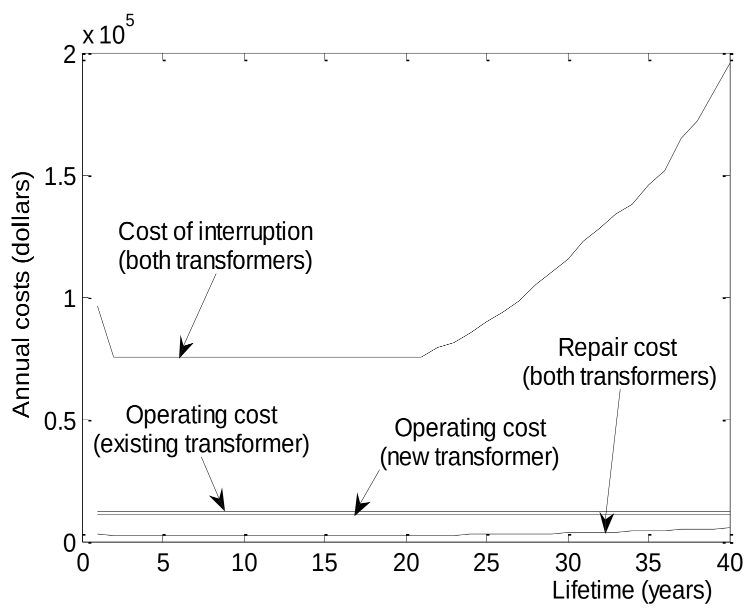

Fig. 6-27 Annual costs of the new and existing transformers for case study II.

6.3.4 Calculation of the EUAC and Replacement Decision

The operating cost, repair cost, interruption cost, and present worth of the new and existing transformers are used to calculate the EUAC curves for both. Fig. 6-28 shows the EUAC curves for the existing transformer. The EUAC curves for the existing transformer are drawn starting from the 24th year and ending at the 40th year (end of useful lifetime of the existing transformer). In case study I, the new transformer had only one EUAC curve because all the costs affecting the EUAC were assumed to be constant. In this case study, the capital cost of the new transformer is considered to increase annually by the amount of 3%. This increase in the capital cost means that annual depreciation cost of the new transformer increases year over year; this is clear from the present worth curves shown in Fig. 6-16. Accordingly, the EUAC curve for the new transformer at the 24th year of the existing transformer age is lower than the EUAC curve for the new transformer at the 25th year and so on, which means that keeping the new transformer in service costs more money if it is bought in the 25th year of the existing transformer lifetime than if it is bought in the 24th year as shown in Fig. 6-28. Similarly, the cost of keeping the new transformer in service increases to reach the maximum EUAC if it is bought at the 40th year of the existing transformer service.

To find the most economical replacement year using the presented method, the EUAC curve for the new transformer is compared with the EUAC curve of the existing transformer at the same year, i.e., the EUAC curve for the new transformer at the 24th year is compared with the EUAC curve for the old transformer at the 24th year and so on. The replacement year is the year at which the minimum value of the EUAC curve for the new transformer (most economical lifetime) is lower than the minimum value of the EUAC curve for the existing transformer (most economical lifetime). The replacement year according to the presented replacement method is the 31st year of the existing transformer lifetime, as shown in Fig. 6-28.

As with case study I, if the transformer replacement is delayed until the end of the useful lifetime (40 years in this case), the transformer operator will face 8 years of higher costs than the costs paid if the transformer is replaced in the 31st year of service.

6.4 Sensitivity Analysis

In this section, the effect of changing the magnitudes of the inputs on the replacement year is studied. The sensitivity study is performed for case study I because it is simple, and because it shows the effect of changing the inputs clearly.

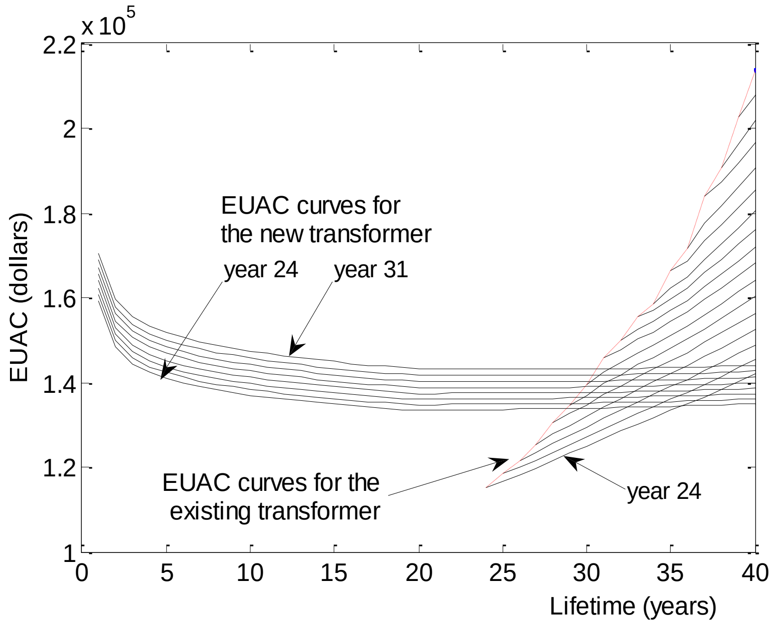

Fig. 6-28 EUAC curves for the new and the existing transformers for case study II.

6.4.1 Effect of Changing the Interest Rate on the Decision

The interest rate represents the interest rate of the money - in other words, the percentage amount paid annually on the invested money. The effect of the interest rate is high for the EUAC of the new transformer (the challenger) because of the long lifetime remaining (the whole lifetime) and the higher initial cost; however, the interest rate effect is lower on the existing transformer because the remaining lifetime is smaller and the present worth is smaller than the new transformer. The general effect of the interest rate is that it varies proportionally with the EUAC. However, the effect is clearer for the new transformer more than for the existing one. Figs. 6-29 and 6-30 show the EUAC for the new and the existing transformers for interest rates of 0.07 and 0.11 respectively. Using the proposed techno-economic replacement method, the transformer should be replaced at the 27th year for an interest rate of 7% and at the 31st year for an interest rate of 11%.

6.4.2 Effect of Changing the Tariff on the Decision

The energy and demand charges have no effect on the choosing of the replacement year, if the no-load and copper losses are equal for the new and existing transformers. Increasing or decreasing the demand or energy charge will increase or decrease all the EUAC curves of the existing and new transformers by nearly the same amount. This simultaneous movement of the EUAC curves of the new and existing transformers will cause the replacement year to remain the same under various values for the demand and energy charges. Figs. 6-31 and 6-32 show that the replacement year of the transformer in case study I is still in the 30th year, even with different combinations of energy and demand charges. However, the effect of the energy and demand charges is higher if the no- load and load losses for the new and existing transformers are different. The transformer with higher losses is affected more by an increase or decrease in the energy and demand charges. The EUAC of the transformer with higher no-load and load losses will reach a higher level than that of the transformer with lower no-load and load losses, if the energy and demand charges increase, and will decrease to a lower level if the energy and demand charges decrease.

6.4.3 Effect of the Capital Cost of the New Transformer (Challenger)

The lower the capital cost of the new transformer, the lower the EUAC of the transformer and as a result the replacement time becomes earlier; and the opposite is also true. Fig. 6-33 shows that reducing the capital cost of the new transformer of case study I from \$250,000 to \$220,000 changes the replacement year to 28 years, i.e., 2 years earlier than the replacement time of the transformer with the capital cost of the new transformer equal to \$250,000. Fig. 6-34 shows that increasing the capital cost of the new transformer of case study I from \$250,000 to \$280,000 changes the replacement year to 31 years, i.e., 1 year later than the original replacement time of section (5-3). These observations mean that the replacement year is non-linearly proportional with the capital cost of the challenger.

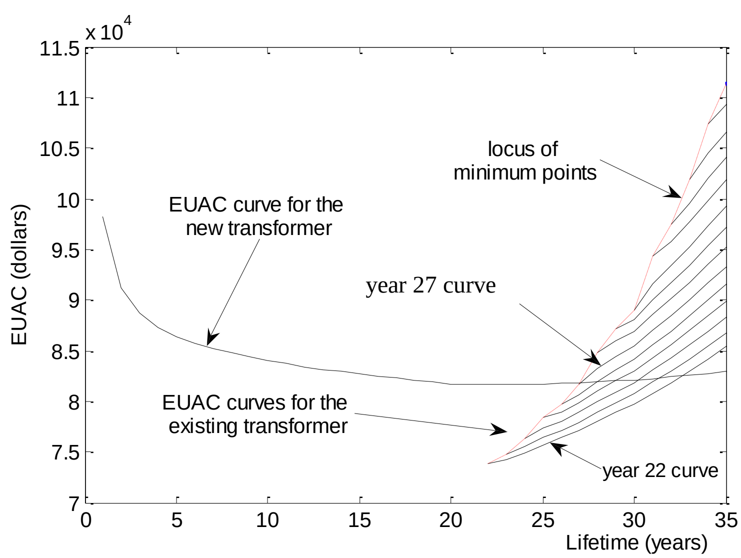

Fig. 6-29 EUACs for the new and the existing transformers at 7% interest rate.

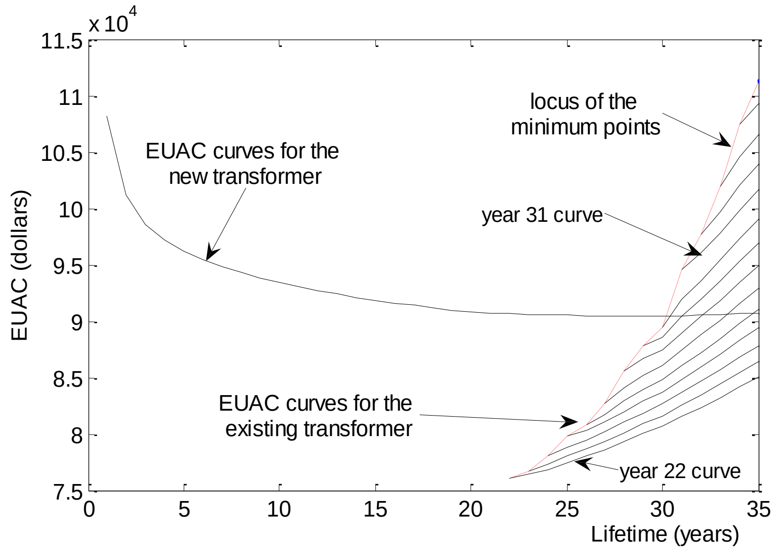

Fig. 6-30 EUACs for the new and the existing transformers at 11% interest rate

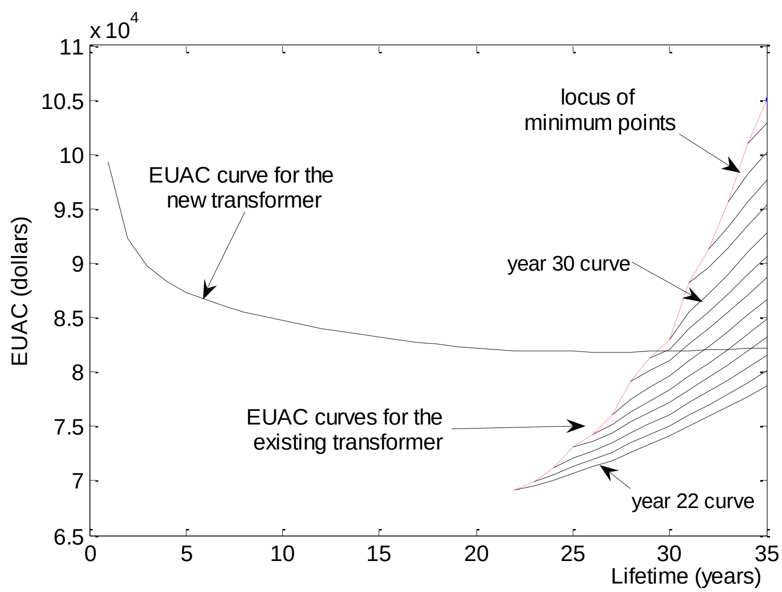

Fig. 6-31 EUACs for the new and the existing transformers at \$1/kW demand charge and \$0.02/kWh energy charge.

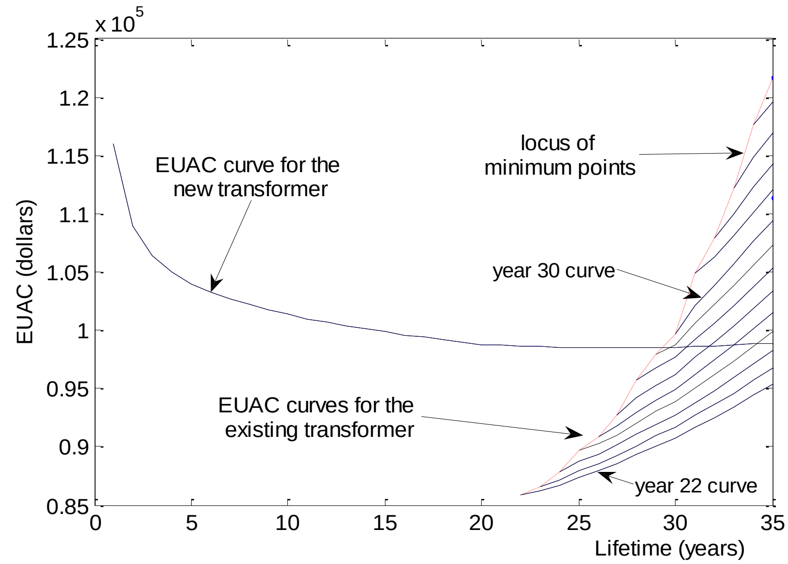

Fig. 6-32 EUACs for the new and the existing transformers at $0.11 /kWh energy charge and $5/kW demand charge.

