LIFETIME PREDICTION AND ESTIMATION OF POWER TRANSFORMER

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A project report submitted in partial

fulfillment of the requirement for the award of the degree

Master of Electrical Engineering

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JANUARY 2013

ABSTRACT

This project presents a method to estimate and predict failure probability related to aging transformer units in power system. Statistically, the sample mean or the average age method is acceptable if it is used in a case where there is a big population. This method obviously is not suitable for power system components with very few samples of end-of-life failures. The essential weakness of the sample mean is that it only uses information of died components. This research proposed an approach to estimate and predict the lifetime of a power transformer by using NGC data. The data with both died and survive transformers will make contribution on estimating the mean life of power transformer. Two methods that used are normal and Weibull distributions. Although the two methods have different estimation approaches and solution techniques, they are related to each other and use the same format of raw data. From this research, the mean life and standard deviation for normal and Weibull distribution estimation should be quite close and also to the shape of the both distribution. Thus, statistical reliability analysis can provide predictions, such percentage of transformer that will fail at a particular time of before a particular age and how many transformers will fail in the next future year by using failure rate model. From that prediction, the forecasted capital expenditure (the cost of replacement and consequential failure cost) also can be specified. Thus, it will avoid asset harvesting and the possibility of having unforeseen costs.

ABSTRAK

Projek ini membentangkan kaedah yang akan digunakan dalam membuat ramalan serta anggaran kebarangkalian kegagalan bagi unit transformer yang telah berusia.Secara statistik, min sampel atau kaedah purata umur boleh diguna pakai jika ia digunakan dalam kes kajian di mana terdapat populasi yang sangat besar. Tetapi, kaedah ini tidak sesuai untuk digunakan bagi komponen sistem kuasa yang mana jumlah sampel kegagalan akibat faktor penuaan sangat sedikit. Malah, kelemahan yang sangat ketara bagi kaedah min sampel ini adalah ia hanya menggunakan data pengubah yang tidak berfungsi/rosak sahaja. Maka, kajian ini mencadangkan satu pendekatan yang digunakan untuk menganggar serta meramal hayat pengubah kuasa dengan membuat analisa terhadap data National Grid Control System. Kedua-dua jenis data iaitu data transformer yang sudah rosak dan juga yang masih lagi berfungsi dengan baik akan digunakan dalam membuat anggaran min hayat pengubah. Dua kaedah yang digunakan adalah taburan normal dan juga taburan Weibull. Walaupun kedua-dua kaedah ini mempunyai pendekatan anggaran dan teknik penyelesaian yang berbeza, ia boleh dihubungkait antara satu sama lain kerana menggunakan sumber data dari format yang sama. Daripada kajian ini, min dan sisihan piawai bagi jangkahayat pengubah dengan menggunakan kaedah anggaran taburan normal dan Weibull cenderung menjadi seakan sama begitu juga dengan bentuk bagi kedua-dua jenis taburan ini. Oleh itu, analisis statistik kebolehupayaan dapat dilakukan bagi menghasilkan ramalan seperti peratusan bagi pengubah yang akan gagal/tidak berfungsi pada suatu masa tertentu sebelum umur tertentu dan berapa jumlah transformer yang akan gagal dalam tahun akan datang dengan menggunakan model kadar kegagalan.Dari hasil ramalan itu, dapat diramalkan modal perbelanjaan (kos penggantian dan kos kegagalan berbangkit) juga dapat dinyatakan. ini dapat mengelakkan pengusahasilan aset dan serta kebarangkalian kos yang tidak diduga.

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LIST OF SYMBOLS & ABBREVIATION

NGC, UK — National Grid Control, United Kingdom

PDF, f(x) — Probability density function

CDF, F(x) — Cumulative distribution function

h(x), λ(x) — Hazard function

H(x) — Cumulative hazard function

S(x), R(x) — Survival function (Reliability function)

β — Shape parameter

α — Scale parameter

μ — Mean time to failure

σ — Standard deviation

$\Gamma(*)$ — Gamma function

x, t — Time, age

kVA — Kilo-Volt ampere

MVA — Mega-Volt Ampere

DP — Degree of polymerization

DGA — Dissolve gas analysis

KEPCO — Korea Electric Power Corporation

$ — U.S Dollar

CHAPTER 1

INTRODUCTION

1.1   Overview

Transformers are required throughout modern interconnected power systems. The size of these transformers ranges from as low as a few kVA to over a few hundred MVA, with replacement costs ranging from a few hundred dollars to millions of dollars. Power transformers are usually very reliable, with a 20-35 year design life. In practice, the life of a transformer can be as long as 60 years with appropriate maintenance. As transformers age, their internal condition degrades, which increases the risk of failure. Failures are usually triggered by severe conditions, such as 9-lightning strikes, switching transients, short-circuits, or other incidents. When the transformer is new, it has sufficient electrical and mechanical strength to withstand unusual system conditions. As transformers age, their insulation strength can degrade to the point that they cannot withstand system events such as short-circuit faults or transient over voltages [1].

To prevent these failures and to maintain transformers in good operating condition is a very important issue for utilities. Traditionally, routine preventative maintenance programs combined with regular testing were used. Without the regulatory, it has become increasingly necessary to reduce maintenance costs and equipment inventories. This has led to reductions in routine maintenance. Although transformer fault are rare, according to more than one thousand years operation experience, the failure of a power transformer may still be catastrophic and can result

in power interruptions to thousands customers. Thus, it is important for utilities to be able to predict life time of transformer before the failure occurs [1, 2].

Ageing equipment is a serious contributing factor to poor system reliability and high operating costs in many utilities [1]. The effects of ageing power transformers can be described as [2] :

- The end-of-life failure tends to increase with age
- Maintenance and breakdown-repair costs tends to increase with age
- Replacement part can become difficult and expensive to obtain.

Therefore, it is important for utilities to know when to replace ageing transformer so that the replacement could be scheduled in a manner to minimize the cost and also the impact on customers.

