Data Requisites for Transformer Statistical Lifetime Modelling—Part II: Combination of Random and Aging-Related Failures

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***Abstract*—Statistical lifetime modeling is of importance for replacement management of aged power transformers. Survival data are recognized as important as failure data in improving the accuracy level of the lifetime models since transformer failures are rare events and most of the units are still in operating condition. This paper argues that differentiating random failures and aging-related failures is also important. Different data requisites for modeling random failures and aging-related failures are analyzed and compared through Monte Carlo simulations. The transformer lifecycle failure model can be built by combining the random and aging-related failure models. A case study is presented to show that through postmortem analysis, the two failure modes can be distinguished and, hence, it helps to improve the accuracy of the combined model.**

***Index Terms*—Censoring rate, lifetime data, Monte Carlo methods, sample size, statistical lifetime model, transformers.**

I. Introduction

As ONE of the capital-intensive assets, power transformers are key components in transmission and distribution networks which are to deliver electrical energy from generators to end users. Since the reliable operation of power transformers greatly influences the reliability of the power system networks, unexpected transformer failure would not only incur a large capital re-investment of the asset itself but also might cause a loss of electricity supply especially when spare transformers are not provided in place. Consequently, efforts have to be made in order to maximally prevent the occurrence of unexpected failures of power transformers. In terms of asset management, transformer units are specifically managed at both individual and population levels [1]–[3].

For each individual unit, the condition of the unit has to be regularly checked and often quantified/categorized based on the understanding of physics of aging and the degradation process; the concept of condition indicators, or referred to as an asset health index, is becoming widely adopted; together with the unit's criticality, the asset health index can act as the main base for the decision-making in terms of whether to run, repair, refurbish, or replace (RRRR) that specific unit [2]–[4]. On the other hand, a large proportion of the transformers was installed in the 1960s and early 1970s and are approaching or have already exceeded their designed lifetime of 40 years [5]–[8]. Their performance is expected to deteriorate and the consequential increase of aging-related failures is therefore of great concern for utilities. A long-term plan for the replacement of the aging transformer population before it reaches an unacceptable state has to be made.

An accurate projection of expenditure into the future—to replace a large quantity of power transformers—is required due to the fact that transformers are high capital cost assets with a long acquisition lead time [9]–[11]. In this respect, historical average failure rates would no longer be applicable for the prediction of failures in the wear-out/aging state [12]. Efficient lifetime models have to be developed so that transformers' failure characteristics throughout their life cycle can be modeled accurately.

In this paper, definitions of early-life random failures and aging-related failures are given specifically for transformer failure statistics, and the requisites toward data quality are systematically studied through sensitivity analysis of censoring rates and failure numbers. A case study, which simulates the transformer fleet data of National Grid, is then given to demonstrate the data quality issue. Finally, the effectiveness of the proposed postmortem approach, of which the sole purpose is to help distinguish random and aging-related failures, is demonstrated in terms of improving the accuracy of transformer statistical life modeling.

II. Transformer Failure Statistics

A. Conceptual Failure Model

Transformer failure occurs, when the withstand strength of a transformer, with respect to one of its key properties, is exceeded by the relevant operational stress [13].

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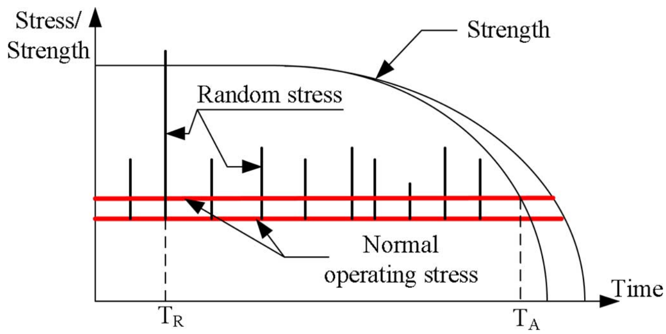

Fig. 1. Conceptual transformer failure model.