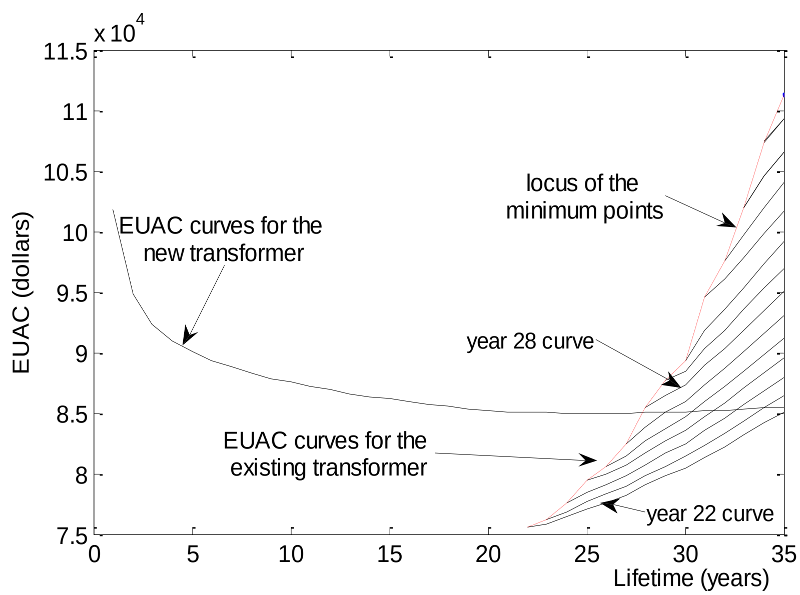

Fig. 6-33 EUACs for the new and the existing transformers at $220,000 capital cost of the new transformer.

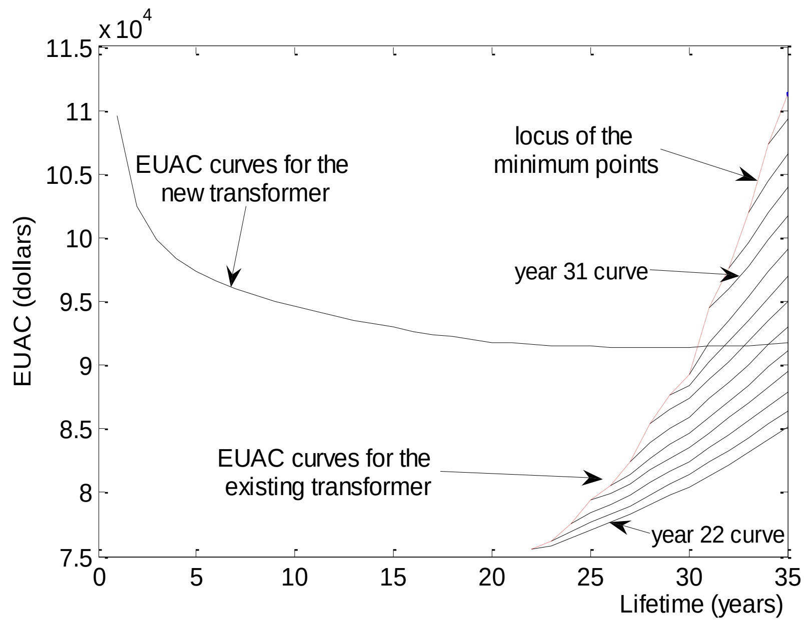

Fig. 6-34 EUACs for the new and the existing transformers at $280,000 capital cost of the new transformer.

6.5 Comparison with Other End of Life and Replacement methods

To the best of the author's knowledge, the concept of using technical data in the economic replacement decision of the transformer is new and has not been tackled in the literature. However, the transformer thermal model is used in the literature, such as the work done in [62], to estimate the transformer replacement time due to the end of transformer life .The work done in [62] relies on using the equivalent aging factor to find the transformer's lifetime. An artificial model for the load using probabilities is used to model the load. More details about the technique can be found in [62]. No economic aspect is used in this model.

A 2 MVA transformer is assumed for the case study. The thermal characteristics according to [4] are listed below:

1. top-oil rise over ambient at rated load, $\Delta\Theta_{TO,R}$= 50 °C;
2. hottest-spot conductor rise over top-oil temperature, at rated load, $\Delta\Theta_{HS,R}$ = 30 °C;
3. ratio of load loss at rated load to no-load loss, R = 3.2;
4. oil thermal time constant for rated load $\tau_{TO,R}$= 3.5 h.

The average daily load served by the transformer has a maximum value of 1 p.u., a minimum value of 0.78 p.u., and a load factor of 0.85 [79]. The standard deviation of the hourly load is 10% of the rated load. After simulating the transformer lifetime fifty times as stated in [62], the average actual usage time in days to reach the end of life is found to be 41631 days or 114.1 years, which is not a realistic lifetime. These types of methods that estimate the transformer lifetime based on the thermal models depend on the transformer's thermal parameters and loading. These methods give sometimes unrealistic outcomes such as in the case under study. Comparing this result with the one obtained in section (5-3), the result obtained in section (5-4) seems to be more realistic.

6.6 Conclusion

The performance evaluation of the transformer techno-economic replacement method proposed in Chapter 5 was presented. Two case studies were used to examine the performance of the proposed replacement method. The replacement time of case study I (simple case study) was found to be 30 years. In the second case study, the transformer was assumed to feed an area with different load types. Moreover, the challenger was assumed to have increasing capital costs year over year. The replacement time of case study II was found to be 31 years. The two case studies show that the transformers should be replaced before the end of the useful lifetime even though the transformers are still working, but they are operating at high cost. These high asset costs can be mitigated by replacing the transformer in the right year using the proposed method. The effect of changing different factors on the replacement year has been studied in this paper in the sensitivity analysis section. The replacement time of the transformer based on its thermal end of life was calculated and compared with the proposed method. It was found that the thermal models give sometimes unrealistic results as shown in section 5.6.

Chapter 7
Determination of a Health Index for Power Transformers

7.1 Introduction

The limited and insufficient research conducted in the area of providing an index to represent transformer health was one of the main motivation for this research. Even the few research papers that discuss this point contain deficiencies as explained in chapter 3. Existing assessment methods that are based on testing of specific transformer are aimed at determining whether a transformer has reached its end of life point. This chapter presents the development of a health index that is appropriate for any power transformer and that can be used to assess the condition of the transformer.

To develop the health index (HI), real data from the field were used. Diagnostic test data were taken from the distribution systems of an industrial company in the Middle East, which had commissioned a specialized Asset Management and Health Assessment consulting company (AMHA) from the UK to derive and populate a health index for the distribution transformers located at one of the company's operation sites. To facilitate this process, AMHA undertook a sampling and test program for 90 oil-filled transformers. The data provided were the water content, acidity, break down voltage (BDV), hydrogen content (H_2), methane content (CH_4), ethylene content (C_2H_4), acetylene content (C_2H_2), ethane (C_2H_6), furans content, loss factor, and total solids in the oil for each transformer: a total of 990 tests for 11 data categories. The health indices for all of the transformers calculated by AMHA were also provided.

Measuring the moisture, acidity, solid contamination, and breakdown strength of the oil provides a good indication of the overall condition of the oil and the internal components. The quality of the oil is a useful indicator of the health of a transformer because it is critical in preventing premature ageing of the transformer and extending service life. Furfuraldehyde (furans) analysis also gives a highly accurate measure of the condition of the paper insulation because the furans content is correlated to the degree of polymerisation of the paper [1, 59]. Furans levels reaching specified values mean that the insulation has effectively broken down and the probability of failure is very high. Analysing the levels of a variety of dissolved gases in the oil also identifies electrical discharge, arcing, and thermal activity within the transformer, which are further indicators of aging.

The method used by AMHA to calculate the heath index is considered a secret and was not provided in the final report presented to the industrial facilities. The values of the AMHA health index range between zero and ten. A health index of zero represents a brand new transformer. A health index of ten means that the transformer should be replaced. Values between zero and ten correlate to good, moderate, or bad levels of transformer health: zero to 4 is good, 4 to 7 is moderate, and 7 to 10 is bad. For the purposes of this research, with the aid of the health indices given by AMHA, three methods were produced in order to determine the relationships between the 11 data categories and to arrive at a health index for each transformer.

7.2 Pre-processing of the Data

Before the data could be used for the analysis required for this research, adjustments were necessary. Elements that contained irregular data were removed; that is, data with attributes that were too high, negative or corrupted. All data were also normalized according to their respective maximum. With regard to irregular data, elements 76 and 31 of the available data seemed to be irregular and were eliminated because the amount of total furans in element 76 was too high and the loss angle of element 31 was too high. These very high inputs could have affected the remaining values in the same category when the normalization was performed. The next step in the pre-processing stage was the normalization of all data categories: all elements in each data category were divided by their respective maximum. The health index was normalized by dividing all health index entries of by the maximum entry of the health index.

7.3 Methods of Determining a Transformer Health Index

This section presents the three methods used for calculating the health indices which were then used to determine the conditions of the transformers. The transformer conditions that resulted from each method were compared with the given transformer conditions as a measure of the accuracy of each method.

7.3.1 Method1: Calculation of HI Using the Correlation Between the Given Health Index and All Data Categories

7.3.1.1 Method 1 Concepts

This method relies on the use of all available data categories in order to find the transformer health index (HI). The health index is assumed to have a linear relationship with all data categories.

$$\begin{aligned}\mathrm{HI}_{k} = {} & W_1 \times water_k + W_2 \times acidity_k + W_3 \times BDV_k + W_4 \times H_{2_k} + W_5 \times CH_{4_k} \\ & + W_6 \times C_2H_{6_k} + W_7 \times C_2H_{4_k} + W_8 \times C_2H_{2_k} + W_9 \times furans_k \\ & + W_{10} \times loss\ \ angle_k + W_{11} \times total\ \ solids_k \end{aligned} \tag{7-1}$$

where W_i are the weights in the linear relationship.

The weights in this linear relationship are considered to be functions of the correlation coefficients between the given health indices and the data categories. The correlation coefficients between the given health index and all data categories are calculated using Pearson's linear correlation coefficient [101]:

$$corr_{xy} = \frac{\sum_{i=1}^{ne} (x_i - \overline{x})(y_i - \overline{y})}{(ne-1)SD_x SD_y} = \frac{\sum_{i=1}^{ne} (x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{ne} (x_i - \overline{x})^2 \sum_{i=1}^{ne} (y_i - \overline{y})^2}} \tag{7-2}$$

where

$corr_{xy}$: the correlation coefficient between the series of numbers (x) and the series of numbers (y);

ne: the number of elements in series (x) or series (y);

$\overline{x}$: the mean of the series of numbers (x);

$\bar{y}$: the mean of the series of numbers (y);

SD_x: the standard deviation of the series of numbers (x);

SD_y: the standard deviation of the series of numbers (y).

Figs. 7-1 to 7-11 show the correlation between the given health index and all data categories. The correlation coefficients between the given health index and all data categories are shown in Table 7-1.

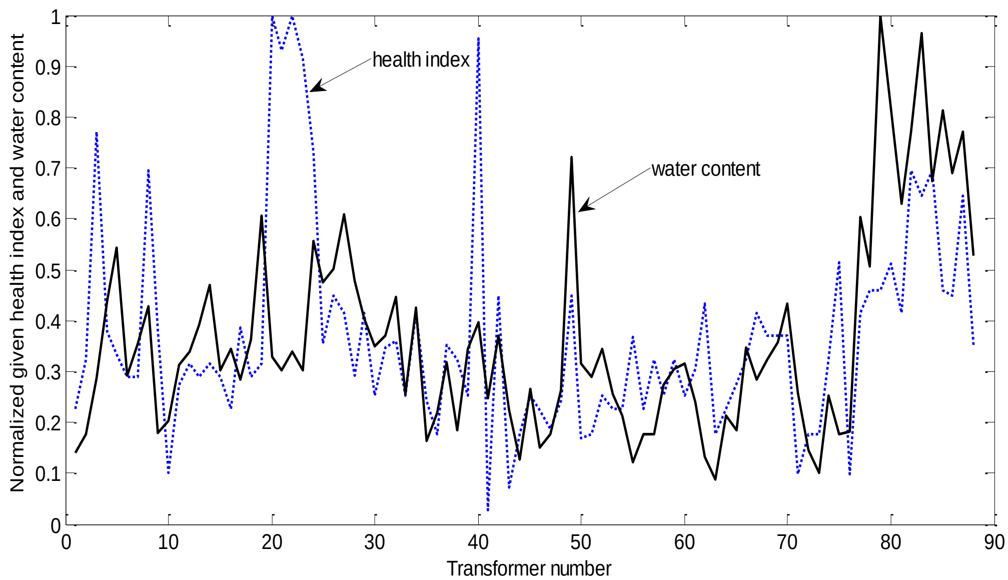

Fig. 7-1 Correlation between the health index and water content.

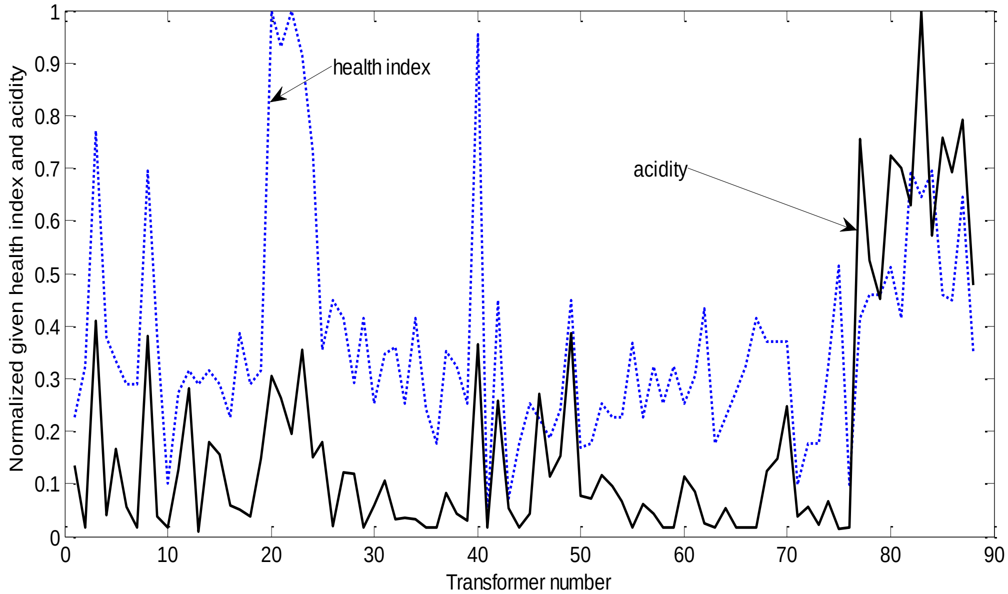

Fig. 7-2 Correlation between the health index and acidity.

