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Life Cycle Cost Estimation of Distribution Transformer Failure from Life Data Exploration

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Abstract: ***Transformers are major equipment in a power system. Their reliability does not only affect the electric energy availability within a supplied area, but also the economical operation of a utility. Many power utilities in the world including Malaysia have distribution transformers that have been in operations for over 30 years. Aged distribution transformer will have higher risk of unexpected failure which will increase the operational cost. Nevertheless, the occurrence of transformer failure can be predicted based on historical events. In this research work, 2-Parameter Weibull distribution is used to model distribution transformer life data. Life data analysis is conducted based on the statistical model and failure prediction for distribution transformers is analysed. Since frequency of failures as a function of time from life data model varies with different manufacturers and affects the life cycle cost, both life data analysis and net present value concept could be combined to establish an enhanced methodology for life cycle cost estimation of distribution transformer failure. A case study was conducted on sample populations where distribution transformer with similar manufacturer and capacity were grouped together. Results for each transformer group were compared and examined. It was pointed by the results that appropriate modelling and analysis had allowed life cycle cost due to transformer failure to be estimated. Outcomes from the assessment would contribute to transformer life cycle management as one of the factors to consider in the decision making for asset replacement, maintenance and planning.***

Keywords: ***Distribution Transformer; Life Data Analysis; Present Value; Life Cycle Cost; Life Expectancy of Distribution Transformer***

I.INTRODUCTION

As one of the major equipment in electrical network, transformer is essential to electrical power distribution. Transformer adapts and transfers electrical energy from one circuit to another. It also changes voltage level between electrical circuits. A transformer must be highly reliable in order to avoid unscheduled downtime and major system failure [1]. Once a transformer is in operation, it must be reliable and function optimally throughout its lifetime.

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However, most of transformers installed in the distribution network are still in service after 30 years of operation. Because of the long years of service, these transformers are now entering their ageing life.It is known that, prolong electrical and environmental stresses increase the risk of unexpected failure especially for ageing transformer [2]. This situation is not favourable because transformer failure does not only cause power supply interruption to the customers, but also imposes high cost to the power utilities [3].

It has been the aim for power utilities to provide uninterruptable power supply to the customer and at the same time minimize operation cost. Therefore, reliability and cost issues related to transformer failure raise a major concern for them. To overcome this issue, it is important for power utilities to reduce the number of unexpected transformer failures.

Theoretically, the occurrence of transformer failure can be predicted based on historical events[4, 5]. For a population of transformer with known survival and failed data, life data analysis can be conducted using statistical distribution that best fit the data. The life data model can be characterised by its distribution parameters which describes the lifetime characteristics of the transformer.

From economic point of view, life data analysis benefits the transformer life cycle cost assessment. Since the obtained life data model gives information on the failure distribution, hence prediction of transformer failure occurrence can be done. Prediction on the transformer failures provide details on frequency and time of failure; this allows failure cost to be estimated. Eventually, life cycle cost due to transformer failure can be calculated. It is expected that outcomes from this assessment would contribute to transformer life cycle management by providing a baseline for decision making in the process of asset replacement, maintenance, and planning.

1.1 Transformer Life Characteristic

In order to determine the life cycle cost, it is important to understand what life means in the context of transformer. Transformer life can be defined based on operational or insulation life, economic life and reliability or statistical life[6]. Gamez in [7] defined life of an asset as the period of time in which the asset will reliably perform its intended function. A transformer functions by transforming incoming power into different levels of voltage and current by means of electromagnetic induction. Primary energy conversion is performed by the conductors and the core. Insulation system on the other hand, ensures conductive element at different voltage level stays electrically insulated.

Transformer will fail and cannot function if the insulation system breaks down[8].

Therefore, life of a transformer is directly linked to the life of its insulation system[7,9].From economic point of view, economic life of a transformer is defined by the term which minimizes the overall annual operation cost for owning and operating a transformer [10]. This definition is supported by Zhao et al. in[11] where optimum economic life of a transformer is referred to the life where equivalent annual cost is at minimum.

In statistical terms, life of an asset can be defined as Mean Time To Failure or MTTF[7]. Based on this definition, for a population of transformers with similar characteristic, the time between initiation of service and failure for each transformer is measured and averaged, providing life expectancy estimation of transformer. This is also known as mean life of the transformer.