The key properties refer to electromagnetic ability, integrity to carry current, dielectric withstand strength (to earth/between phases/between windings), and mechanical withstand strength (to short-circuit current and resulting mechanical force) [13], [14]. The operational stresses include normal and transient loading conditions as well as some disturbances, such as lighting overvoltages, switching operations, or system short-circuit faults [13].

Although the actual origins or causes of failure may be different from transformer to transformer, a conceptual failure model (Fig. 1) can still be adopted to illustrate the general modes of transformer failures, representing their statistical characteristics [15]. In the figure, "strength" and "stress" are generic terms used to cover any of the aforementioned properties and stresses. Failures occurred at time T_A, and T_R represent two types of failure modes (i.e., aging-related failure and random failure, respectively) and they will be separately discussed in 1) and 2).

1) Definition of Aging-Related Failures: During the course of its life, a transformer will experience irreversible deleterious changes to its serviceability and this is defined as the aging processes in [16]. Due to the existence of these aging processes, the withstand strengths of the transformer gradually decrease and may deteriorate faster than normal if some abnormal or destructive deterioration process occurs [13].

As shown in Fig. 1, at time T_A, the strength of a transformer deteriorates to such a level that it is no longer enough to cope with the normal operational stress, resulting in a failure at this specific moment. This type of failure is mainly caused by the deterioration of strength with regard to the normal operational stress and is hereafter categorized as aging-related failure. Aging-related failures, as revealed in Fig. 1, are mostly concentrated in older ages of transformers' life cycles.

2) Definition of Random Failures: The other types of failures occurring at time T_R, as shown in Fig. 1, are the ones caused by the random stresses that accidentally exceed the strengths of a transformer. This type of failure is hereafter referred to as random failure.

Although it may happen throughout the lifetime of a transformer, for a transformer fleet, random failures, however, are the most prominent ones observed at younger ages.

As pointed out in [17], the report published by CIGRE SC 12 [18] is still considered as the most up-to-date international survey of transformer reliability. The study analyzes

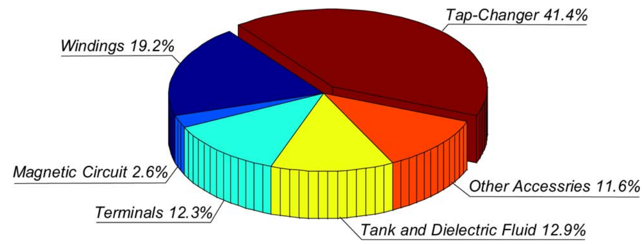

Fig. 2. Proportions of transformer failures related to components [18].

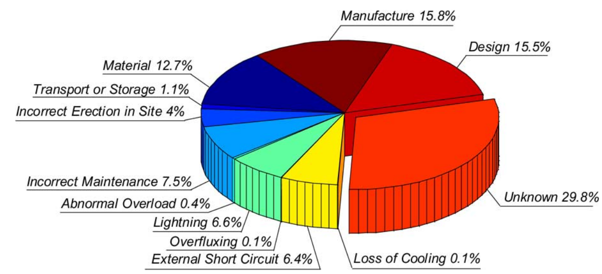

Fig. 3. Proportions of assumed causes of random failures [18].

transformer failure data collected from 13 countries on three different continents, covering transformers up to the age of 20 years but unfortunately not beyond. It is revealed in the report that the origins of random failures are mostly related to transformer accessories rather than the main tank itself, where tap-changer failures take up 41% of the total failures. The proportions of transformer failures related to components are presented in Fig. 2. Various causes can contribute to the random failures of transformers as shown in Fig. 3.

The survey also pointed out that failures related to aging tend not to be obvious at younger ages. This corresponds to Doble Engineering Company's experiences, which is that, so far, most transformer failures are not due to old age, but due to some limitations in the design and manufacturing process, or due to some localized damages caused during operations and maintenance [14].