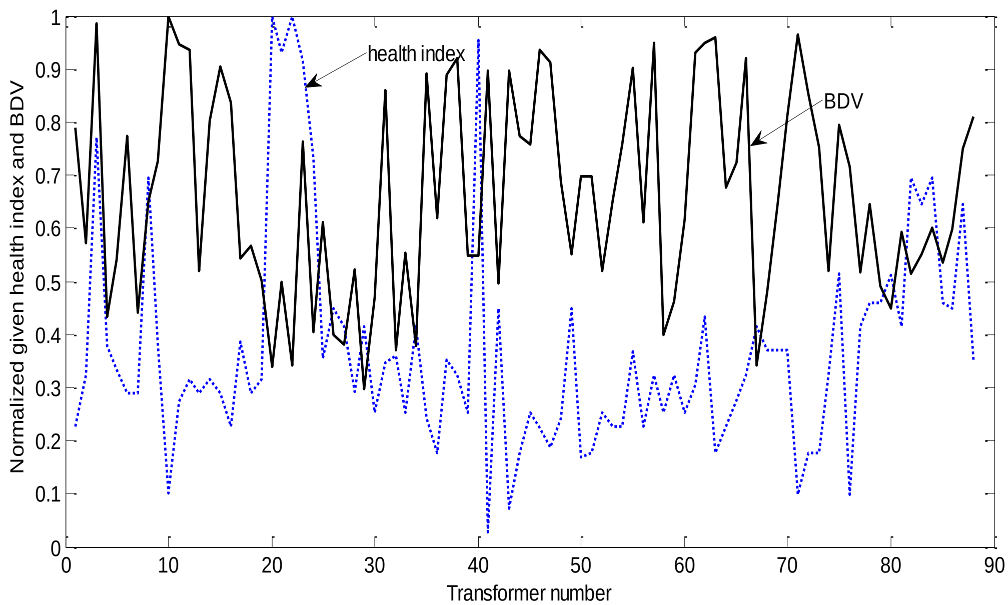

Fig. 7-3 Correlation between the health index and BDV.

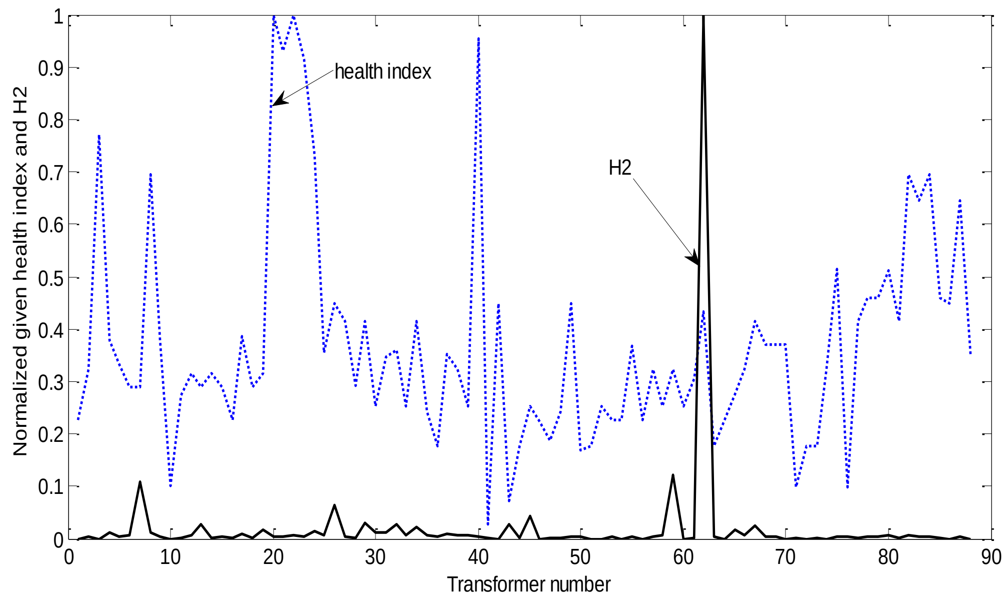

Fig. 7-4 Correlation between the health index and H_2.

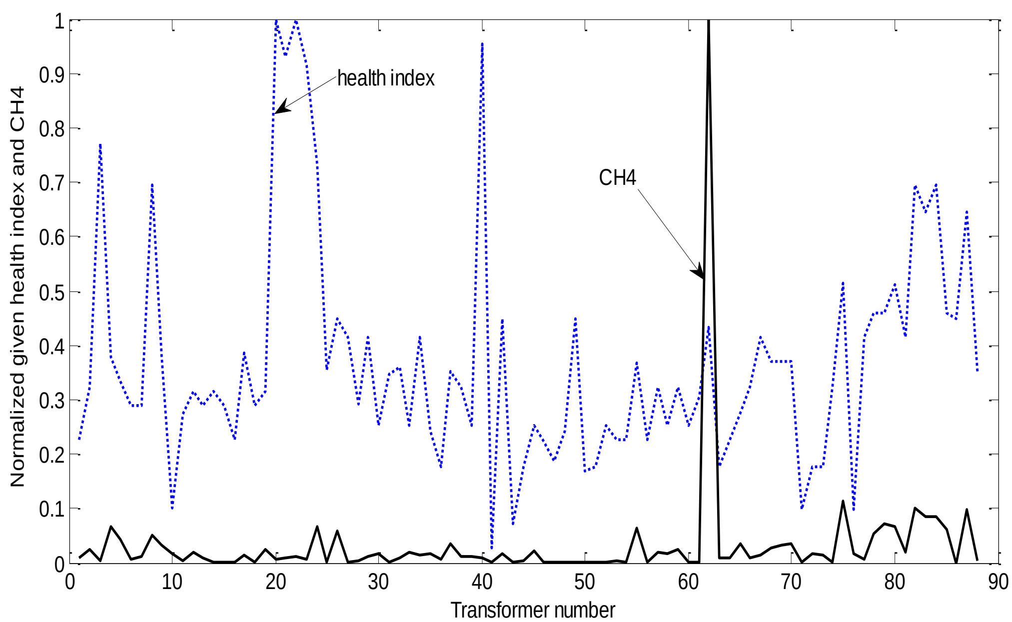

Fig. 7-5 Correlation between the health index and CH_4.

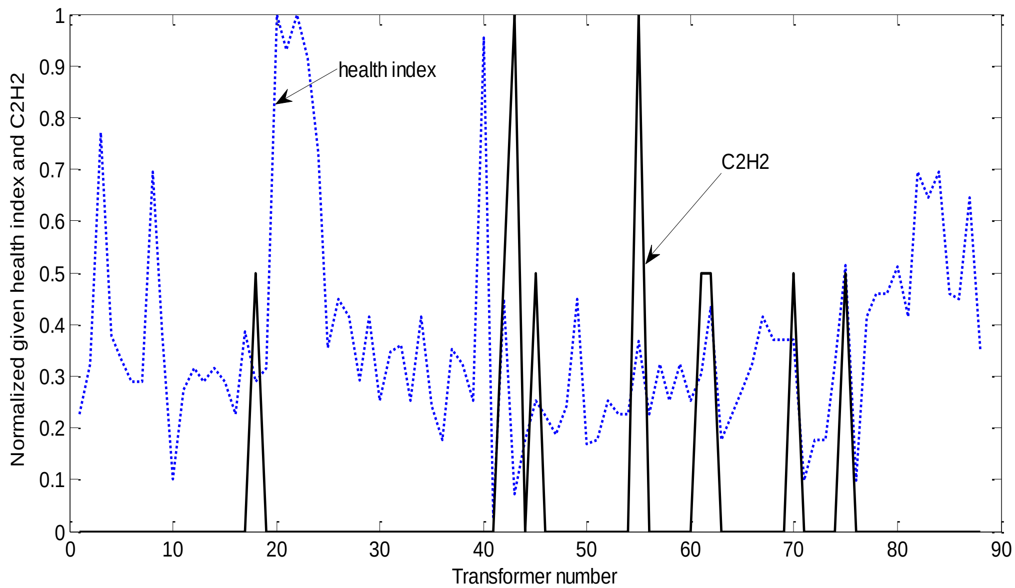

Fig. 7-6 Correlation between the health index and C_2H_2.

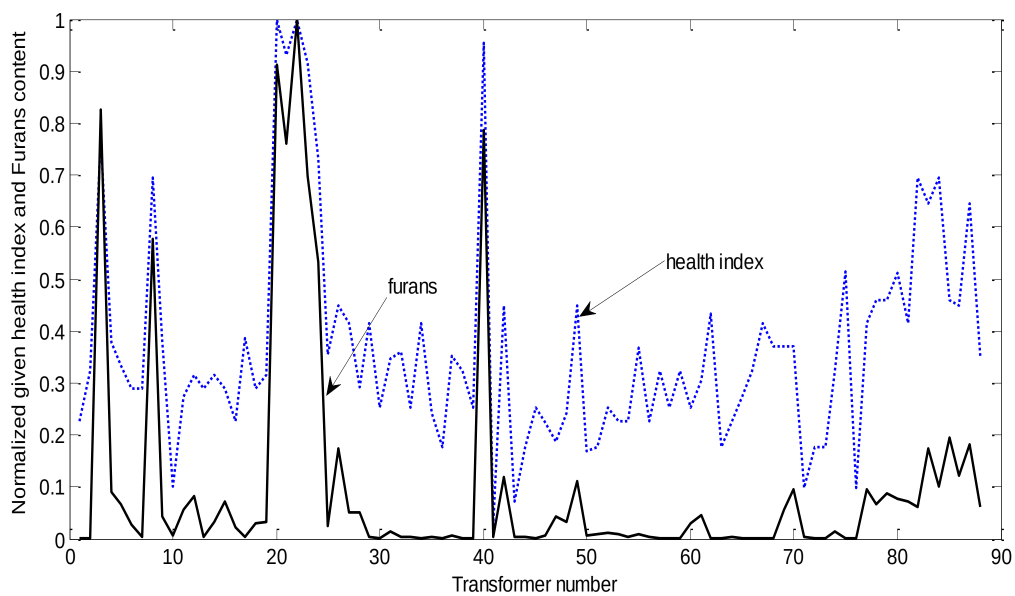

Fig. 7-7 Correlation between the health index and furans.

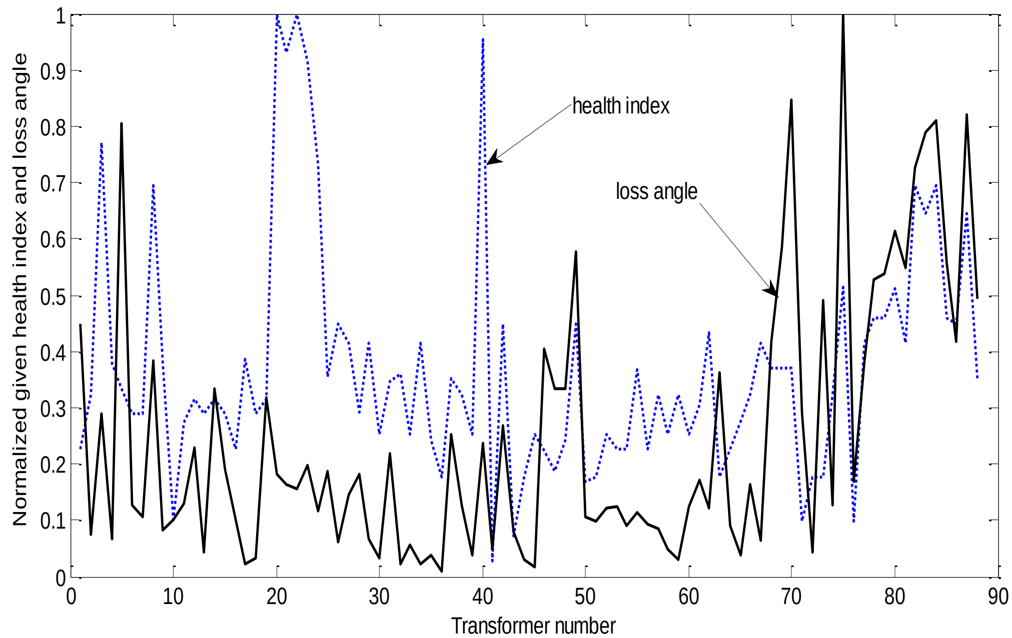

Fig. 7-8 Correlation between the health index and loss factor.