The current practice for the asset failure projection is to use the probabilistic failure curve of asset group (hazard function) which is convolved with asset demographic information [3]. The projected number of failures in one future year is obtained by the summation of the product of the number of units in each age bracket multiplying the value of the hazard function for the age bracket as shown in figure 1.1. Moreover, forecasted capital expenditures for future replacement can be estimated by multiplying the projected number of failures with consequential failure and replacement costs for every future [4].
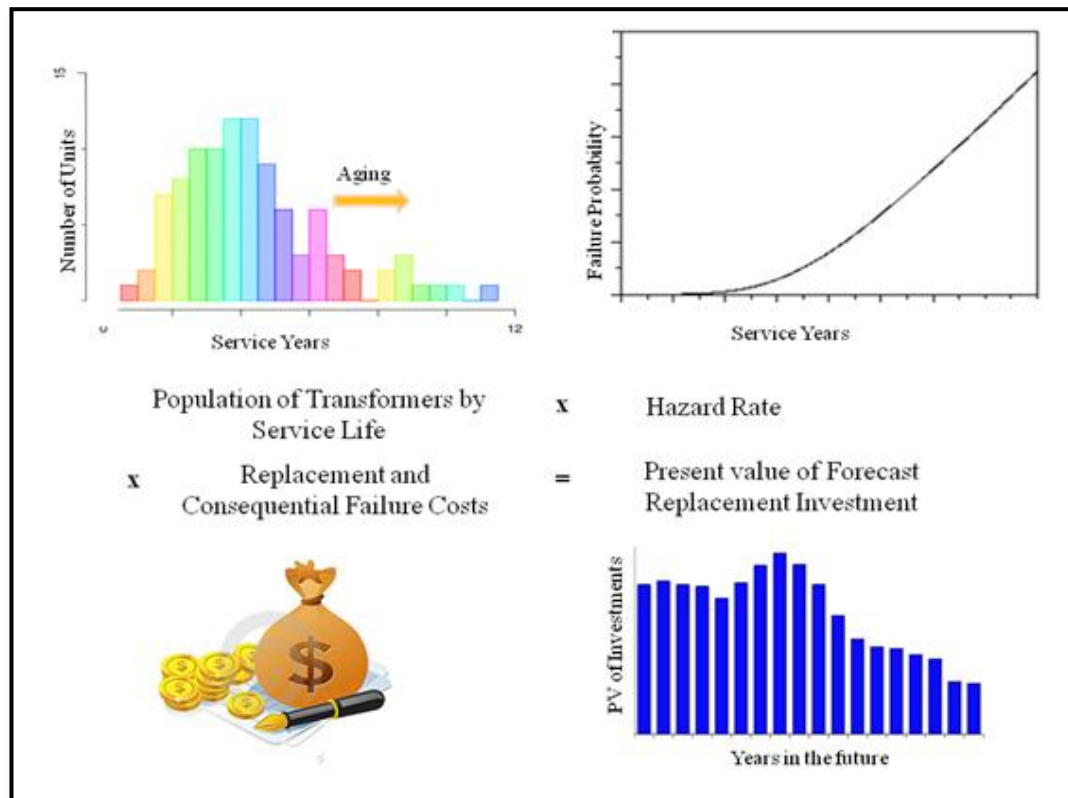
Figure 1.1 : Projection of investment needs for a population assets.

The transformer hazard function is vital important for accurately projecting transformer replacement volume. Thus, the general relationship between the failure rate or hazard function and time (age) can be graphically expressed using curve called the bath tub curve.

The bathtub curve can be divided into three stages. The first stage is called infant mortality period or also known as early failure period. Infant mortality failures are caused by defects in the product such as manufacturing errors or improper design which cause it to fail early in its lifetime. In this period, the failure rate decreases sharply with time or age.

The second stage is constant failure rate or also known as normal operating stage. During this period, the failure rate is almost constant which means that failures occur more in a random pattern. It can be said that the failure rate is almost the same as at early age in the age of normal operating stage.

The final stage of the bathtub curve represents the time when and after the product begins to reach the end of its useful life. It is called the wear out period. It can be argued that the failure rate at this period increases dramatically with the time. This period reflects the effect of ageing process. These are usually only a few wear

out failure mechanisms, which result from the stresses accumulated over the life of the product [5].
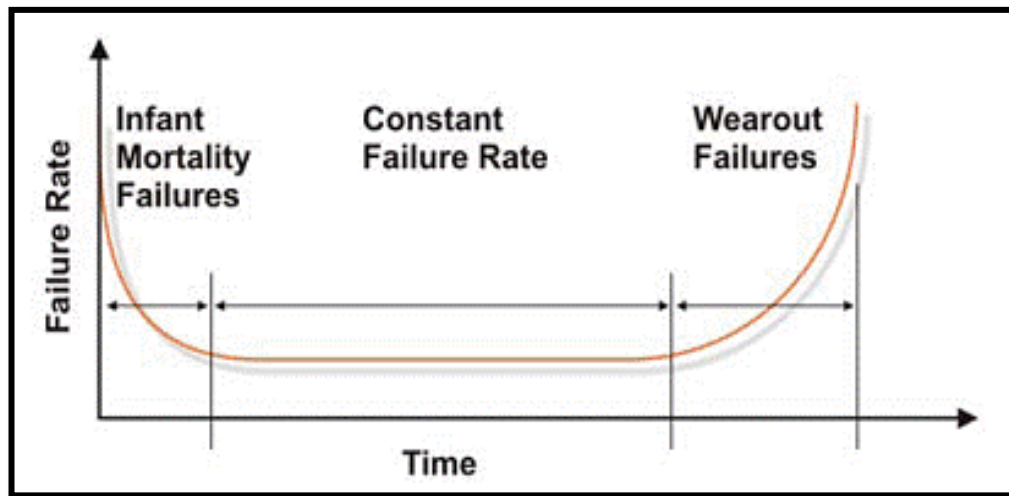
Figure 1.2: Bathtub curve for failure of equipment

1.2   Statement of the Problem

Power transformer is the most expensive equipment in electrical network. Since most of power transformers today were installed during the 1950s [6], it can be argued that most utilities are operating a significant number of ageing transformer even some of these transformers may still be operating satisfactorily but they are approaching or past the designed lifetime. Besides, the policy such as the equipment is continuously used until it dies. Unfortunately, it will take more than one year to complete the whole replacement process including the purchase, transportation, installation and commissioning of new equipment. The power system may be exposed to severe risks of being unable to meet security criteria during the replacement period.

Predicting the lifespan of a power transformer has been considered an important issue for energy companies for some time. Power transformers that reach the end of its life usually do so unexpectedly, causing power reliability problems, higher system risk due to higher failure probability and possible system damage following the end of life failure which consequences cost a lot of money. Knowing the mean and also the standard deviation of power transformer could help power companies to determine how long a power transformer have before breaking down

and allow them to perform any necessary action before the power transformer starts giving problems.

Besides, almost all methods presented so far only considered the repairable failure mode of system components. A recent development has been performed to model and incorporate end-of-life failures in power system reliability assessment [7, 8]. An important step in modeling end-of-life failures is to estimate the mean life of components and standard deviation. The most popular and simple method in current applications is to calculate the average age of died components in historical records. This is called as the first moment estimator. The statistics theory also provides a general maximum likelihood estimation method. However, it may not be workable for power system components.

A normal or Weibull distribution is often used in the aging failure model of power system components. Unfortunately, for a normal distribution, the maximum likelihood estimation creates a sample mean as the estimated result which is still the average of ages of died components [9]. For a Weibull distribution, the maximum likelihood estimation leads to an extremely complex equation with multiple solutions for the shape and scale parameters and cannot directly obtain the mean life [10]. The value of estimating the mean life of power transformer is not just its use for the end-of-life failure modeling in power system reliability assessment. The estimate of mean life itself for various transformers is also useful information for engineering judgment on the equipment status, system aging and maintenance policy.

1.3   Objective of the Research

The main objectives of this project are listed as follows:

i.   To predict the lifetime of transformers base on National Grid Control (NGC) Data.

ii.   To study and implement two different estimation approach techniques which is normal distribution method and Weibull distribution method to estimate the remaining life of the transformer.

iii.   To estimate number of failure in one future year and forecast capital expenditures for future replacement .