However, aging transformers are inevitable and it is expected that aging-related failure will become the dominating mode of transformer failures in the future, when considering the operating transformers' age profile.

B. Mathematical Models for Transformer Failures

Mathematically, random failures are characterized by the instantaneous failure rate remaining relatively constant over time, corresponding to the flat region of the bathtub curve, whereas the aging-related failures are characterized by an increasing instantaneous failure rate with age, corresponding to the back-end phase of the bathtub curve. Both failure modes can be represented by the two-parameter Weibull distribution functions since this type of distribution, with different parameters, is flexible in representing different relationships of instantaneous failure rate versus age [19], [20].

The cumulative distribution function (CDF) of the two-parameter Weibull distribution is given as

$$F_x(x;\eta,\beta) = 1 - \exp[-(x/\eta)^{\beta}] \tag{1}$$

where

x failure time, expressed as a variable;

η scale parameter;

β shape parameter.

The instantaneous failure rate versus age relationship of the Weibull distribution $h(x)$ is shown

$$h(x) = \frac{\beta}{\eta}\left(\frac{x}{\eta}\right)^{(\beta-1)}. \tag{2}$$

h(x) is determined by the value of the shape parameter so that:

- $\beta = 1$ represents the "random failures" where the instantaneous failure rate remains constant over time;
- $\beta > 1$ represents the "aging-related failures" where the instantaneous failure rate increases with age.

As for the scale parameter, η, it represents the age by which 63.2% of the transformer units are expected to have failed. For the extreme case of $\beta = 1$, where random failures are concerned, the mean lifetime of the distribution is equal to the value of η.

In this paper, random and aging-related failure models are mathematically represented by Weibull distribution functions, and the parameters are chosen as $F_x(x, 500, 1)$ and $F_x(x, 100, 5)$, representing a utility's current understanding on the level of random failure rate and aging-related failure rate, respectively. Detailed explanations will be provided in Section IV. Moreover, all of the exemplar discussions on data-quality issues will be based on these parameters, that is, $F_x(x, 500, 1)$ and $F_x(x, 100, 5)$, and so is the combined transformer failure model.

III. Data Requisites for Weibull Lifetime Models

In this section, data requisites for accurately modelling the random failure are analyzed when comparing the case of aging-related failure modelling. The same modeling procedures for the aging-related failures as discussed in [21] are adopted. In order to make consistent comparisons between these two failure modes, multiple trials of Monte-Carlo simulations are conducted to simulate 10 000 sets of random and aging-related failures, respectively, in various sampling scenarios. Each sampling scenario represents a combination of sample size (i.e., total number of lifetime data) and the censoring rate (i.e., proportion of surviving units). The sample size is chosen to be in the range from 40 to 1000, and the censoring rate is chosen to be in the range from 0% to 95%. The maximum-likelihood method [22] is then adopted to estimate the parameters of the two-parameter Weibull distribution for each set of lifetime data.

Adopted as the evaluation criteria for the estimated results, the relative root mean square error (RRMSE), as defined in (3), and the relative difference between the estimated median value and the true value (RD), as defined in (4), are both calculated for estimated Weibull parameters

$$\text{RRMSE} = \sqrt{[SD(\hat{\theta})]^2 + [\text{Bias}(\hat{\theta})]^2}/\theta \tag{3}$$

where

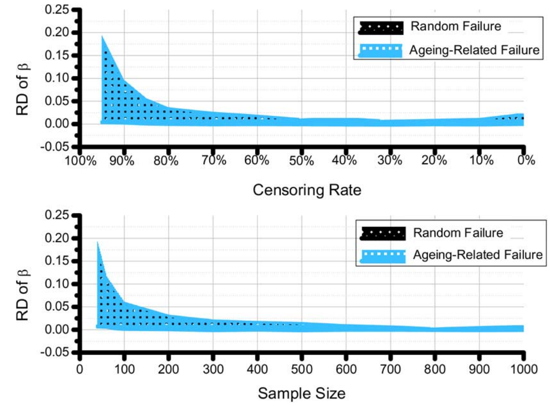

Fig. 4. RDs of the estimated shape parameter in various censoring rates (upper figure) and various sample sizes (lower figure).