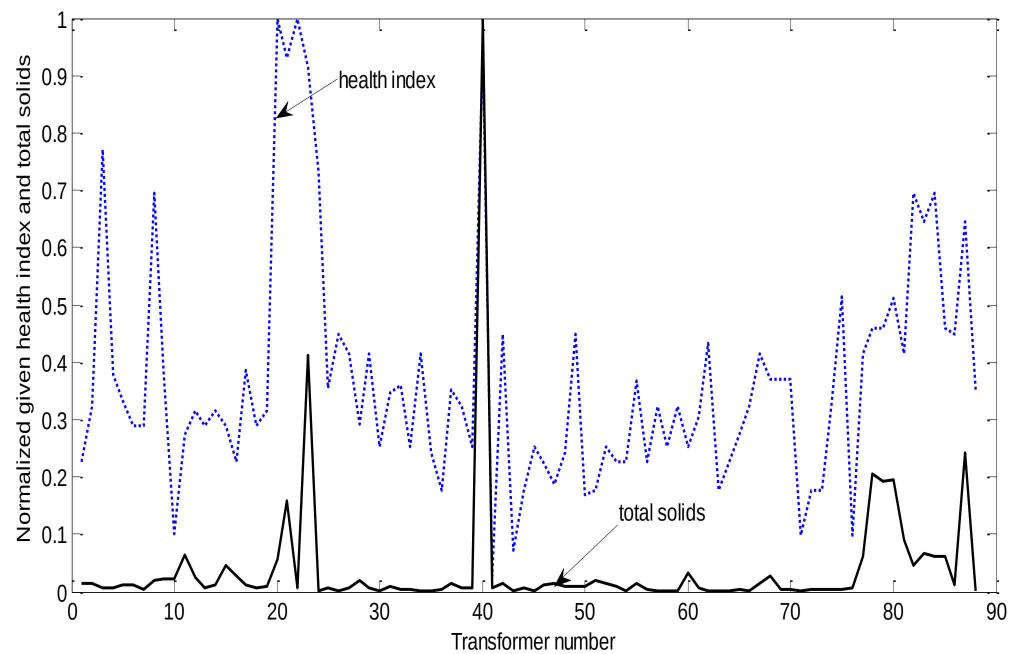

Fig. 7-9 Correlation between the health index and total solids.

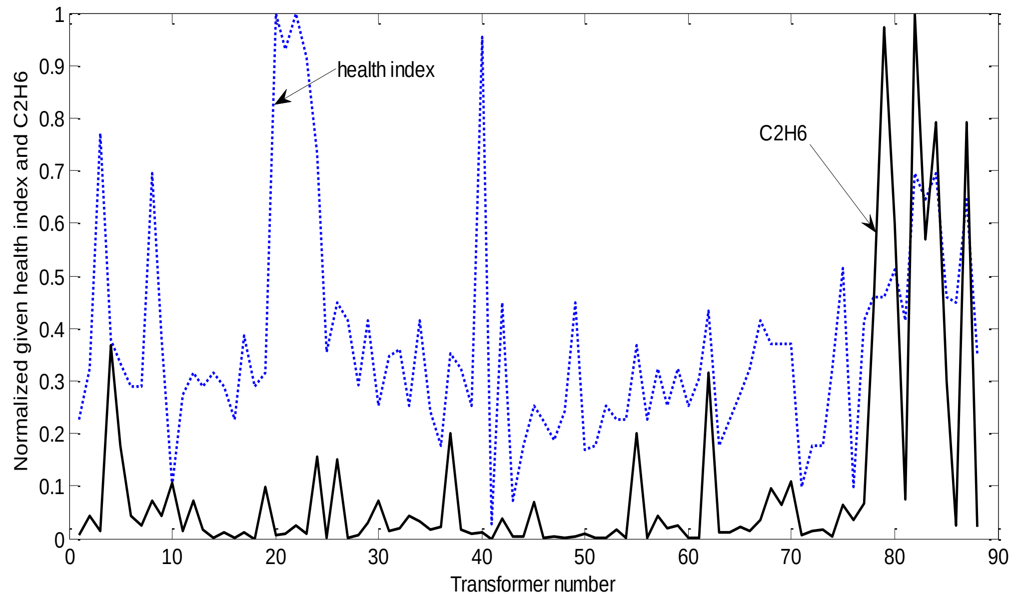

Fig. 7-10 Correlation between the health index and C_2H_6.

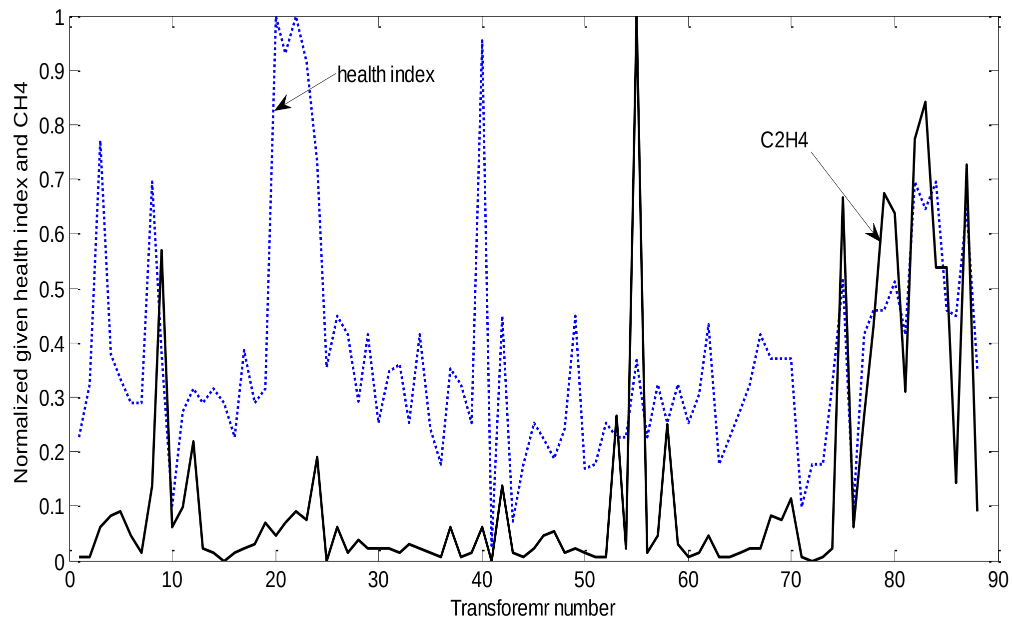

Fig. 7-11 Correlation between the health index and C_2H_4.

Table 7-1 Correlation coefficients between the given health index and all data categories

Data Category	Correlation Coefficient
water	0.417
acidity	0.521
BDV	-0.38
H_2	0.0285
CH_2	0.124
C_2H_6	0.332
C_2H_4	0.345
C_2H_2	-0.082
furans	0.850
loss angle	0.282
total solids	0.497

It is clear from Table 7-1 that the correlation coefficients between the given health index and both BDV and C_2H_2 are negative. The negative correlation between the BDV and the health index is clear because the higher the BDV, the better the transformer insulation and the lower the corresponding value of the health index (better health). However, the value of the health index would be expected to be proportional to the C_2H_2 level [102] because the correlation between the C_2H_2 content and the condition of the transformers in the given samples is unclear. Fig. 7-6 shows that the maximum value of C_2H_2 is one ppm. According to [102], if the value of the C_2H_2 content is less than unity, the transformer condition is considered to be good. A quick look at the remaining data categories for all transformers and at the given health index by AMHA shows many transformers to be in a moderate or bad condition, which means that the correlation between the C_2H_2 content and the condition of the transformers in the given samples is unclear. In addition, the condition of a transformer based on key gas analysis does not depend only on one key gas; instead, it depends on all gases [102].

The basis of this method is that highly correlated data categories will have a higher contribution to the health index than data categories with lower correlations. The first step was therefore to determine an appropriate share of the attributes in the health index by calculating a weight for each.

$$W_i = (corr_i \times 10)^3 \tag{7-3}$$

where $corr_i$ is the correlation between the given health index and the data category (i).

To avoid negative values in the calculated health index, all values of W_i should be positive. To achieve this, the calculated correlation coefficients for the BDV and C_2H_2 were replaced by the correlation coefficients between the given health index and (1-BDV) and (1-C_2H_2). The new correlation coefficients are shown in Table 7-2. The new formula for calculating the health index was changed accordingly as follows

$$\begin{aligned} \mathrm{HI}_k = {} & W_1 \times water_k + W_2 \times acidity_k + W_3 \times (1 - BDV_k) + W_4 \times H_{2_k} \\ & + W_5 \times CH_{4_k} + W_6 \times C_2H_{6_k} + W_7 \times C_2H_{4_k} + W_8 \times (1 - C_2H_{2_k}) \\ & + W_9 \times furans_k + W_{10} \times loss\ angle_k + W_{11} \times total\ solids_k \end{aligned} \tag{7-4}$$

Table 7-2 Correlation coefficients between the given health index and the modified data categories

Data Category	**Correlation Coefficient**
water	0.417
acidity	0.521
BDV	0.38
H_2	0.0285
CH_2	0.124
C_2H_6	0.332
C_2H_4	0.345
C_2H_2	0.082
furans	0.850
loss angle	0.31
total solids	0.497

In this way, highly correlated data categories have a very high influence on the health index, and the data categories with low correlation have very low influence. The rationale for this weighting system is that highly correlated data categories such as furans should be dominant in the calculation of the health index. Table 7-3 shows the weights calculated for the eleven data categories.

The values of the weights shown in Table 7-3 will give very high health index values when they are substituted in (7-4). To keep the range of the normalized health index between zero and one, the values of the weights shown in Table 7-3 were reduced without losing the relative percentages. To achieve this goal, each individual weight was divided by the summation of all weights. The new weights are shown in Table 7-4.

Fig. 7-12 shows the calculated health indices and the given health indices. The correlation coefficient between the given health indices and the calculated health indices was determined according to equation (7-2). The correlation coefficient was found to be 0.8925.

Table 7-3 Weights of all data categories

Attribute	**Weight (W_i)**
water	72.5648
acidity	141.4948
1-BDV	54.8768
H_2	0.0233
CH_4	1.9145
C_2H_6	36.5458
C_2H_4	40.9267
1-C_2H_2	0.5563
furans	614.7952
loss angle	30.4556
Total solids	124.2396

Table 7-4 New weights of all data categories

Attribute	**Weight (W_i)**
water	0.0649
acidity	0.1265
1-BDV	0.0491
H_2	0.0000001
CH_4	0.0017
C_2H_6	0.0327
C_2H_4	0.0366
1-C_2H_2	0.0005
furans	0.5497
loss angle	0.0272
Total solids	0.1111

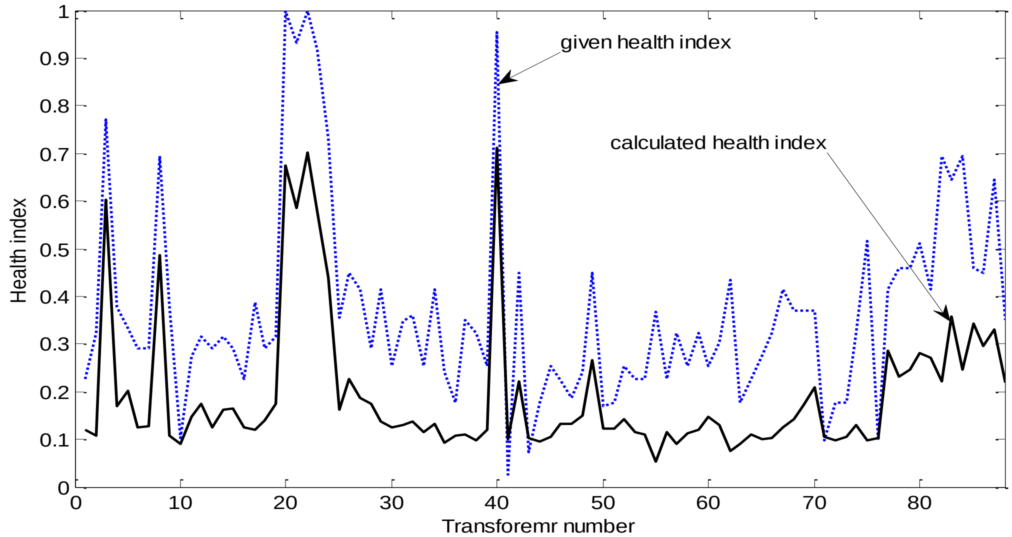

Fig. 7-12 The calculated health indices versus the given health indices.

7.3.1.2 Discussion

The two curves representing the estimated health indices and the given health indices shown in Fig 7-12 do not coincide. However, it is not, in fact, essential for the estimated and target indices (given health indices by AMHA) to coincide. It is sufficient only to have them very close to each other. The main purpose of the health index is to indicate the condition of the transformer: good, moderate, or bad. In general terms, an asset in good condition would be expected to continue to operate satisfactorily for the foreseeable future, that is, to have a long remaining lifespan, and not to require any significant change to the current operation and maintenance. Transformers with a moderate health condition would not be at immediate risk but may become increasingly unreliable in the medium term (5-10 years). Assets in this condition are potential candidates for life extension measures, enhanced maintenance, refurbishment, etc. Transformers in bad condition are at risk in the short term, and this risk will increase relatively quickly. Significant investment (replacement) is required in order to prevent an unacceptable probability of failure. For electricity network assets, this condition often equals to effective end of life.

The next step was to define new thresholds for differentiating between a good condition, a moderate condition, and a bad condition, according to the calculated health index. The thresholds were found to be 0.21 and 0.42, i.e., a transformer is considered to be in good condition if the calculated health index is between 0 and 0.21, a transformer is considered to be in moderate condition if the calculated health index is between 0.21 and 0.42, and a transformer is considered to be in bad condition if the calculated health index is between 0.42 and 1. Thus, using the 11 previously discussed measurements for any transformer by employing the same normalization standards used in this method, and then applying (7-4) using the weights shown in Table 7-4 enables the health index to be determined. Using the developed threshold levels, the condition of the transformer can then be assessed as good, moderate, or bad. The accuracy of the calculated index with respect to the given index is shown in Table 7-5. The developed method correctly identified the condition of 82 of the 88 transformers: 93.18% accuracy, which is considered good accuracy.

Table 7-4 shows that the largest weights in all data categories are the weights for furans, acidity, total solids, and water content. The data categories with large weights make a greater contribution to the health index; in other words, they are very good measures of the age of a transformer. Levels of furans, acidity, and water content were expected to play a significant role in the health index because they are currently used for condition assessment of transformers and the determination of end of life [1, 2, 55, 57, 59, 103]. Total solids are also an accepted indication of the transformer degradation.