1.4 Scope of the Research

Power transformer loss of life can be determined by using two methods in estimating the mean life and its standard deviation with NGC data. One is for normal distribution method and another for the Weibull distribution method. Unlike the conventional sample mean technique which only uses ages of died transformers, the methods that will be presented are based on died and surviving transformer and will provide a more accurate estimation. In the method of the normal distribution, the estimation can be obtained from a set of simple calculation formulas while for the Weibull distribution, linear regression technique will be used to obtain the estimates of the mean and its standard deviation as well as the shape and scale parameter.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

Equipment aging is a fact of life in power system although there may be different cause of aging for different types of equipment. As a piece of equipment ages, it fails more frequently, needs longer times to repair, and eventually reaches its end of life. The direct consequence of equipment aging is higher system risk due to higher failure probability and possible system damage following the end-of-life failure.

Power transformers perform both technical and economic function in power system. There are several concepts of lifetime for power system equipment [11]:

i.   Physical lifetime : A piece of equipment starts to operate from its brand-new condition to a status in which it can no longer be used in the normal operating state and must be retired. Preventive maintenance can prolong its physical lifetime.

ii.   Technical lifetime: A piece of equipment may have to be replaced due to technical reasons although it may still be physically used.

iii.   Economic lifetime: A piece of equipment is no longer valuable economically, although it still may be usable physically.

In general, a manufacturer provides an estimated mean life of transformer, which is based on theoretical calculations and many assumptions. The manufacturer's estimate is usually inadequate since it does not and cannot include actual operating and environmental conditions of the equipment. Statistically, the

sample mean or the average age method is often used to estimate a mean life. The essential weakness of the sample mean is that it only uses information of components that have died. The approaches that are base on the Weibull or normal distribution will be developed to estimate the mean life and its standard deviation. The merit of the probability-distribution-based approaches is due to the contribution of both dead and surviving components to the mean life which will be taking into consideration.

This research generally involves comprehensive knowledge on lifetime of power transformer. To develop the probability-distribution-based model about lifetime of power transformer, the information and data will be collected based on the review of journals, thesis and internet sources to make the research develop successfully.

2.2 Past Project Background Review

2.2.1 Transformer Life Prediction Using Data from Units Removed from Service and Thermal Modeling

The paper of Paul Jarman, Ruth Hooton, Leon Walker, Qi Zhong, Taufiq Ishak, Zhongdong Wang entitles Transformer Life Prediction Using Data from Units Removed from Service and Thermal Modeling is purposely to design the end-of-life model based on years of previous experience over several lifecycles of equipment of a type representative of that still in service at that time. It is not easy to establish large power transformers model because they still in the first asset lifecycle and many of the transformers installed when the National Grid system was first developed are still in service well beyond their original design life.

This paper gives the historical failure rate of the transformers used on the National Grid system in the UK and shows that failures to date are random in nature and not statistically age related. This means that traditional approaches to build a statistical end-of-life model cannot be used. Based on the analysis of the insulation of transformers removed from service for any reason indicates a very wide range of condition, some samples show severe thermal ageing and it is clear that age-related failures can be expected if replacement is not carried out, other samples show little ageing and for these transformers it appears that very long lifetimes might be expected if other ageing mechanisms do not become apparent.

They did their analysis at National Grid England and there have transformers about 780 units. Good data on transformer failures is only available since 1962 and so transformer years experience in service is only counted since that date in order to be consistent with the failure data. There is substantial operating experience of transformers up to about 40 years in service but the experience is limited beyond that, making statistical analysis of the reliability of older transformers problematic.

Since almost all the transformers that have been scrapped, either due to failure or replacement, since 1993 have had insulating paper samples taken from representative parts of the windings and analyzed for degree of polymerization (DP). DP is widely accepted as an indicator of thermal ageing of paper with a value of 200 taken as end of life [12].

A plot of 1/DP against age for each of the sampled transformers can be seen form figure 2.1. It shows three points (red, blue and green) for each sampled transformer, the red square indicates the lowest DP sample (highest value of 1/DP) the blue triangle represents the average DP of the samples taken from a single transformer and the green diamond the highest. It may be seen that the lowest DP values from each transformer (shown in red, one point for each scrapped transformer) are widely scattered above and below the black line representing the expected value of 1/DP against age for a transformer lifetime of 55 years.
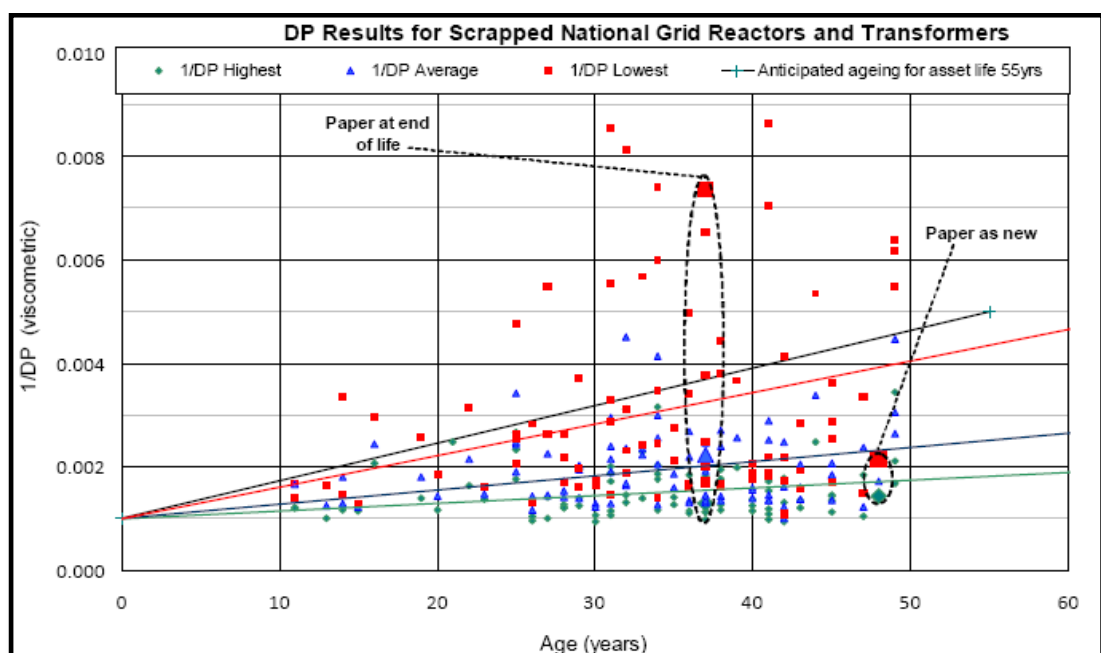
Figure 2.1: DP results for scrapped National Grid Reactors and Transformers