$\text{Bias}(\hat{\theta}) = E(\hat{\theta} - \theta)$;

θ value of the parameter;

$\hat{\theta}$ estimated value of the parameter

$$\text{RD} = (\text{Median}(\hat{\theta}) - \theta)/\theta \tag{4}$$

where $\text{Median}(\hat{\theta})$ is the median value of the estimated parameters.

As specified in [23], in order to evaluate the modelling accuracy effectively, two aspects of the test results as trueness and precision are considered, respectively, and they can be computed as bias and standard deviation (SD). RRMSE hence serves the purpose for an overall evaluation criterion as bias and standard deviation are computed into this combined value, as shown in (3). RRMSE, however, bears a disadvantage, which could be affected by any single extreme value that can either too high or too low compared with the rest of the results. In such a case, RRMSE, on its own, cannot reflect the true accuracy level of the estimated results; therefore, RD, as it is immune to extreme values, is then adopted to provide additional information on the central tendency of the results.

The two values, that is, RRMSE and RD, complement each other for an effective evaluation. It is expected that the closer the RRMSE and the RD are to zero, the higher the accuracy level of the estimated parameters will be. Consequently, the influence of different combinations of sample size and censoring rate on the accuracy of the estimated Weibull parameters can be revealed through the comparison of changes of RRMSE and RD with changes in sampling size and censoring rate. As a result, these are the differences between the modelling random and aging-related failures under the same sampling scenario.

The RDs and RRMSEs of the estimated β values in various censoring rates and sample sizes are presented in Figs. 4 and 5, respectively. The black lines indicate the estimated results in the case of random failure, and the blue lines indicate the estimated results in the case of aging-related failure; the same graphic format is maintained for all of the following figures in this section.

As seen in Fig. 4, RDs of the estimated β values are the same in the case of random failure and the case of aging-related

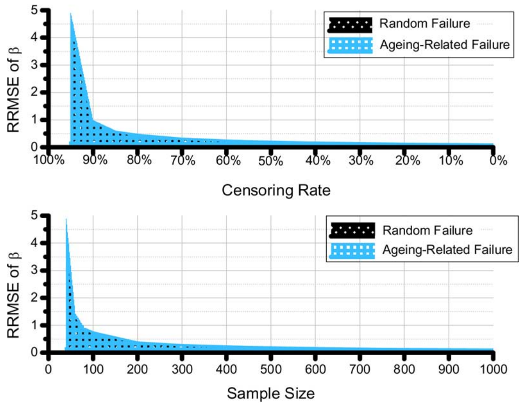

Fig. 5. RRMSEs of estimated shape parameter in various censoring rates (upper figure) and various sample sizes (lower figure).

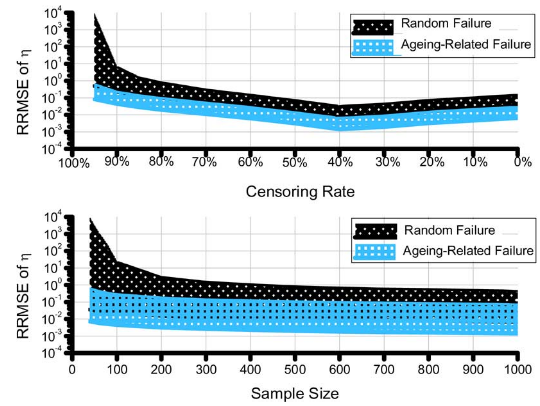

Fig. 7. RRMSEs of the estimated scale parameter in various censoring rates (upper figure) and various sample sizes (lower figure).