Table 7-5 Accuracy of method 1

	Good	**Moderate**	**Bad**	**Total**
Good	60	0	0	60
Moderate	0	14	6	20
Bad	0	0	8	8

7.3.2 Method 2: Use of Artificial Intelligence

7.3.2.1 Method Concepts

Artificial intelligence is the term used to refer to systems that act in a way that to any observer would appear to be intelligent [104]. One of the most important branches of artificial intelligence is the artificial neural network (ANN). An ANN is an information processing paradigm that was inspired by the biological nervous systems in the human brain [104]. The key element of this paradigm is the novel structure of the information processing system, which is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. This principle is true of ANNs as well.

Neural networks have a remarkable ability to derive meaning from complicated or imprecise data. They can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyze. Given new situations of interest, this expert can then be used to provide projections and to answer "what if" questions [105].

An ANN was used to estimate the health index of a transformer. The data available for the 88 transformers were used to train a feed forward artificial neural network (FFANN) in order to determine the health index of a transformer [106]. The measurements available for the 88 transformers were divided into two sets: a training set and a testing set. The training set consisted of the data for randomly selected 59 transformers (67% of the available data). The testing set consisted of the data for the remaining 29 transformers (33% of the available data).

A four-layer FFANN was used to estimate the health indices of the transformers. The FFANN is shown in Fig. 7-13. The neural network used consists of one input layer, one output layer, and two hidden layers. The input layer consists of 11 neurons; the input to the input layer are the previously mentioned 11 data categories for the 88 transformers. The output layer consists of one neuron representing the health index for the transformer under study. The output of the output layer neuron is in the range of zero to one: zero represents a brand new transformer and one represents a transformer in a very bad condition, which should be replaced. With respect to the hidden layers, it is customary that the number of neurons in the hidden layers be selected by trial and error, so this approach was employed in the development of the algorithm. The number of hidden layers was found to be two, with four neurons in the first hidden layer and two neurons in the second hidden layer. The weights matrices of the trained ANN is shown in Appendix D.

A comparison of the given health indices for the 59 transformers used in the training of the FFANN and the health indices output by the FFANN for the training set is shown in Fig. 7-14. It is clear from Fig. 7-14 that the output of the FFANN is very close to the original health indices of the training set of transformers. The trained FFANN was tested using the testing set, which included 29 transformers. The given health indices for the testing set and the output of the FFANN for the testing set are shown in Fig. 7-15. Fig. 7-15 shows that the estimated health indices for the testing set are numerically close to the given health indices for the same set. Table 7-6 shows the given health indices for the testing set and the corresponding output of the FFANN.

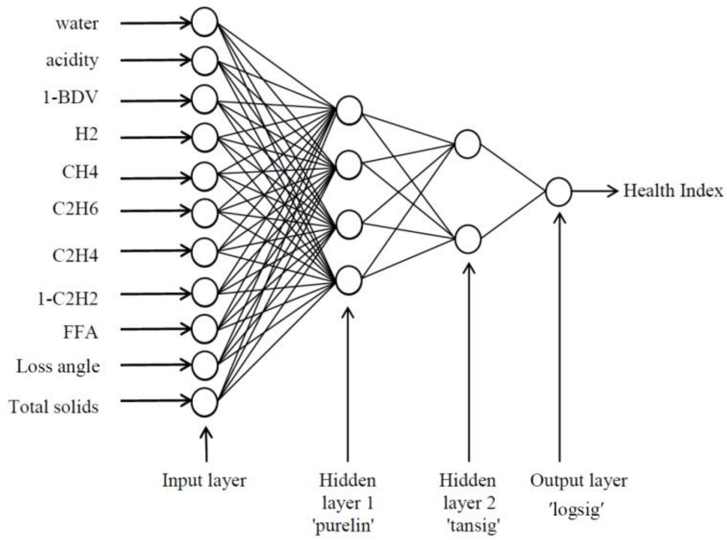

Fig. 7-13 FFANN configuration.

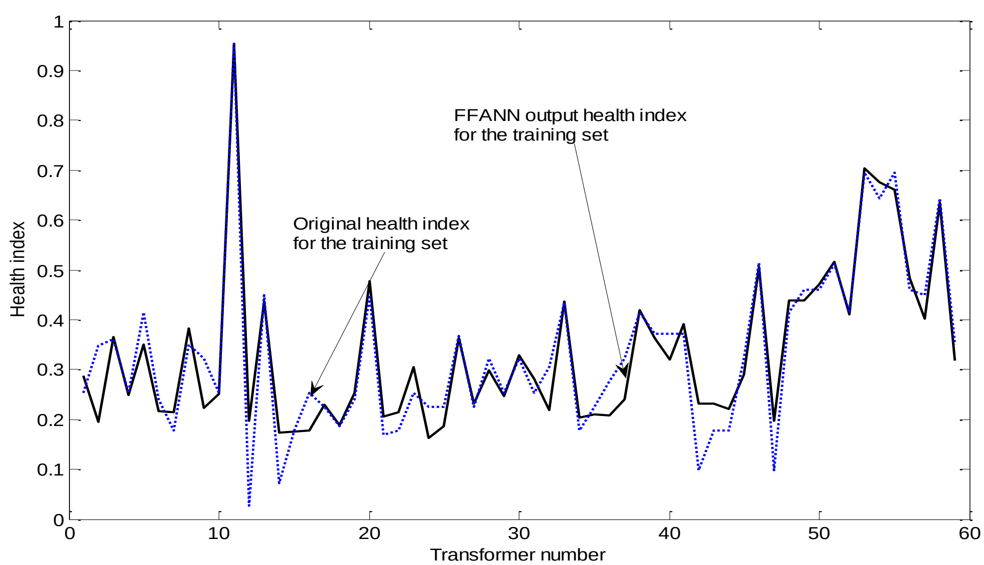

Fig. 7-14 The given health indices for the 59 transformers used in the training of the FFANN and the health indices output by the FFANN for the same training set.

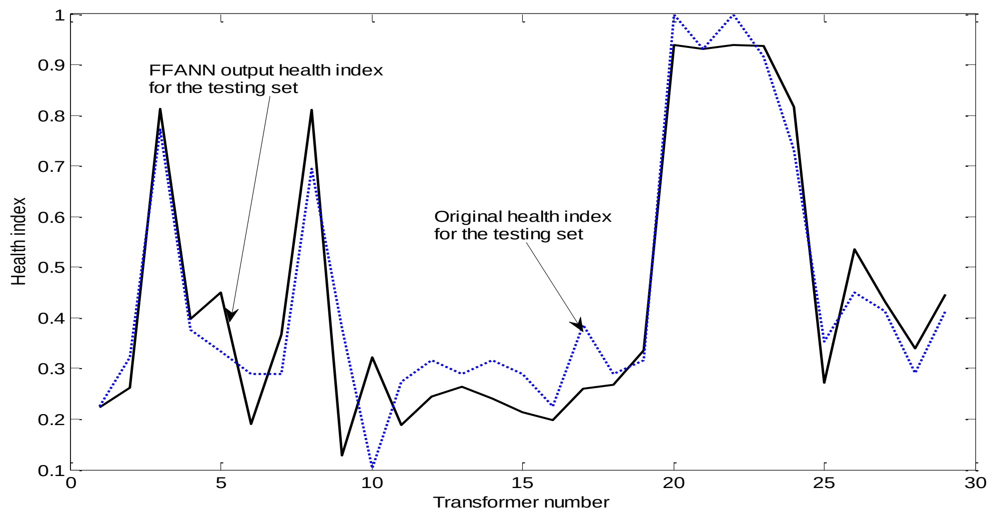

Fig. 7-15 The given health indices for the 29 transformers used in the testing of the FFANN and the health indices output by the FFANN for the same testing set.

Table 7-6 Given health indices for the testing set and the corresponding output of the FFANN

Transformer number	Given health index	FFANN output health index	Transformer number	Given health index	FFANN output health index
1	0.226	0.224	16	0.226	0.199
2	0.322	0.261	17	0.387	0.259
3	0.772	0.813	18	0.29	0.269
4	0.377	0.398	19	0.316	0.337
5	0.334	0.45	20	1	0.94
6	0.29	0.19	21	0.931	0.931
7	0.29	0.367	22	1	0.939
8	0.701	0.81	23	0.916	0.937
9	0.381	0.129	24	0.732	0.8156
10	0.102	0.323	25	0.354	0.271
11	0.274	0.189	26	0.45	0.535
12	0.316	0.245	27	0.414	0.432
13	0.29	0.264	28	0.291	0.339
14	0.316	0.241	29	0.414	0.4467
15	0.29	0.214			

7.3.2.2 Discussion

As mentioned in the discussion of method 1, determining the condition of a transformer is the main goal of the investigation. From this perspective, it can be said that the trained FFANN can classify the condition of the transformers with excellent accuracy. The estimated and target health indices for the testing set of transformers shown in Table 7-7 were converted into health conditions (good, moderate, or bad) according to the previously mentioned criteria. Table 7-8 shows the accuracy of the FFANN classifier based on the health condition criteria.

Table 7-8 shows that the FFANN classifier correctly classified 28 of the 29 test cases: 96.55% accuracy. Moreover, a quick look at Table 7-6 reveals that the incorrectly classified case is case 5. The calculated and given health indices of case 5 are 0.45 and 0.334, respectively. The given health index indicates that the transformer is at the end of the good condition zone, and the calculated health index indicates that the transformer is in the beginning of the moderate condition zone, which means that the two output values are not actually widely divergent.

Table 7-7 The transformer condition output by the FFANN and the target conditions of the transformer testing set

Transformer number	**Given health index**	**FFANN output health index**	**Transformer number**	**Given health index**	**FFANN output health index**
1	good	good	16	good	good
2	good	good	17	good	good
3	bad	bad	18	good	good
4	good	good	19	good	good
5	good	moderate	20	bad	bad
6	good	good	21	bad	bad
7	good	good	22	bad	bad
8	bad	bad	23	bad	bad
9	good	good	24	bad	bad
10	good	good	25	good	good
11	good	good	26	moderate	moderate
12	good	good	27	moderate	moderate
13	good	good	28	good	good
14	good	good	29	moderate	moderate
15	good	good			

Table 7-8 Accuracy of the FFANN classifier with respect to the transformer condition

	Good	**Moderate**	**Bad**	**Total**
Good	18	1	0	19
Moderate	0	3	0	3
Bad	0	0	7	7

The trained FFANN can be used by utilities and industries to determine the health index for any transformer by feeding the 11 previously mentioned measurements for any transformer into the trained FFANN after normalization with the use of the same standards.

7.3.3 Method 3: Least Squares Curve Fitting

7.3.3.1 Method Concepts

In method 3, the given data categories and health indices were used to find the weights for each data category using a least squares curve fitting. The weights (W_i) from (7-1) were calculated in order to minimize the square error between the calculated health indices and the given health indices.

The data for the 59 transformers in the training set were used to find the weights, which were then used to determine the health indices of the testing set of 29 transformers. MATLAB© was used to solve this overdetermined set of linear equations. The calculated weights are shown in Table 7-9.

Table 7-9 Weights calculated using method 3

Attribute	**Weight (W_i)**
water	0.5213
acidity	-0.2810
1-BDV	0.1289
H_2	0.1024
CH_4	0.1911
C_2H_6	-0.0701
C_2H_4	0.2129
C_2H_2	-0.0536
FFA	0.7770
Loss angle	0.1278
Total solids	0.0914

© MATLAB is a trademark of Mathworks Inc.

Fig. 7-16 shows the given health indices for the 59 transformers used in the optimization and the output health indices for the same training set. Fig. 7-17 depicts the given health indices for the 29 transformers used in the testing of the least squares output and the output health indices for the same testing set.

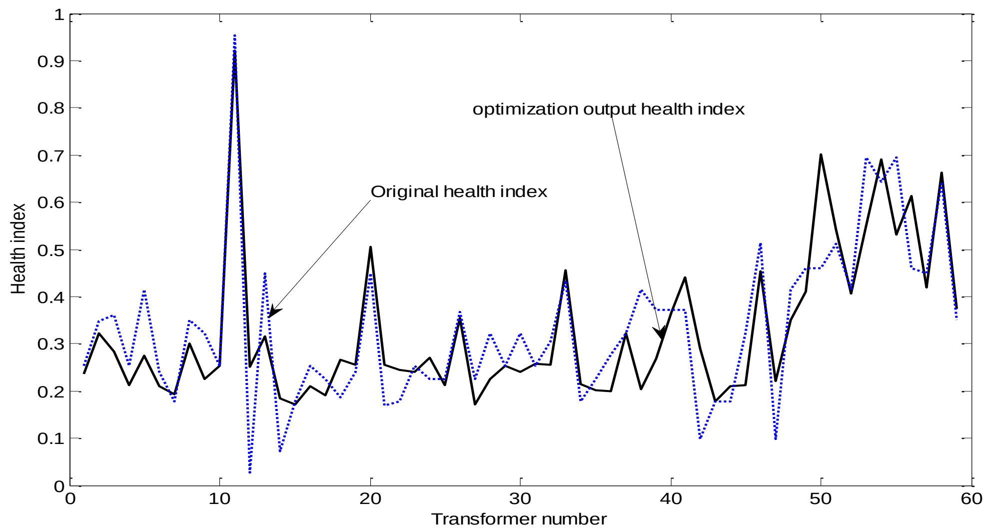

Fig. 16 The given health indices for the 59 transformers used in the optimization and the output health indices for the same training set.