Two particular cases are highlighted, one where the paper insulation in the transformer was at end of life at 37 years and one where the paper was almost as new at 47 years. An alternative view of some of the same data is given in Figure 2.2 where the lifetime of individual scrapped transformers is predicted from the lowest DP obtained assuming that ageing would have continued at the same rate if the transformer had remained in service [5].
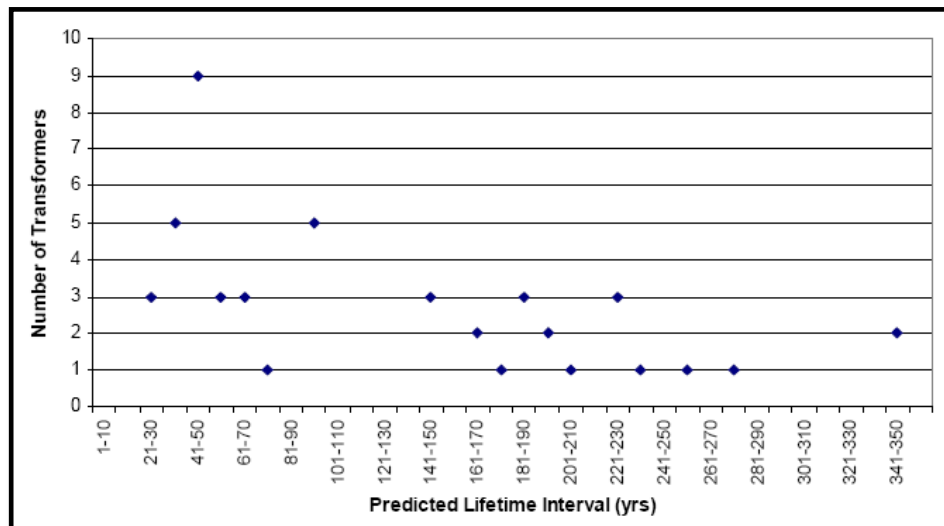
Figure 2.2: Distribution of Lifetime prediction by DP

This data is not representative of the whole transformer population as some transformers were scrapped because of their aged condition, however the longer predicted lifetimes are from transformers that were removed from service for other than age-related reasons (for example tap-changer failure) and these show a wide spread of predicted thermal lifetimes. It can be argued that condition based replacement means that statistical analysis of failure rates is not helpful in modeling lifetimes, but data from scrapped and failed transformers has been used to demonstrate that age-related failures (or replacements because of very poor condition before failure) in the population of large network transformers are starting to occur at around 40 years in service.

2.2.2   Evaluating Mean Life of Power System Equipment with Limited End of Life Failure Data

The paper present by Wenyuan Li entitles Evaluating Mean Life of Power System Equipment With Limited End of Life Failure Data propose two methods to estimate the mean life and its standard deviation of a power system equipment group with limited end-of-life or aging failure data. One is for the normal distribution model and another for the Weibull distribution model. The presented methods are based on all the information in an equipment group including both died and surviving components and provide a more accurate estimation. An equipment group containing 100 reactors with only four retired units was used as an application example to illustrate the procedure.

The presented methods have been applied to several equipment groups including reactors, transformers and underground cables. A 500-kV reactor group at BC Hydro is used as an example to demonstrate an application of the methods. This group contains 100 single-phase reactors with only four end-of-life failures in the past 31 years. The reference year used in the study is Year 2000. The four retired reactors were based on the field assessment which justified their end-of-life. From following observations, it can be said that:

Table 2.1: Mean life and its standard deviation (real case four retired reactors)

MEAN LIFE AND ITS STANDARD DEVIATION (REAL CASE FOR FOUR RETIRED REACTORS)		
Parameter	Normal	Weibull	Sample mean
Mean life (years)	37.628	38.363	25.0
Sd (years)	6.896	6.293	
Shape parameter		7.341	
Scale parameter		40.950	

- The estimates of the mean life and standard deviation for the normal and Weibull distribution models are quite close in this case. The estimates of the

shape and scale parameter are 7.3 and 41 respectively. This suggests that the shape of the Weibull distribution is close to that of the normal distribution.

- The estimated mean life of 37 or 38 years obtained using the presented methods is much more reasonable than 25 years (using the sample mean method).

- The presented methods can be also used for the case where there is a big population of retired components. In this case, the difference between the mean life estimates obtained using the presented and sample mean methods will be dramatically decreased.

An experimental test has been performed and it is artificially assumed to have 16 more retired reactors for same example. The additional retired reactor is not a real data. Assumed retire at ages from 27 to 31. The estimates using the presented and sample mean methods for the assumed case are given in Table 2.2. The sample mean of the 20 retired reactors is 29 years. It can be seen that the mean life estimate from the sample mean method is very close to the results obtained using the presented method. The 20 retired reactors accounts for 20% of the total reactor number, which represents a large population size of end-of-life failures. It can be also seen that the standard deviation in this case is much smaller.

Table 2.2: Mean life and its standard deviation (assume case for 20 reactors)

MEAN LIFE AND ITS STANDARD DEVIATION (ASSUMED CASE FOR 20 RETIRED REACTORS)			
Parameter	Normal	Weibull	Sample mean
Mean life (years)	30.191	29.727	29.0
Sd (years)	3.650	3.909	
Shape parameter		9.407	
Scale parameter		31.361	

The contributions of surviving components are dynamic since the current year as a reference is varied in calculating their ages. If time advances one more year and no more end-of-life failure happens, all components in an equipment group will have survived for one more year, which means that the mean life of this equipment

group should be increased. The estimates of the mean life and standard deviation using the normal and Weibull distribution models are close in this case. By comparison between the estimates using the presented methods and the sample mean technique against the information in the raw data, it is clear that the presented methods provide more reasonable results.

2.2.3 Prediction of Remaining Life of Power Transformers Based on Left Truncated and Right Censored Lifetime Data

The paper of Yili Hong, William Q. Meeker and James D. McCalley entitles Prediction of Remaining Life of Power Transformers Based on Left Truncated and Right Censored Lifetime Data is purposely to develop statistically based predictions for the lifetimes of an energy company's fleet of high-voltage transmission and distribution transformers. Since the data records begin in 1980, there is no information about units that were installed and failed before. Thus, the data are left truncated and right censored. They used a parametric lifetime model to describe the lifetime distribution of individual transformers and also developed a statistical procedure, based on age-adjusted life distributions, for computing a prediction interval for remaining life for individual transformers now in service.

They presented prediction intervals for the remaining life for individual transformers based on using the Weibull distribution and a stratification cutting at year 1987. Figure 2.3 shows 90% prediction intervals for remaining life for a subset of individual transformers that are at risk. In particular, for a group of relatively young transformers in the same group and with the same values of the explanatory variables, the prediction intervals are similar. For a unit in such a group, the lower endpoints of the interval are very close to the current age of the unit. That was predicted to be at especially high risk for failure in the near term are sometimes outfitted with special equipment to continuously monitor and archive transformer condition measurements that are useful for detecting faults that may lead to figure 2.3 failure.