The process of estimating mean life of transformer using statistical approach is called life data analysis.One important aspect to consider when conducting life data analysis is reliability bathtub curve which is a plot of failure rate of equipment against time. The reliability bathtub curve is illustrated as in Figure 1.

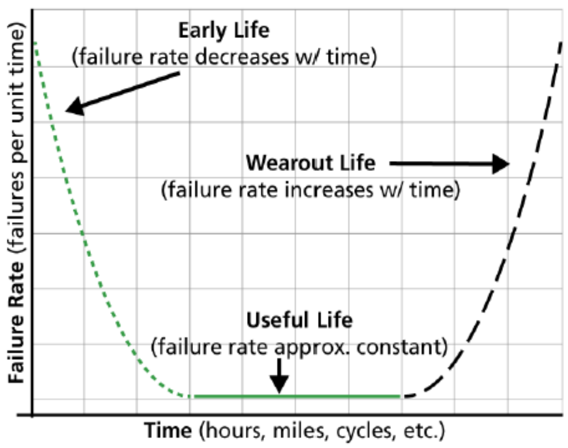

Fig. 1 Reliability Bathtub Curve [12]

As indicated inFigure 1, failure rate decreases with time in the early years of the equipment life. This represents the early-type failure of equipment, which usually occurs due to design problem, poor workmanship and other problems related to manufacturing. As the time goes by, the equipment enters useful operation life. Failure of equipment occurs randomly at this stage of life; hence, the failure rate is constant. When equipment has been operating for a long time, the failure rate increases with time. This behaviour indicates wear-out stage where the equipment has aged due to usage.

1.2 2-Parameter Weibull Distribution

The most common statistical model used for life data analysis of high voltage power equipment is 2-Parameter Weibull distribution[13]. Hence, this research work will also use 2-Parameter Weibull distribution for modelling the transformer life data. In addition,2-Parameter Weibull is chosen due to its flexibility. This is because, the shape parameter β of 2-Parameter Weibull probability density function (pdf) can resemble the characteristic of other distribution such as exponential and normal distribution[12]. It is also flexible in terms of representing the relationship between failure rate and failure type.

The 2-Parameter Weibull distribution probability density function (pdf) is represented by [12,14]

$$f(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^{\beta}} \quad \textbf{(1)}$$

Where t is time express in year, βis the shape parameter and ηis the scale parameter. In life data analysis, the probability density function shows the failure distribution or frequency of failure. Furthermore, mean time to failure (MTTF) and failure rate, λ(t) can be derived from the probability density function.

The shape parameter, β in Equation (1) affects failure rate, λ(t). For population with $\beta<1$, failure rate decreases with time. If $\beta=1$, failure rate is constant and if $\beta>1$ failure rate increases with time[15-17]. This characteristic is useful to explain the relationship between reliability bathtub curve which exhibits different β throughout the lifetime of an equipment, with type of failure. The relationship is summarised in Table 1.

Table. 1 Relationship between β, λ(t) and failure type

β	**λ(t)**	**Failure type**
β < 1	decreasing	Early-type failure
β =1	constant	Random failure
β >1	increasing	Wear-out /ageing failure

II.METHODOLOGY

Figure 2 shows the flowchart of methodology for this research work; it is divided into three parts which are Life Data Analysis, Failure Prediction and Life Cycle Cost Estimation of Transformer Failure. Each part consists of several activities.

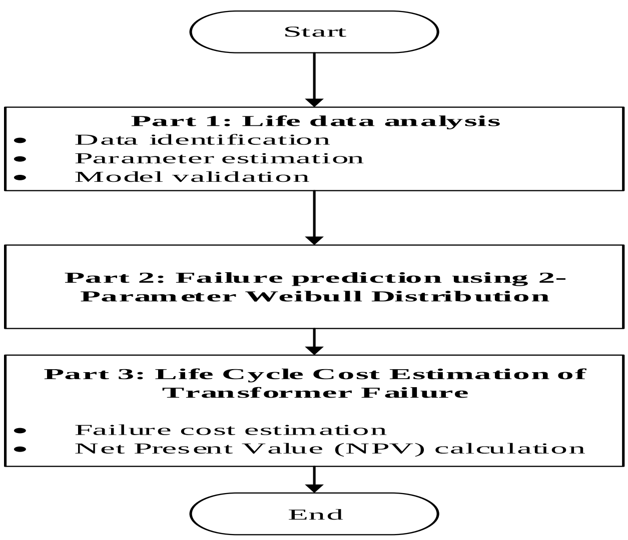

Fig. 2 Flowchart of the methodology

Life data analysis is the process of modelling lifetime of an equipment; in this case statistical distribution for distribution transformer is used. Three major activities in life data analysis are data identification, parameter estimation and model validation[12,18]