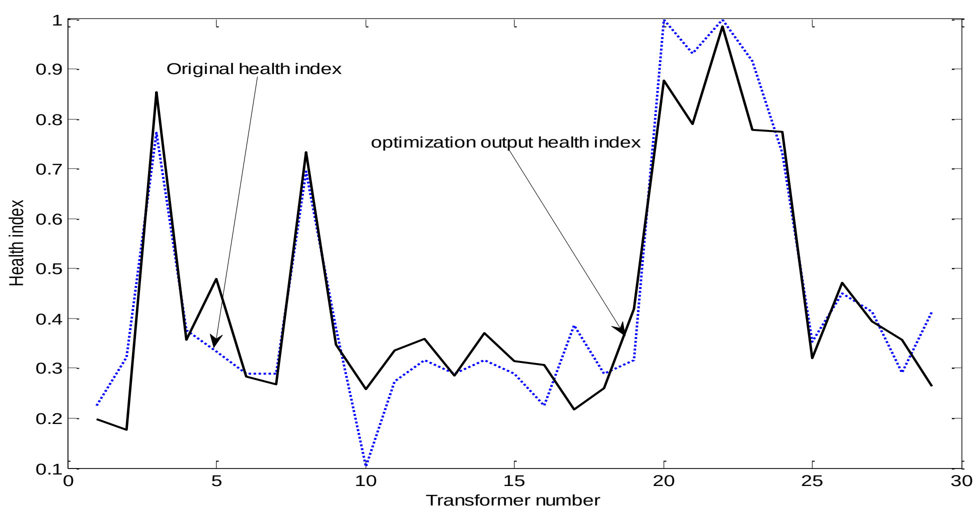

Fig. 17 The given health indices for the 29 transformers used in the testing of the least squares output and the output health indices for the same testing set.

Table 7-10 shows the calculated health indices and the target health indices for the testing set of transformers.

Table 7-10 Given health indices for the testing set and the corresponding estimates using method 3

Transformer number	Given health index	Estimated health index	Transformer number	Given health index	Estimated health index
1	0.226	0.199	16	0.226	0.306
2	0.322	0.176	17	0.387	0.218
3	0.772	0.853	18	0.29	0.261
4	0.377	0.358	19	0.316	0.419
5	0.334	0.479	20	1	0.876
6	0.29	0.283	21	0.931	0.790
7	0.29	0.269	22	1	0.985
8	0.701	0.733	23	0.916	0.778
9	0.381	0.348	24	0.732	0.774
10	0.102	0.258	25	0.354	0.321
11	0.274	0.336	26	0.45	0.471
12	0.316	0.359	27	0.414	0.401
13	0.29	0.286	28	0.291	0.357
14	0.316	0.37	29	0.414	0.264
15	0.29	0.315			

7.3.3.2 Discussion

Table 7-11 shows the calculated health conditions and the given health conditions for the testing set of transformers. The method failed to correctly classify only three of the 29 testing cases: 89.7% accuracy. Table 7-12 shows the accuracy of method 3. Method 3 can therefore be applied in the same way as methods 2 and 3. To find the health index of any transformer, the 11 previously mentioned measurements for any transformer are normalized using the same standards, and then are substituted for the 11 variables of (7-1). In this case, the weights shown in Table 7-9 are used in (7-1).

Table 7-11 The output transformer health conditions using method 3 and the given health conditions for the transformer testing set

Transformer number	Given health index	Estimated health index	Transformer number	Given health index	Estimated health index
1	good	good	16	good	good
2	good	good	17	good	good
3	bad	bad	18	good	good
4	good	good	19	good	moderate
5	good	moderate	20	bad	bad
6	good	good	21	bad	bad
7	good	good	22	bad	bad
8	bad	bad	23	bad	bad
9	good	good	24	bad	bad
10	good	good	25	good	good
11	good	good	26	moderate	moderate
12	good	good	27	moderate	moderate
13	good	good	28	good	good
14	good	good	29	moderate	good
15	good	good			

Table 7-12 Accuracy of method 3

	Good	Moderate	Bad	Total
Good	17	2	0	19
Moderate	1	2	0	3
Bad	0	0	7	7

7.4 Conclusion

Three methods for calculating the health index of any transformer have been presented in this chapter. Actual data were used in this investigation: the measurement of the water content, acidity, break down voltage (BDV), hydrogen content (H_2), methane content (CH_4), ethylene content (C_2H_4), acetylene content (C_2H_2), ethane content (C_2H_6), furans content, loss factor, and total solids in oil for 90 working transformers. The first and third methods assume a linear relationship between the health index and all data categories. The weights of the linear relationship in method 1 were found using the correlation coefficients between the given health index and all data categories. The weights of the linear relationship in method 3 were found using least squares curve fitting concept. The second method is based on the use of an ANN to calculate the health index. The results show that the errors in the calculation of the health index using all three methods are small. Using any of the three methods presented, the health condition of any working transformer can therefore be evaluated (good, moderate, bad). Electrical utilities and industrial plants can thus readily evaluate the health condition of their transformers by performing the 11 specified measurements and inputting them into the linear relations used in either method 1 or 3 after normalization. The trained ANN employed in method 2 can also be used to determine the health condition of a transformer using the 11 specified measurements.

Chapter 8
Conclusions, Contributions, and Future Research

8.1 Conclusions

The research presented in this thesis focuses mainly on the problems associated with assessing of end of life and replacement of power transformers. The following list summarizes the work completed for this thesis.

- The thesis includes a survey of the different topics related to the management of the transformer assets: condition monitoring and condition assessment of the transformer, performing maintenance plans, and assessment of health and end of life. Methods of monitoring and assessing the condition of transformers were highlighted and discussed. Existing maintenance plans were presented, along with the advantages and disadvantages of each maintenance scheme.
- Special attention was given to assessment of the health and end of life of transformers because these topics formed the main theme of this work. A chapter was developed to an analysis of all aging mechanisms, including the main ones for transformers: physical aging and economic aging. The techniques for assessing physical aging were discussed and their deficiencies highlighted. Existing methods of assessing economic end of life were introduced and their drawbacks presented. Existing techniques for assessing the condition of transformer health were introduced and their deficiencies highlighted.
- Regarding the physical end of life, a new thermal model has been developed for assessing the end of life of power transformers, the main cause of which is solid insulation failure. The new method is based on an algorithm for determining the end of life point of transformer insulation. The monthly average temperature and solar clearness index are used to model the ambient temperature surrounding the transformer. Transformer loading is modeled based on the average daily load curve. A Monte Carlo simulation was used in order to take into consideration the uncertainties associated with the daily load and ambient temperature, on the basis which, the average lifetime of the transformer can be calculated. A case study has been presented to demonstrate the implementation and effectiveness of the developed method.

- To highlight the superiority of the new method, the developed method for assessing the thermal end of life was compared with existing work.
- An additional area of investigation was economic end of life of transformers, and a new techno-economic method has been developed. Using this method, the transformer operator can implement an economical replacement decision that is based on the technical factors affecting the transformer. With this method, the present worth, cost of operation, cost of repair, and cost of interruptions are used to find the EUAC for both a new and an existing transformer in order to arrive at the expected time when the replacement of the transformer would be cost effective.
- Two case studies demonstrated the performance of the developed techno-economic method. In the first case study, the challenger transformer was assumed to have constant capital cost. The second case study was more complex because the effect of inflation and increase in raw material costs were factored into the capital cost of the challenger transformer. The results of the two case studies show that it was most economical to retire the existing transformer before the end of its useful lifetime; otherwise, the transformer operator will be faced with higher costs.
- The effects of changing the interest rate, the energy and demand charges, and the capitals cost on the final result are studied in a sensitivity analysis section. It is shown that the changes of transformer capital cost and interest rate have more effect on replacement year than the energy and demand charges.
- The calculation of the transformer health index and corresponding health condition was presented in Chapter 7. Real tests of 11 parameters for 90 working transformers (total of 990 tests) were used in order to determine a systematic approach to the calculation of the health index of a transformer, based on which the health condition of the transformer can be evaluated (good, moderate, or bad). Three methods were presented, and their accuracy was tested using the health indices provided by a specialized consulting company. Any of the presented methods can be used directly by electrical utilities and industries as a means of assessing the health condition of any of the working transformers in their fleet.

8.2 Contributions

The following is a summary of the contributions of this research:

- A complete presentation of most transformer asset management techniques and related topics.

- A novel method of calculating the ambient temperature surrounding a transformer using the average monthly temperature and the solar clearness index.
- A new method of modeling transformer loading that takes into account the average daily load curve and the associated uncertainty.
- The use of a Monte Carlo simulation to determine the thermal lifetime of a transformer using the ambient temperature and load models.
- The utilization of important technical information about the transformer, such as the failure rate, in the calculation of the most economical replacement time.
- The use of the bathtub failure model to calculate a transformer's present worth.
- The calculation of the cost of repairs and interruptions in alignment with a real accepted deterioration model, i.e., the bathtub model.
- Consideration of the uncertainties inherent in the failure and repair rates that are considered in a techno-economic replacement decision.
- Employment of a Monte Carlo simulation technique to account for the uncertainties in the failure and repair rates.
- Introduction of the cost of interruptions as an important factor among other factors in the techno-economic replacement decision.
- Presentation of three systematic methods of determining a transformer health index and corresponding health condition.

8.3 Suggestions of Future work

The following are suggestions for possible future work:

- The thesis presented a new method of calculating the thermal lifetime of regular transformers. Modifying this approach to enable the calculation of the thermal lifetime of transformers that supply non-sinusoidal loads is a possible extension of the work.
- The presented techno-economic replacement method could be modified to enable the determination of an appropriate replacement year for circuit breakers and underground cables.

- The available data for the 90 transformers could be used as a basis for proposing more refined systematic methods of determining the health index of working transformers.

Appendices

Appendix A
Hot Spot Temperature Calculation

According to IEEE STD. C57.91-1995 [3] the HST can be calculated as follows:

$$\theta_{HS} = \theta_A + \Delta\theta_{TO} + \Delta\theta_H \qquad \text{(A-1)}$$

where

Θ_{HS}: temperature of hot spot in ^oC;

Θ_A: ambient temperature in ^oC;

$\Delta\Theta_{TO}$: top oil temperature rise over ambient in ^oC;

$\Delta\Theta_H$: winding HST rise over top oil in ^oC.

The top-oil temperature rise at a time after a step load change is given by the following Formula [3]:

$$\Delta\theta_{TO} = (\Delta\theta_{TO,U} - \Delta\theta_{TO,i}) \times (1 - e^{-\frac{1}{\tau_{TO}}}) + \Delta\theta_{TO,i} \qquad \text{(A-2)}$$

where

$\Delta\Theta_{TO,U}$: the ultimate top oil temperature rise over ambient for load L in ^oC;

$\Delta\Theta_{TO,i}$: the initial top oil temperature rise over ambient for t=0 in ^oC;

τ_{TO} : the top oil time constant for load L in hrs.

For the two-step overload cycle, the initial top-oil rise ($\Delta\Theta_{TO,i}$) is given by the following [3]:

$$\Delta\theta_{TO,i} = \Delta\theta_{TO,R}\left(\frac{K_i^2 R + 1}{R + 1}\right)^x \tag{A-3}$$

where

$\Delta\Theta_{TO,R}$: top oil temperature rise over ambient at rated load in ^{o}C;

K_i: the initial ratio of load *L* to rated load, per unit;

R: the ratio of load loss at rated load to no-load loss.

The ultimate top-oil rise ($\Delta\Theta_{TO,U}$)is given by the following [3]:

$$\Delta\theta_{TO,U} = \Delta\theta_{TO,R}\left(\frac{K_U^2 R + 1}{R + 1}\right)^x \tag{A-4}$$

where

K_U: the ultimate ratio of load *L* to rated load, per unit.

The top oil time constant can be calculated as follows [3]:

$$\tau_{TO} = \tau_{TO,R} \times \frac{\left(\frac{\Delta\theta_{TO,U}}{\Delta\theta_{TO,R}}\right) - \left(\frac{\Delta\theta_{TO,i}}{\Delta\theta_{TO,R}}\right)}{\left(\frac{\Delta\theta_{TO,U}}{\Delta\theta_{TO,R}}\right)^{1/x} - \left(\frac{\Delta\theta_{TO,i}}{\Delta\theta_{TO,R}}\right)^{1/x}} \tag{A-5}$$

Where, $\tau_{TO,R}$ is the top oil time constant at rated load in hrs and can be calculated as [3]:

$$\tau_{TO,R} = \frac{C\Delta\theta_{TO,R}}{P_{T,R}} \tag{A-6}$$

where

TC : the thermal capacity of the transformer, Watt-hours/°C and it depends on the weights of core , winding, and tank, and the volume of oil;

$P_{T,R}$: the total loss at rated load, watts.

The winding HST rise over top oil temperature can be calculated as follows:

$$\Delta\theta_{H} = (\Delta\theta_{H,U} - \Delta\theta_{H,i})\left(1 - e^{-\frac{t}{\tau_w}}\right) + \Delta\theta_{H,i} \tag{A-7}$$

where

τ_w: the winding time constant at hottest spot location in hrs;

$\Delta\Theta_{H,U}$: ultimate winding HST rise over top oil in ^{o}C at load L and it can be calculated as follows [3]:

$$\Delta\theta_{H,i} = \Delta\theta_{H,R}K_{i}^{2y} \tag{A-8}$$

$\Delta\Theta_{H,i}$: initial winding HST rise over top oil in ^{o}C at at t=0 and it can be calculated as follows [3]:

$$\Delta\theta_{H,U} = \Delta\theta_{H,R}K_{U}^{2y} \tag{A-9}$$

where $\Delta\Theta_{H,R}$ is the rated winding HST rise over top oil in ^{o}C at load L and it can be calculated as follows [3]:

$$\Delta\theta_{H,R} = \Delta\theta_{H/A,R} - \Delta\theta_{TO,R} \qquad \text{(A-10)}$$

where $\Delta\Theta_{H/A,R}$ is the winding hot spot rise over ambient at rated load in ^{o}C.

The variables x and y are exponents for temperature rise equations and their values depend on the method of transformer cooling. The values of n and m could be found in [3].

Appendix B
Data for Case Study I –Chapter 6

Tables B-I to B-IV show the existing and new transformers' parameters for case study I.