These measurements were taken from the transformer insulating oil and indicated the presence of dissolved gases but also may indicate other attributes, including moisture content and loss of dielectric strength. Dissolved gas analysis (DGA) was automatically-performed by these monitors and is important in the

transformer maintenance process, because it can be used to predict anomalous and dangerous conditions such as winding overheating, partial discharge, or arcing in the transformer. If an imminent failure can be detected early enough, the transformer can be operated under reduced loading until replaced, to avoid costly catastrophic failures that sometimes cause explosions.
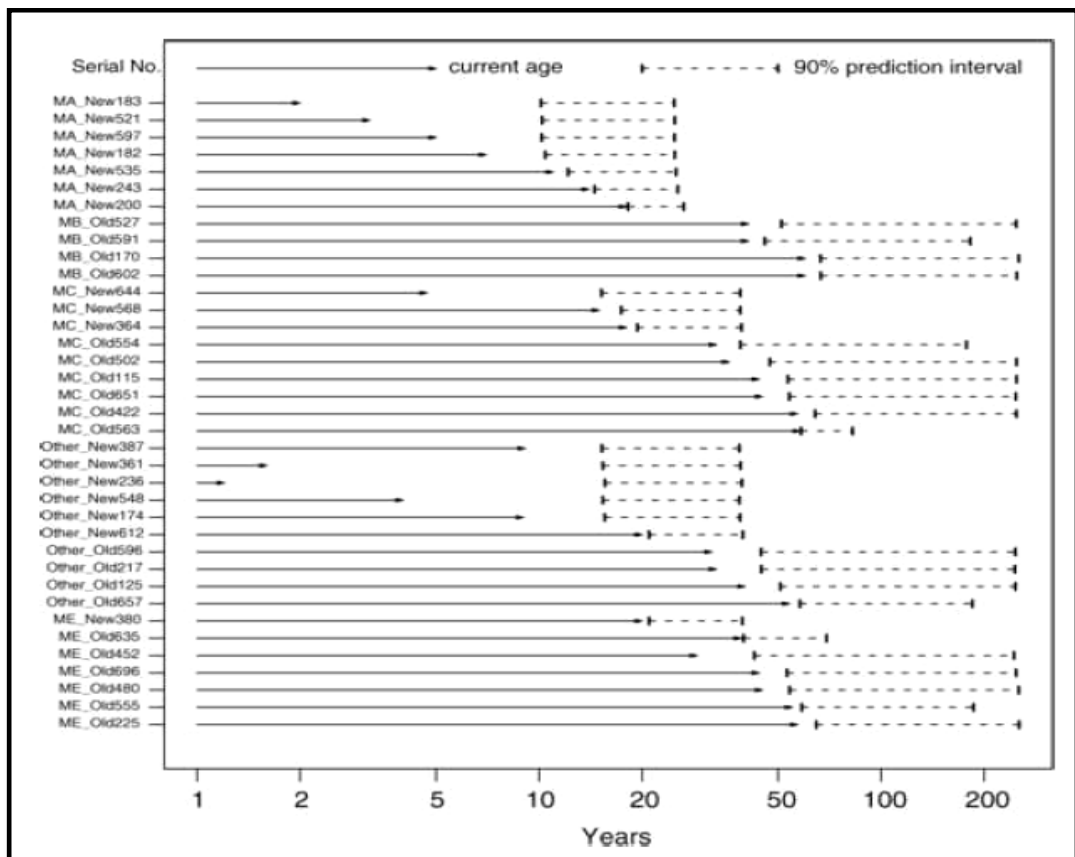
Figure 2.3 : Weibull distribution 90% prediction intervals for remaining life for a subset of individual at-risk transformers

Then, they presented the results for predicting the cumulative number of failures for the population of transformers that are at risk, based on the Weibull distribution regression model with the stratification cutting at year 1987. Figure 2.4 gives Weibull distribution predictions and prediction intervals for the cumulative number of future failures with the Old and New groups combined. There are 648 units in risk set. Similar predictions for the Old and New groups combined.

Figure 2.4 : Weibull distribution predictions and prediction intervals.

2.2.4 Failure Probability Prediction in Generating Units with Aging

The paper of Sung-Hoon Lee, Jong-Man Cho, Seung-Hyuk Lee and Jik-O Kim entitles Failure Probability Prediction in Generating Units with Aging is purposely to present a method to predict failure related to the aging of generating units in power system. In order to calculate failure probability, 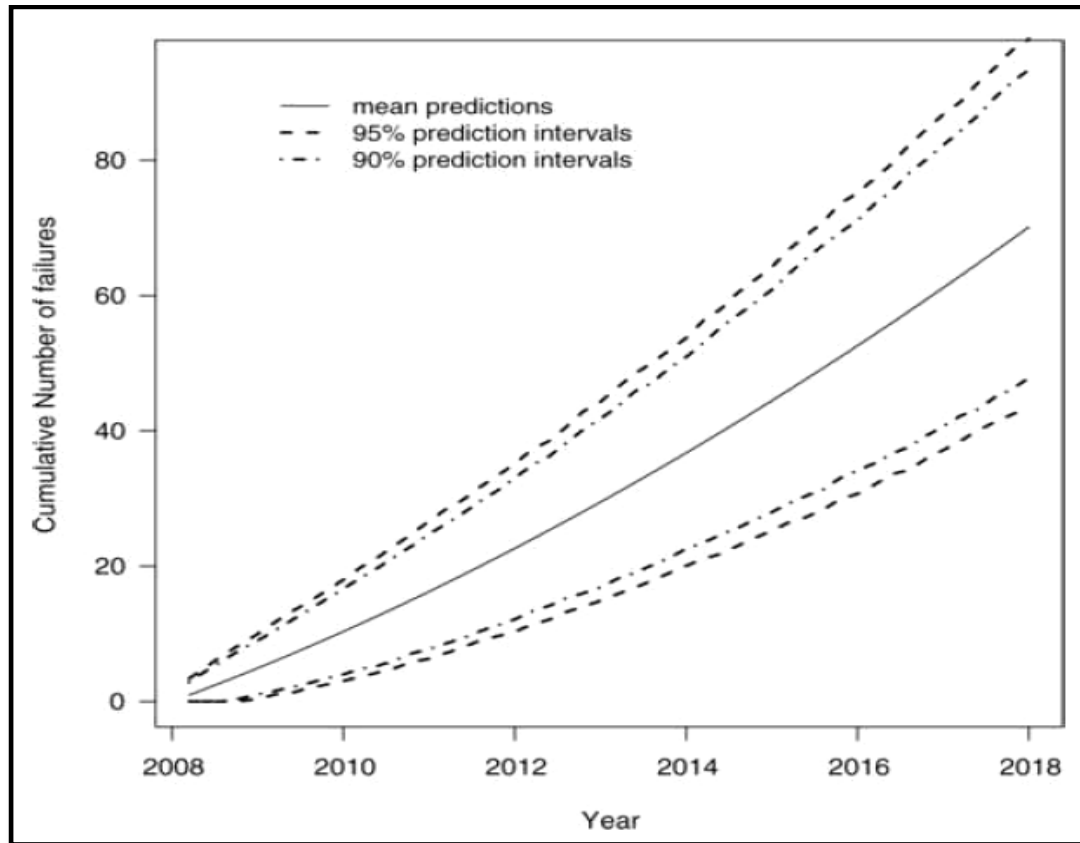the Weibull distribution is used due to age-related reliability. The parameters of Weibull distribution can be estimated by using gradient descent method. This method has the relative accuracy of results, but the extremely complexity of calculating process. Therefore each estimated parameter is obtained from Data Analytic Method (Type II Censoring) which is relatively simpler and faster than the traditional calculation methods for estimating parameters. Besides, this paper shows the calculation procedures of a probabilistic failure prediction through a stochastic data analysis. Consequently, the proposed methods would be likely to permit utilities to reduce overall costs in the new deregulated environment while maintaining appropriate reliability level.