Data identification is done by categorising distribution transformers with same manufacturer and capacity into the same group. Then, the transformers are further sorted according to the state (i.e survive or fail) and years of service. Life data model for each distribution transformer group is obtained by fitting the survival and failed data of the sample population into 2-Parameter Weibull distribution as represented by Equation (1). Shape parameter, β and scale parameter, η for the distribution is estimated using Maximum Likelihood (MLE) method. Moreover, mean time to failure (MTTF) is also estimated from the statistical distribution.

Model validation is conducted to ensure that the life data model generated in this analysis represents ageing transformers. As explained by the reliability bathtub curve in Figure 1, shape parameter, β and failure rate, λ(t) can be used to indicate the equipment mode of failure.A proper ageing model of distribution transformer should satisfy two conditions: i) shape parameter, β should be greater than 1 and ii) failure rate, λ(t) value should increase with time, t.

The 2-Parameter Weibull distribution is also used to predict failure occurrence of the transformers. From the probability density function, the fraction of distribution transformer thatfail in a particular year, from the initial number of the units in the group sample population is obtained. Consequently, the cost of transformer failure can be estimated.

Life cycle cost estimation of transformer failure considers two components which are the annual failure cost estimation and Net Present Value (NPV) calculation.Failure cost of transformer relates to the cost incurred due to failing transformer. The annual failure cost,FC(t)is estimated as in Equation (2).

$$FC(t) = f(t) \times C_f \qquad \textbf{(2)}$$

Where, f(t) is the frequency of failure and Cfis the failure consequence cost of a unit distribution transformer.

Once annual failure cost FC(t) has been estimated, present value (PV) for each year iscomputed using Equation (3)[19]. This PV reflects future failure cost discounted to the present year. Next, life cyclecost of distribution transformer failure is determined by computing Net Present Value (NPV) using Equation (4)[19].FV in Equation (3) & (4) is Future Value which is the future failure cost estimated by Equation (2). The time or year is represented by t and the discount rate is represented by i.

$$PV=\frac{FV}{(1+i)^t} \qquad \textbf{(3)}$$

$$NPV = \sum \frac{FV}{(1+i)^t} \qquad \textbf{(4)}$$

III.RESULTS AND DISCUSSIONS

A case study is conducted on sample population of 750 KVA distribution transformers in a metropolitan area. Samples are taken from three different distribution transformer manufacturers which are X, Y and Z. The survival and failed data of the three manufacturers are identified and fit into 2-Parameter Weibull distribution. Table 2 shows the resulting estimated β and η parameters as well as mean life or MTTF for each distribution transformer group.

Table. 2 β, η and MTTF for distribution transformer X,Y and Z

Transformer Group	β	η	MTTF (Year)
X	11.37	30.62	29.29
Y	7.61	32.22	30.27
Z	5.82	35.06	32.48

From Table 2, it can be observed that each transformer group has different β and η values. Distribution transformer life data models are then obtained by substituting β and η values in Equation (1). This results in different mean time to failure (MTTF) for each transformer group. It can be seen that transformer group with high shape parameter, β and low scale parameter, η has early mean time to failure (MTTF). In contrast, transformer group with low shape parameter, β and high scale parameter, η has late mean time to failure (MTTF). This indicates that each life data model has different characteristic, which is the results of the variation in shape parameter, β and scale parameter, η.

Figure 3 shows the plot for failure rate, λ(t) of the three transformer groups. It is confirmed from the plot in Figure3 that failure rate, λ(t) increases with time. It is also verified from the parameter estimation results in Table 2 that all of the three manufacturers have β greater than 1.

These two conditions match the criteria of ageing or wear out life in reliability bathtub curve shown in Figure 1.Thus, these distributions are valid representation of ageing transformer for this study.