Table B-I Transformer Technical Data for Case Study I

Transformer rating (MVA)	2
Useful lifetime (years)	35
Infant region duration (years)	1
Normal region duration (years)	19
Salvage value ($)	0
Failure rate in the normal region (failure/year)	0.07
Max scaling factor in the infant region	1.5
Max scaling factor in the wear-out region	3
Frequency of maintenance (times/year)	0.2
Mean time of maintenance (hours)	10
Mean time to repair (hours)	24
Mean time to switch (hours)	1
Transformer load losses at rated load (kW)	15
Transformer no load losses (kW)	10
Transformer auxiliary losses (kW)	0
Probability of operation of auxiliary equipment	0

Table B-II Load data Case Study I

Maximum load (KW)	1700
Load factor	0.8

Table B-III Financial Data for Case Study I

New transformer capital cost ($)	250000
Existing transformer capital cost ($)	150000
Demand charge per month($/kW)	5
Energy charge ($/kWh)	0.05
interest rate	0.1
Constant part of the cost of repair and maintenance ($)	250
Variable part of the cost of repair and maintenance ($/hour)	540

Table B-IV SCDF of the Industrial Load for Case Study I

SCDF	Interruption cost ($/kW)			
	20 min	1 hr	4 hr	8 hr
	3.868	9.085	25.163	55.808

Appendix C
Data for Case Study II –Chapter 6

Tables C-I to C-V show the existing and new transformers parameters for case study II.

Table C-I Transformer Data for Case Study II

Transformer rating (MVA)	3
Useful lifetime (years)	40
Infant region duration (years)	1
Normal region duration (years)	19
Salvage value ($)	3000
Failure rate in the normal region (failure/year)	0.07
Max scaling factor in the infant region	1.5
Max scaling factor in the wear-out region	4
Frequency of maintenance (times/year)	0.2
Mean time of maintenance (hours)	10
Mean time to repair (hours)	24
Mean time to switch (hours)	1
Existing transformer copper losses at rated load (kW)	25
Existing transformer no load losses (kW)	12
New transformer copper losses at rated load (kW)	23
New transformer no load losses (kW)	11
Existing and new transformers auxiliary losses (kW)	4
Probability of operation of auxiliary equipment	0.06

Table C-II Financial Data for Case Study II

New transformer capital cost ($)	390000
Existing transformer capital cost ($)	200000
Demand charge per month($/kW)	4
Energy charge ($/kWh)	0.04
interest rate	0.1
Constant part of the cost of repair and maintenance ($)	250
Variable part of the cost of repair and maintenance ($/hour)	630

Table C-III Load Data for Case Study II

Maximum load (KW)	2400
Load factor	0.8

Table C-IV SCDF Data for Case Study II

Load type	Interruption cost ($/kW)			
	20 min	1 hr	4 hr	8 hr
Residential load	0.093	0.482	4.914	15.69
Industrial load	3.868	9.085	25.163	55.808
Commercial load	2.969	8.552	31.317	83.008

Table C-V GCDF for the Combined Load

GCDF	Interruption cost ($/kW)			
	20 min	1 hr	4 hr	8 hr
	2.5646	6.7211	22.5624	56.6585

Appendix D
Weights Matrices for the ANN in Chapter 7

Tables D-1 to D-2 show the weights of the trained ANN between the input layer and two hidden layers, while Table D-3 shows the weights of the trained ANN between second hidden layer and the out layer.

Table D-1 Weights of ANN between input layer and first hidden layer

	Input layer										
Hidden layer 1	0.327	-0.101	0.038	-0.366	-0.196	0.731	-0.223	0.2048	-0.833	-0.823	-1.38
	-1.03	-0.247	-1.31	0.4138	-0.486	0.0258	0.256	-0.153	-1.052	-0.444	-0.2
	-0.35	0.0292	-0.99	-1.626	1.6625	0.0957	0.2047	-0.047	-0.611	0.0637	-0.86
	0.391	0.3208	-0.08	-0.015	0.3886	-0.732	0.6777	-0.010	0.6616	0.0631	-0.32

Table D-2 Weights of ANN between first hidden layer and second hidden layer

	Hidden layer 1			
Hidden layer 2	0.109	-0.291	0.757	-0.015
	-0.47	0.3165	-1.287	-0.145

Table D-3 Weights of ANN between second hidden layer and output layer

	Hidden layer 2	
Output layer 2	6.809	4.4417

Bibliography

[1] A. E. B. Abu-Elanien and M. M. A. Salama, "Asset management techniques for transformers," *Electr. Power Syst. Res.*, vol. 80, pp. 456-464, 2010.

[2] J. P. Van Bolhuis, E. Gulski and J. J. Smit, "Monitoring and diagnostic of transformer solid insulation," *IEEE Transactions on Power Delivery*, vol. 17, pp. 528-536, 2002.

[3] "IEEE guide for loading mineral-oil-immersed transformers," *IEEE Std C57.91-1995*, 1996.

[4] "IEEE guide for loading mineral-oil-immersed power transformers up to and including 100 MVA with 55 degrees C or 65 degrees C average winding rise," *ANSI/IEEE Std C57.92-1981*, 1981.

[5] S. Yakov, M. de Nigris and P. G. Antonioli, "Study of the life consumption of distribution transformers and assessment of end-of-life criteria," in *proc. 12th International Conference on Electricity Distribution, CIRED*, 1993, pp. 1.16/1-1.16/5 vol.1.

[6] W. Young, "Transformer life management-condition monitoring," in *proc. IEE Colloquium on Transformer Life Management*, 1998, pp. 2/1-2/4.

[7] C. Myers, "Transformers-conditioning monitoring by oil analysis large or small; contentment or catastrophe," in *proc. First IEE/IMechE International Conference on Power Station Maintenance - Profitability through Reliability*, 1998, pp. 53-58.

[8] A. E. B. Abu-Elanien and M. M. A. Salama, "Survey on the transformer condition monitoring," in *proc. 2007 Large Engineering Systems Conference on Power Engineering, ,* 2007, pp. 187-191.

[9] Jouni K. Pylvanainen, Kirsi Nousiainen and Pekka Verho, "Studies to Utilize Loading Guides and ANN for Oil-Immersed Distribution Transformer Condition Monitoring," *IEEE Transactions on Power Delivery*, vol. 22, pp. 201-207, 2007.

[10] W. H. Tang, Q. H. Wu and Z. J. Richardson, "Equivalent heat circuit based power transformer thermal model," *IEE Proceedings Electric Power Applications*, vol. 149, pp. 87-92, 2002.

[11] J. Q. Feng, P. Sun, W. H. Tang, D. P. Buse, Q. H. Wu, Z. Richardson and J. Fitch, "Implementation of a power transformer temperature monitoring system," in *proc. International Conference on Power System Technology, PowerCon 2002*, 2002, pp. 1980-1983 vol.3.

[12] O. Roizman and V. Davydov, "Neuro-fuzzy algorithms for power transformers diagnostics," in *proc. International Conference on Power System Technology, PowerCon 2000*, 2000, pp. 253-258 vol.1.

[13] Ji Shengchang, Shan Ping, Li Yanming, Xu Dake and Cao Junling, "The vibration measuring system for monitoring core and winding condition of power transformer," in *proc. of 2001 International Symposium on Electrical Insulating Materials, (ISEIM 2001).*, 2001, pp. 849-852.

[14] Pengju Kang and D. Birtwhistle, "Condition assessment of power transformer on-load tap-changers using wavelet analysis," *IEEE Transactions on Power Delivery,* vol. 16, pp. 394-400, 2001.

[15] P. Kang and D. Birtwhistle, "Condition Assessment of Power Transformer on-Load Tap-Changers Using Wavelet Analysis and Self-Organizing Map: Field Evaluation," *IEEE Power Engineering Review,* vol. 22, pp. 69-69, 2002.

[16] S. M. Strachan, S. D. J. McArthur, M. D. Judd and J. R. McDonald, "Incremental knowledge-based partial discharge diagnosis in oil-filled power transformers," in *proc. the 13th International Conference on Intelligent Systems Application to Power Systems,* 2005, pp. 6 pp.

[17] A. Zargari and T. R. Blackburn, "Acoustic detection of partial discharges using non-intrusive optical fibre sensors [current transformers]," in *proc. IEEE 6th International Conference on Conduction and Breakdown in Solid Dielectrics, ICSD '98.,* 1998, pp. 573-576.

[18] S. D. J. McArthur, S. M. Strachan and G. Jahn, "The design of a multi-agent transformer condition monitoring system," *IEEE Transactions on Power Systems,* vol. 19, pp. 1845-1852, 2004.

[19] M. D. Judd, S. D. J. McArthur, J. R. McDonald and O. Farish, "Intelligent condition monitoring and asset management. Partial discharge monitoring for power transformers," *Power Engineering Journal,* vol. 16, pp. 297-304, 2002.

[20] J. S. Foo and P. S. Ghosh, "Artificial neural network modelling of partial discharge parameters for transformer oil diagnosis," in *proc. Annual Report Conference on Electrical Insulation and Dielectric Phenomena,* 2002, pp. 470-473.

[21] A.I. Megahed, A.M. Moussa and A.E. Bayoumy, "Usage of wavelet transform in the protection of series-compensated transmission lines," *IEEE Transactions on Power Delivery,* vol. 21, pp. 1213-1221, 2006.

[22] A. E. B. Abu-Elanien and M. M. A. Salama, "A Wavelet-ANN Technique for Locating Switched Capacitors in Distribution Systems," *IEEE Transactions on Power Delivery,* vol. 24, pp. 400-409, 2009.

[23] Hao Zhang, T. R. Blackburn, B. T. Phung and M. S. Naderi, "A novel wavelet de-noising method for on-site PD measurements on HV cables," in *proc. International Symposium on Electrical Insulating Materials, (ISEIM 2005),* 2005, pp. 845-848 Vol. 3.

[24] Hu Mingyou, Hengkun Xie, Tan Boon Tiong and Xinyan Wu, "Study on a spatially selective noise filtration technique for suppressing noises in partial discharge on-line monitoring," in *Proc. 6th International Conference on Properties and Applications of Dielectric Materials,* 2000, pp. 689-692 vol.2.

[25] P. Werle, A. Akbari, H. Borsi and E. Gockenbach, "Partial discharge localisation on power transformers using neural networks combined with sectional winding transfer functions as knowledge

base," in *Proc. International Symposium onElectrical Insulating Materials, (ISEIM 2001)*, 2001, pp. 579-582.

[26] "IEEE Guide for the Interpretation of Gases Generated in Oil-Immersed Transformers," *IEEE Std C57. 104-1991*, pp. 0_1, 1992.

[27] M. K. Domun, "Condition monitoring of power transformers by oil analysis techniques," in *proc. IEE Colloquium on Condition Monitoring and Remnant Life Assessment in Power Transformers,* 1994, pp. 2/1-2/3.

[28] P. Pahlavanpour, Eklund and M. A. Martins, "Insulating paper ageing and furfural formation," in *Proc. Electrical Insulation Conference and Electrical Manufacturing & Coil Winding Technology Conference,* 2003, pp. 283-288.

[29] Y. C. Huang and C. M. Huang, "Evolving Wavelet Networks for Power Transformer Condition Monitoring," *IEEE Power Engineering Review,* vol. 22, pp. 63-63, 2002.

[30] P. M. Nirgude, B. Gunasekaran, Channakeshava, A. D. Rajkumar and B. P. Singh, "Frequency response analysis approach for condition monitoring of transformer," in *proc. Annual Report Conference on Electrical Insulation and Dielectric Phenomena, CEIDP '04.*, 2004, pp. 186-189.

[31] N. Al-Khayat, L. Haydock and G. McDowell, "Swept frequency response tests for condition monitoring of power transformers," in *proc. IEE Colloquium on Condition Monitoring of Electrical Machines,* 1995, pp. 7/1-7/5.

[32] S. Birlasekaran and F. Fetherston, "Off/on-line FRA condition monitoring technique for power transformer," *IEEE Power Engineering Review*, vol. 19, pp. 54-56, 1999.

[33] A. Kingsmill, S. Jones and J. Zhu, "Application of new condition monitoring technologies in the electricity transmission industry," in *proc. 6th International Conference on Electrical Machines and Systems, ICEMS*, 2003, pp. 852-855 vol.2.

[34] S. D. J. McArthur, E. M. Davidson, V. M. Catterson, A. L. Dimeas, N. D. Hatziargyriou, F. Ponci and T. Funabashi, "Multi-Agent Systems for Power Engineering Applications—Part I: Concepts, Approaches, and Technical Challenges," *IEEE Transactions on Power Systems,* vol. 22, pp. 1743-1752, 2007.

[35] S. D. J. McArthur, E. M. Davidson, V. M. Catterson, A. L. Dimeas, N. D. Hatziargyriou, F. Ponci and T. Funabashi, "Multi-Agent Systems for Power Engineering Applications—Part II: Technologies, Standards, and Tools for Building Multi-agent Systems," *IEEE Transactions on Power Systems,* vol. 22, pp. 1753-1759, 2007.

[36] O. Wilhelmsson, *Evaluation of the introduction of RCM for hydro power generators at vattenfall vattenkraft,* MSc dissertation, Department of Electrical Engineering, Royal Institute of Technology, KTH, 2005.

[37] A. Setayeshmehr, A. Akbari, H. Borsi and E. Gockenbach, "A procedure for diagnosis and condition based maintenance for power transformers," in *proc. Conference Record of the 2004 IEEE International Symposium on Electrical Insulation,* 2004, pp. 504-507.

[38] Yongli Zhu, Lizeng Wu, Xueyu Li and Jinsha Yuan, "A transformer condition assessment framework based on data mining," in *proc. IEEE Power Engineering Society General Meeting*, 2005, pp. 1875-1880 Vol. 2.

[39] M. Wang, A. J. Vandermaar and K. D. Srivastava, "Review of condition assessment of power transformers in service," *IEEE Electrical Insulation Magazine,* vol. 18, pp. 12-25, 2002.