There are some papers, which have considered the aging failure of power system components. Wenyuan Li utilized two methods mentioned previously that have been developed for the normal and Weibull distribution, respectively. Although these two methods have different estimation approaches and solution technique, they are related to each other and use the same format of original data. The parameters of Weibull distribution were estimated by using gradient descent method. However, these method have both the relative inaccuracy of results and the extremely complexity of calculating process.

This paper proposes the estimation of the shape and scale parameters and presents the method to predict the failure probability considering the conditional probability in real data of Korea Electric Power Corporation (KEPCO) system. To estimate the parameters, two methods are used. The former is conducted by the gradient descent method, and the latter is executed by the data analytic method (Type II censoring). The presented methods are based on all the information in an equipment group including both died and surviving components and therefore, can produce a more accurate estimation. The more detailed stages of gradient descent method for Weibull distribution would like to refer to reference. By comparison between both results, it is clear that the proposed method provide not only the accurate estimation but also more simple calculation process. Therefore Type II censoring can be proposed instead of gradient descent method.

2.3   Comparison between Four Papers Above

Table 2.3 : Comparison between four related journals.

Journal	Objective	Method	Outcome
Transformer Life Prediction Using Data from Units Removed from Service and Thermal Modeling	i. Predict the transformer life by using insulating paper from scrapped transformers ii. Analyze for degree of polymerization (DP)	Condition assessment: i. Dissolve Gas Analysis ii. Degree of polymerization	Condition based replacement means that statistical analysis of failure rates is not helpful in modeling lifetimes, but data from scrapped and failed transformers has been used to demonstrate that age-related failures
Evaluating Mean Life of Power System Equipment With Limited End of Life Failure Data	i. Introduce two methods to estimate the mean life of a power system equipment ii. Use information data including both died and surviving components	i. Normal Distribution method ii. Weibull distribution method	The estimates of the mean life using the normal and Weibull distribution models are close in this case. Comparison between the estimates using the presented methods and the sample mean technique, the presented methods provide more reasonable results
Prediction of Remaining Life of Power Transformers Based on Left Truncated and Right Censored Lifetime Data	i. Prediction of the remaining life of power transformer. ii. Use left truncated and right censored data	i. Log-location-scale distribution for lifetime model for left truncated and right censored data. ii. Weibull distribution method	Better predictive model that would more accurately predict individual lifetimes by using environmental information for the individual transformers
Failure Probability Prediction in Generating Units with Aging	i. Predict failure probability related to aging of generating units. ii. Estimate the parameters of Weibull distribution	i. Data analytic method (type II censoring)	By comparison between gradient descent method and data analytic method, it is clear that the proposed method provide not only the accurate estimation but also more simple calculation process.

CHAPTER 3

METHODOLOGY

3.1   Overview

Methodology is one the important part of doing a research. It is important to ensure the project would not face any problem during the implementation. It is also to make sure the project satisfy the scope and achieve the objectives. The research will go through several stages:

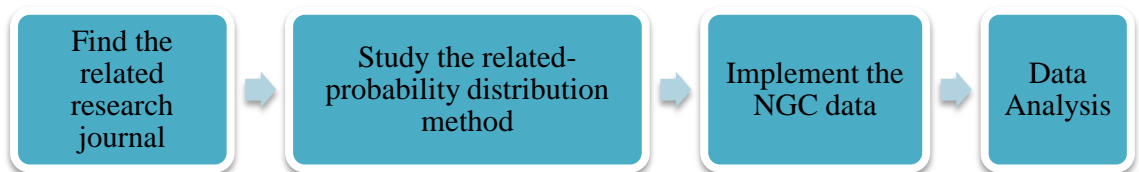| Find the related research journal	→	Study the related-probability distribution method	→	Implement the NGC data	→	Data Analysis

Figure 3.1: General block diagram of the project

i.   Find the research journal.

To start this project, find any research journal that related to the topic. Read and study about the journal and use the important data and knowledge related to the main research.

ii. Study the related probability-distribution method.

From the journal, study the related method that researcher used and also the differences between every method. Gather all the information related to the research and try to read and understand.

iii. Implement the NGC data

Model the NGC data in the normal distribution method and Weibull distribution method.

iv. Data Analysis.

Analyze the result from both methods. Compare the both results with sample mean and come out with a hypothesis.