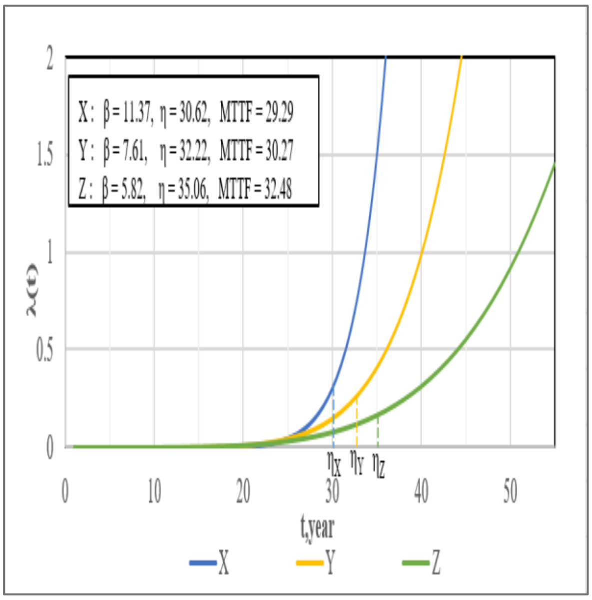

Fig. 3 Failure rate, λ(t) plot

The frequency of failure, f(t) obtained from the 2-Parameter Weibull distribution varies as a function of time depending on the shape and scale parameters β and η. As such, Figure 4 shows the estimated life cycle cost of transformer failure and corresponding Net Present Value (NPV).

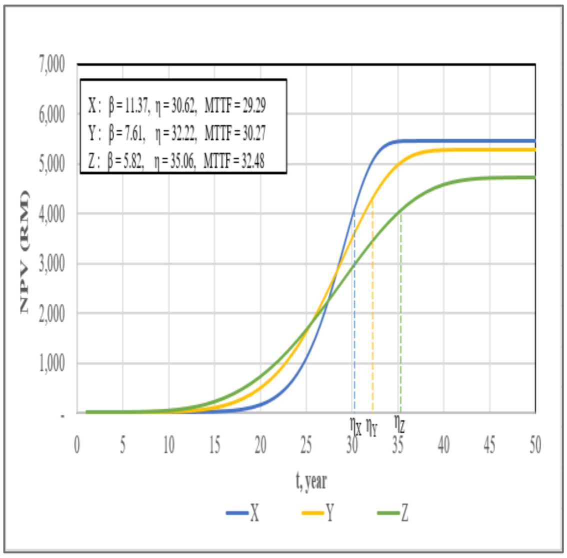

Fig. 4 Net Present Value (NPV) for Life Cycle Cost Estimation of Transformer Failure

Net Present Value (NPV) plots of transformers in Figure 4 indicates that as the transformer age exceeds mean time to failure (MTTF), the life cycle cost of transformer failure for X increases at the highest rate as compared to the other two transformer groups. The second highest increment rate of life cycle cost of transformer failure belongs to Y and the lowest is Z.

In addition, Figure 4shows that transformer group with low shape parameter, β and high scale parameter η, has less steep slope for the NPV plot. Therefore, failures of these transformers are more distributed over the years with more failure occurs during later years and at higher discounted value of money. Hence, Net Present Valueand the life cycle cost of transformer failure are lower.

The economic assessment of distribution transformer failure points out that life cycle cost estimation of distribution transformer is affected by frequency of failure as a function of time and present value of failure cost. It is understood that high number of failure results in high cost. However, this is no longer true when time value of money concept is applied. This concept has proven that failure in later years cost less than failure in early years.

IV.CONCLUSION

Life data analysis has proven that transformer ageing characteristic for different manufacturers varies and can be characterized by 2-Parameter Weibull distribution. The ageing transformer model is validated by the shape parameter $\beta > 1$ and failure rate $\lambda(t)$ plot which increases with time. It is also learnt from the analysis that the transformer failure occurrence and its frequency of failure can be predicted based on probability density function of the distribution. The failure cost analysis also points out that life cycle costof transformer failure is affected by failure distribution and time value of money. This can be confirmed from the life cycle cost estimation results where lower failure cost is observed for transformer which fails in later years.

This research work has successfully utilised life data analysis to represent ageing life of transformer. In addition, this research work also has accomplished to economically evaluate the impact of failure time to the life cycle cost. Thus, a comprehensive and enhanced methodology for life cycle cost estimation of transformer failure has been introduced. It is anticipated that the results from this research work will ease decision making for asset replacement, maintenance and planning strategies.

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