[40] S. Costa and A. F. Brandao Jr., "Optimization of the maintenance of oil filled power transformers based on reliability criteria," in *proc. IEEE/PES Transmission and Distribution Conference and Exposition: Latin America,* , 2004, pp. 297-301.

[41] M. E. Beehler, "Reliability centered maintenance for transmission systems," *IEEE Transactions on Power Delivery,* vol. 12, pp. 1023-1028, 1997.

[42] B. Handley, M. Redfern and S. White, "On load tap-changer conditioned based maintenance," *IEE Proceedings Generation, Transmission and Distribution,* vol. 148, pp. 296-300, 2001.

[43] G. Theil, "Parameter evaluation for extended markov models applied to condition- and reliability-centered maintenance planning strategies," in *proc. International Conference on Probabilistic Methods Applied to Power Systems,* 2006, pp. 1-6.

[44] Na Liu, Wensheng Gao, Kexiong Tan, Liufang Wang, Guodong Liang and Wei Li, "Decision on maintenance period for power transformer based on monte carlo simulation of reliability," in *proc. the 7th International Conference on Properties and Applications of Dielectric Materials,* 2003, pp. 479-482 vol.1.

[45] I. P. Siqueira, "Software requirements for reliability-centered maintenance application," in *proc. International Conference on Probabilistic Methods Applied to Power Systems, PMAPS,* 2006, pp. 1-7.

[46] A. K. S. Jardine and A. H. C. Tsang, *Maintenance,Replacement, and Reliability: Theory and Applications.* Florida: Boca Raton, 2006.

[47] L. Wenyuan, E. Vaahedi and P. Choudhury, "Power system equipment aging," *IEEE Power and Energy Magazine*, vol. 4, pp. 52-58, 2006.

[48] CIGRÉ Working Group 05, An international survey on failures in large power transformers in service, CIGRÉ,1983.

[49] M. Arshad and S. M. Islam, "A novel fuzzy logic technique for power transformer asset management," in *proc. 41st IAS Annual Meeting Conference Record of the 2006 IEEE Industry Applications Conference,* 2006, pp. 276-286.

[50] H. Herman, M. J. Shenton, G. C. Stevens and R. J. Heywood, "A new approach to condition assessment and lifetime prediction of paper and oil used as transformer insulation," in *proc. the 2001 IEEE 7th International Conference on Solid Dielectrics, ICSD '01.,* 2001, pp. 473-476.

[51] A. J. Kachler and I. Hohlein, "Aging of cellulose at transformer service temperatures. Part 1: Influence of type of oil and air on the degree of polymerization of pressboard, dissolved gases, and furanic compounds in oil," *IEEE Electrical Insulation Magazine,* vol. 21, pp. 15-21, 2005.

[52] B. Pahlavanpour and A. Wilson, "Analysis of transformer oil for transformer condition monitoring," in *proc. IEE Colloquium on an Engineering Review of Liquid Insulation,* 1997, pp. 1/1-1/5.

[53] M. Ali, C. Eley, A. M. Emsley, R. Heywood and X. Xaio, "Measuring and understanding the ageing of kraft insulating paper in power transformers," *IEEE Electrical Insulation Magazine,* vol. 12, pp. 28-34, 1996.

[54] M. Mirzaie, A. Gholami and H. Tayyebi, "Thermal degradation of cellulose paper insulation in power transformers," in *proc. IEEE International Conference on Solid Dielectrics, ICSD '07.,* 2007, pp. 673-676.

[55] R. D. Stebbins, D. S. Myers and A. B. Shkolnik, "Furanic compounds in dielectric liquid samples: Review and update of diagnostic interpretation and estimation of insulation ageing," in *proc. the 7th International Conference on Properties and Applications of Dielectric Materials,* 2003, pp. 921-926 vol.3.

[56] T. A. Prevost, H. P. Gasser, R. Wicks, B. Glenn and R. Marek. Estimation of insulation life based on dual temperature aging model. Presented at Weidmann-ACTI Inc. Fifth Annual Tech. Conf..

[57] T. K. Saha, "Review of modern diagnostic techniques for assessing insulation condition in aged transformers," *IEEE Transactions on Dielectrics and Electrical Insulation,* vol. 10, pp. 903-917, 2003.

[58] A. M. Emsley, X. Xiao, R. J. Heywood and M. Ali, "Degradation of cellulosic insulation in power transformers. Part 2: formation of furan products in insulating oil," *IEE Proceedings Science, Measurement and Technology,* vol. 147, pp. 110-114, 2000.

[59] I. Chendong, "Monitoring paper insulation aging by measuring Furfural Contents in oil," in *proc. 7Th Int. Symp. on High Volt. Eng.* 1991.

[60] A. M. Emsley and G. C. Stevens, "Review of chemical indicators of degradation of cellulosic electrical paper insulation in oil-filled transformers," *IEE Proceedings Science, Measurement and Technology,* vol. 141, pp. 324-334, 1994.

[61] "IEEE Guide for Loading Mineral-Oil-Immersed Overhead and Pad-Mounted Distribution Transformers Rated 500 kVa and Less With 65 Degrees C Or 55 Degrees C Average Winding Rise," *ANSI/IEEE Std C57. 91-1981,* pp. 0_1, 1981.

[62] K. T. Muthanna, A. Sarkar, K. Das and K. Waldner, "Transformer insulation life assessment," *IEEE Transactions on Power Delivery,* vol. 21, pp. 150-156, 2006.

[63] W. J. McNutt, "Insulation thermal life considerations for transformer loading guides," *IEEE Transactions on Power Delivery,* vol. 7, pp. 392-401, 1992.

[64] P. K. Sen and P. Sarunpong, "Overloading and loss-of-life assessment guidelines of oil-cooled transformers," in *proc. Rural Electric Power Conference,* 2001, pp. B4/1-B4/8.

[65] J. A. Jardini, H. P. Schmidt, C. M. V. Tahan, C. C. B. De Oliveira and S. U. Ahn, "Distribution transformer loss of life evaluation: a novel approach based on daily load profiles," *IEEE Transactions on Power Delivery,* vol. 15, pp. 361-366, 2000.

[66] M. S. Bowman, *Applied Economic Analysis for Technologists, Engineers, and Managers.* Prentice Hall, 1999.

[67] E. P. Degarmo, W. G. Sullivan and J. A. Bontadelli, *Engineering Economy.* Macmillan publishers, 1993.

[68] P. E. M. Kurtz, *Handbook of Engineering Economics.* McGraw- Hill, 1984.

[69] A. Naderian, S. Cress, R. Piercy, F. Wang and J. Service, "An approach to determine the health index of power transformers," in *proc. Conference Record of the 2008 IEEE International Symposium on Electrical Insulation, ISEI 2008.,* 2008, pp. 192-196.

[70] A. Jahromi, R. Piercy, S. Cress, J. Service and W. Fan, "An approach to power transformer asset management using health index," *IEEE Electrical Insulation Magazine,* vol. 25, pp. 20-34, 2009.

[71] M. K. Pradhan and T. S. Ramu, "Criteria for estimation of end of life of power and station transformers in service," in *proc. Annual Report Conference on Electrical Insulation and Dielectric Phenomena, CEIDP '04.* 2004, pp. 220-223.

[72] A. M. Emsley, X. Xiao, R. J. Heywood and M. Ali, "Degradation of cellulosic insulation in power transformers. Part 3: effects of oxygen and water on ageing in oil," *IEE Proceedings Science, Measurement and Technology,* vol. 147, pp. 115-119, 2000.

[73] N. Dominelli, "Equipment health rating of power transformers," *IEEE International Symposium on Electrical Insulation,* 2004.

[74] S. Miletic, "Asset condition assessment by health index benchmarking," in *proc. 20th International Conference on Electrical Distribution, CIRED,* Prague, Czech Republic, 2009.

[75] A. E. B. Abu-Elanien and M. M. A. Salama, "A Monte Carlo Approach for Calculating the Thermal Lifetime of Transformer Insulation," *Submitted to Electrical Power Systems Research Journal,* 2011.

[76] H. A. Al-Hinai and S. M. Al-Alawi, "Typical solar radiation data for Oman," *Applied Energy*, vol. 52, pp. 153-163, 1995.

[77] D. L. G. Erbs, "Estimation of degree days and ambient temperature bin data from monthly average temperature," *ASHRAE Journal,* vol. 25, no.6, pp. 60-65, June, 1983.

[78] K. Ulgen and A. Hepbasli, "Prediction of Solar Radiation Parameters Through Clearness Index for Izmir, Turkey," *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects,* vol. 24, pp. 773-785, 2002.

[79] R. J. Sarfi, Reduction of distribution system losses and improvement of service quality: a novel knowledge based and numerical methods, Ph.D. dissertation, Electrical and computer department, University of Waterloo, Waterloo, ON, 1996.

[80] A. B. Ocnasu, Y. Besanger, J. Rognon and P. Carer, "Distribution system availability assessment –Monte carlo and antithetic variates method," in *proc. 19Th International Conference on Electricity Distribution, C I R E D,* Vienna, 2007, .

[81] R. Billinton and W. Li, *Reliability Assessment of Electrical Power Systems using Monte Carlo Methods.* Springer, 1994.

[82] P. Johnson, and M. Beverlin "Beta Distribution," 2006. [online] available http://pj.freefaculty.org/stat/Distributions/Beta.pdf

[83] P. R. Barnes, J. W. Van Dyke, B. W. McConnell and S. Das, "Determination analysis of energy conservation standards for distribution transformers," US Department of Energy, Oak Ridge, TN, Tech. Rep. ORNL--6847, 1996.

[84] J . Bloom, "Equipment failure model and data for substation transformers," EPRI, Palo Alto, CA, USA, Tech. Rep. 1012503, 2006.

[85] A. E. B. Abu-Elanien, M. M. A. Salama and R. Bartnikas, "A Techno-Economic Method for Replacing Transformers," *IEEE Transactions on Power Delivery,* vol. 26, pp. 817-829, 2011.

[86] R. E. Brown, *Electric Power Distribution Reliability.* Marcel Dekker, 2002.

[87] M. Modarres, *What Every Engineer should Know about Reliability and Risk Analysis.* New York: Marcel Dekker, 1993.

[88] B. Retterath, S. S. Venkata and A. A. Chowdhury, "Impact of time-varying failure rates on distribution reliability," *International Journal of Electrical Power & Energy Systems,* vol. 27, pp. 682-688, 2005.

[89] "Equipment failure model and data for substation transformers," EPRI, Palo Alto, CA, Tech. Rep. 1012503, December. 2006.

[90] J. McCalley, T. V. Voorhis, Y. Jiang and A. P. Meliopoulos, "Risk-based maintenance allocation and scheduling for bulk transmission system equipment," PSERC, Ithaca, NY, Tech. Rep. 03-26, October. 2003.

[91] D. G. Newnan, *Engineering Economic Analysis.* Engineering Press, Inc, 1983.

[92] R. Billinton and G. Lian, "Monte Carlo approach to substation reliability evaluation," *IEE Proceedings Generation, Transmission and Distribution,* vol. 140, pp. 147-152, 1993.

[93] P. J. Balducci, J. M. Roop, L. A. Schienbein, J. G. DeSteese and M. R. Weimar, "Electrical power interruption cost estimates for individual industries, sectors, and U.S. economy," U.S. Department of Energy, Springfield, VA, Tech. Rep. DE-AC06-76RL01830, February. 2002.

[94] R. Billinton and W. Wangdee, "Approximate methods for event-based customer interruption cost evaluation," *IEEE Transactions on Power Systems,* vol. 20, pp. 1103-1110, 2005.

[95] A. A. Chowdhury and D. O. Koval, "Value-based power system reliability planning," *IEEE Transactions on Industry Applications,* vol. 35, pp. 305-311, 1999.

[96] R. F. Ghajar and R. Billinton, "Economic costs of power interruptions: a consistent model and methodology," *International Journal of Electrical Power & Energy Systems,* vol. 28, pp. 29-35, 2006.

[97] J. F. Barlow, *Excel Models for Business and Operations Management.* John Wiley& Sons, 1999.

[98] A. A. Chowdhury and D. E. Custer, "Reliability cost-benefit assessments in urban distribution systems planning," in *proc. IEEE PES Power Systems Conference and Exposition,* 2004, pp. 1335-1343 vol.3.

[99] W. H. Bartley, "Analysis of transformer failures," in *proc. International Association of Engineering Insurers 36Th Annual Conference,* Stockholm, 2003.

[100] A. E. B. Abu-Elanien, M. M. A. Salama and R. Bartnikas, "A New Techno-Economic Replacement Technique for Transformers," Accepted in *IEEE PES General Meeting,* 2011.

[101] J. Mun, *Modeling Risk:Applying Monte Carlo Risk Simulation, Strategic Real Options, Stochastic Forecasting, and Portfolio Optimization.* New Jersey, USA: John Wiley and Sons, 2010.

[102] "IEEE Guide for the Interpretation of Gases Generated in Oil-Immersed Transformers," *IEEE Std C57. 104-2008 (Revision of IEEE Std C57. 104-1991),* pp. C1-27, 2009.

[103] M. R. Meshkatoddini, "Aging study and lifetime estimation of transformer mineral oil," *American J. of Engineering and Applied Sciences,* vol. 1, pp. 384-388, 2008, 2008.

[104] B. Coppin, *Artificial Intelligence Illuminated.* Sudbury, Massachusetts, USA: Jones and Bartlett Publishers, 2004.

[105] C. Stergiou and D. Siganos, "Neural Networks," [online]. available: http://www.doc.ic.ac.uk/~nd/surprise_96/journal/vol4/cs11/report.html, 2009.

[106] A. E. B. Abu-Elanien, M. M. A. Salama and M. Ibrahim, "Determination of transformer health condition using artificial neural networks," *Accepted in the International Symposium on Innovations in Intelligent Systems and Applications, INISTA 2011*, Istanbul, Turkey, 2011, .