3.2 Project Sequence Overview

This research is completed in two semesters. So it is very important to have a systematic planning and implementation in order to complete the research and get the result on time. Figure 3.2 shows the flow chart for research progression PS I and Figure 3.3 shows the flow chart for research progression PS II.
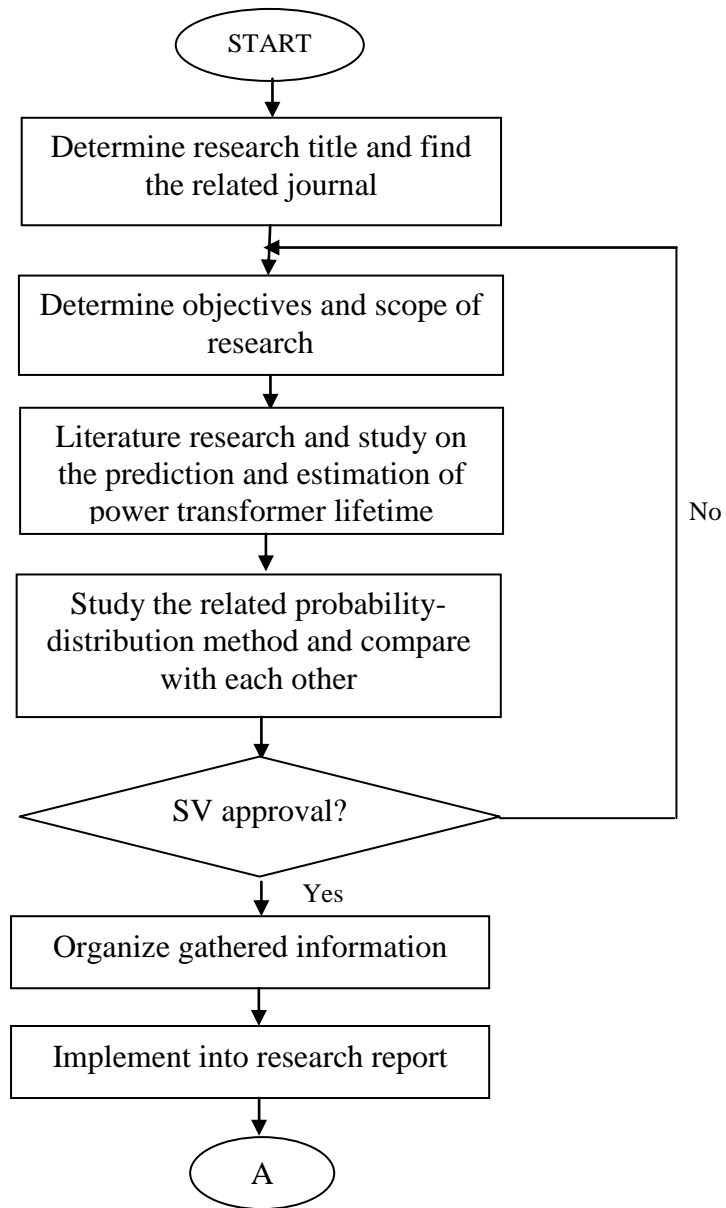
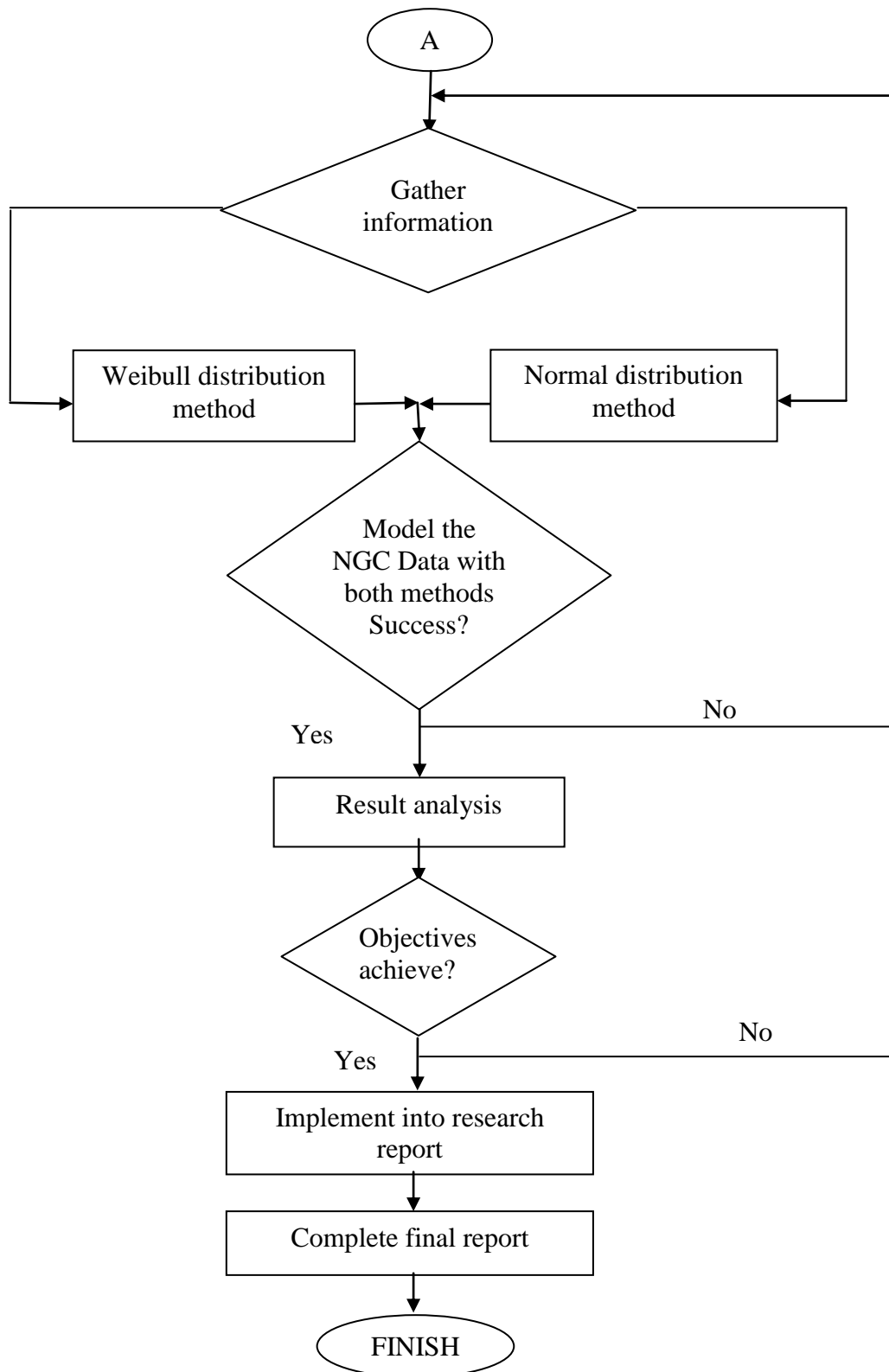Figure 3.2 : Flowchart for research progression PS1.

Figure 3.3: Flowchart for research progression PS II

3.3   Assessing End-of-Life Failure Probability

With the estimated mean life and age of transformer, its aging status can be qualitatively judge since can be known how far away it is from the mean life. The reason about concerning the aging status is because of the risk that will be caused by end-of-life failure of aged transformer. In order to quantify the risk of aging failures, it is necessary to assess the end-of-life failure probability of aged transformers. As is well known, the relationship between the failure rate or failure probability and the age can be graphically expressed using a so-called bath tub curve.

It can be seen from the figure 3.4 that the failure rate at the wear out stage increases dramatically with the age. In fact, the bath tub curve can be mathematically modeled using a Weibull or normal distribution [11].
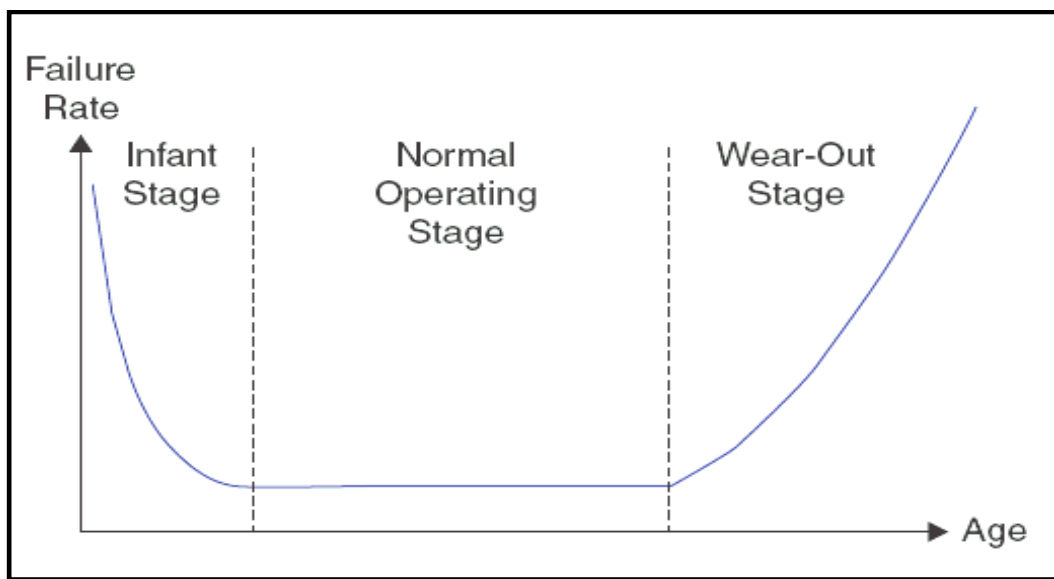

Figure 3.4: Bath tub curve for failure rate of equipment

Figure 3.5 shows the relationship between the failure rate and age for a normal distribution failure density function.
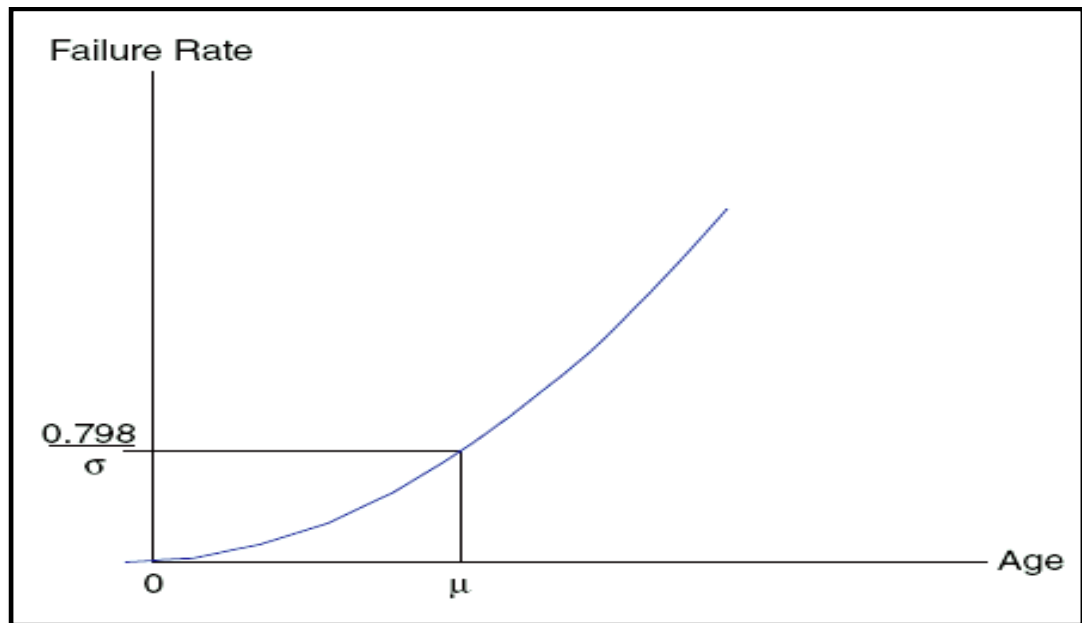
Figure 3.5 : Relationship between failure rate and age for a normal probability distribution

Figure 3.6 shows the same relationship for a Weibull distribution failure density function. The μ and σ in Figure 3.5 are the mean and standard deviation of the normal distribution, whereas β and α in Figure 3.6 are the shape and scale parameters of the Weibull distribution. It can be seen that the relationship shown in the two figures is consistent with that expressed in the wear-out stage of the life bath tub curve. Indeed, the Weibull distribution can be used to model all the three portions of the bathtub curve: $\beta<1$ for the infancy stage, $\beta = 1$ for the normal operating stage, and $\beta>1$ for the wear-out stage.
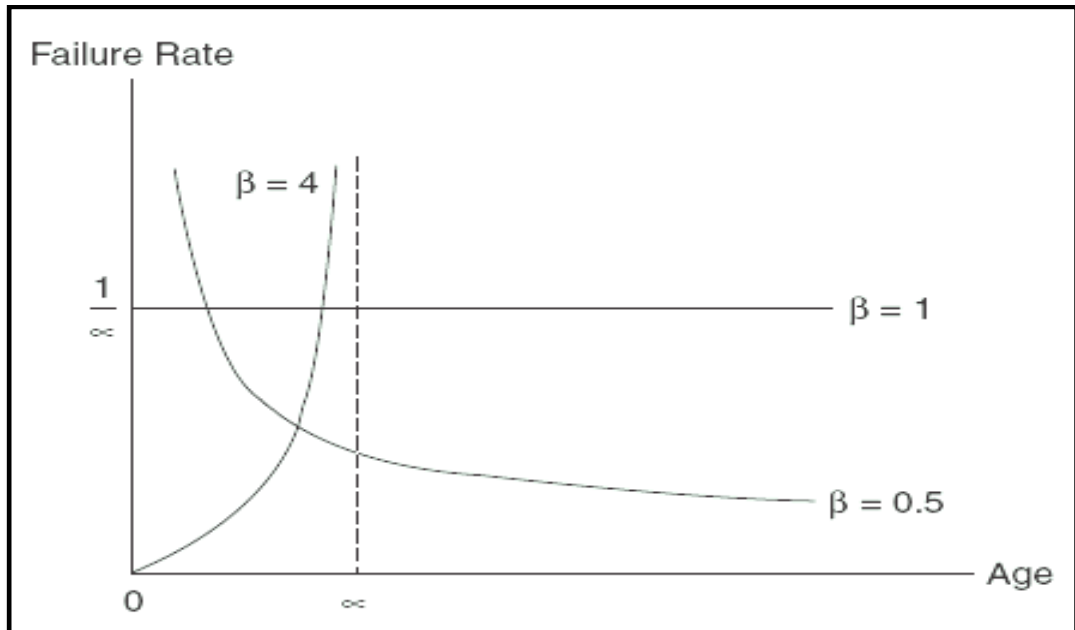
Figure 3.6 : Relationship between failure rate and age for a Weibull probability distribution

3.4   Estimating Parameter in Aging Failure Models

It is necessary to estimate the mean life of transformers and its standard deviation for the normal distribution model or shape and sale parameter of the Weibull distribution model. Intuitively, its looks as if the mean life is nothing else than the average age of dead or retired transformers and that the sample mean concept could be used. Statistics theory also provides the maximum likelihood estimation approach. For the normal distribution, the maximum likelihood estimation still creates the sample mean as the estimated result, that is, the average of dead components. For the Weibull distribution, it leads to an extremely complex set of equations with multiple solutions for the shape and scale parameters.

Unfortunately, the sample mean method is generally not workable for the mean life estimation of power system components. The power system components such as transformers, generator and etc have a long life, up to or even beyond 50 years, and therefore, there are very limited aging failure data in a utility. When applied to the mean life estimation, the essential weakness of the sample mean is that only the information of dead components is used. For an equipment group with very few dead members, not only dead components but also survivors should make contributions to the mean life estimation.

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