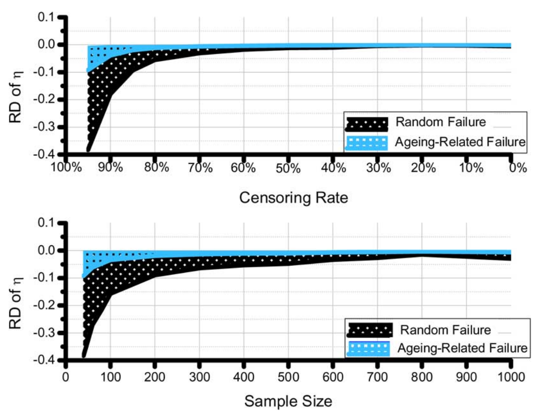

Fig. 6. RDs of the estimated scale parameter in various censoring rates (upper figure) and various sample sizes (lower figure).

TABLE I
REQUIREMENT OF THE MINIMUM SAMPLE SIZE AND NUMBER OF FAILURES SELECTED AT THE CENSORING RATE UNDER AN EXPECTED ACCURACY LEVEL

Failure Mode		**Censoring Rate**			
		95%	**90%**	**85%**	**80%**
Random Failure	*RRMSE of η $\leq$0.25*	**3100**	**900**	**400**	**200**
	RRMSE of β $\leq$0.25	400	200	150	100
	Minimum No. of Failures	**155**	**90**	**60**	**40**
Ageing-Related Failure	*RRMSE of η $\leq$0.25*	150	40	20	10
	RRMSE of β $\leq$0.25	**400**	**200**	**150**	**100**
	Minimum No. of Failures	**20**	**20**	**23**	**20**

failure as black lines overlap blue lines. The same observation for RRMSEs of the estimated β values can be also made as in Fig. 5. This implies that the same level of accuracy for the estimated β values can be achieved for the same sampling scenario irrespective of the true underlying distribution, that is, whether it is in the random failure mode or aging-related failure mode.

The RDs and RRMSEs of the estimated η values in various sampling scenarios are presented in Figs. 6 and 7, respectively. RRMSEs are presented in log scale in order to differentiate the values in the two cases of random failure and aging-related failure.

As shown in Fig. 6, RDs of the estimated η values in the case of aging-related failure are closer to zero when compared to the results in the case of random failure. The RRMSEs of the estimated η values in the case of aging-related failure are generally lower than the results in the case of random failure, as revealed in Fig. 7. These imply that the accuracy of the estimated η values is dependent on the true underlying distribution of the lifetime data; to be precise, in the same sampling scenario, a higher level of accuracy for the estimated η values is expected for modelling aging-related failures than random failures. This means that in order to reach the same level of accuracy as the aging-related failure model, a larger sample size with a lower censoring rate is of necessity for the random failure model.

As discussed in [21], the value of RRMSE can be directly taken as a measure of accuracy level for an estimated parameter, that is, shape parameter or scale parameter, and an expected accuracy level of RRMSE $\leq$ 0.25 is found to be appropriate to determine the requirement of minimum sample size for each specified censoring rate.

By choosing $\mathrm{RRMSE} \leq 0.25$ as the expected accuracy of estimated η and β for the cases of random failure and aging-related failure, their corresponding minimum sample sizes are obtained as listed in Table I.

As shown in Table I, the accuracy of the lifetime model in the case of random failure is controlled by the accuracy level of the estimated η value, as a larger sample size is required to reach the expected accuracy level of η. The accuracy of the lifetime model in the case of aging-related failure, however, is controlled by the accuracy level of the estimated β value.

Taking the censoring rate of 90% as an example, to reach an accuracy level of RRMSE$\leq$0.25 for estimated η or β, the random failure model would require a sample size of 900 or 200, respectively, whereas the aging-related failure requires 40 or 200 samples. Therefore, to obtain RRMSE $\leq$0.25 for η and β parameters, a sample size of 900 with 90 failures is of necessity for the random failure mode, whereas only a sample size of 200 with 20 failures is required for the aging-related failure.

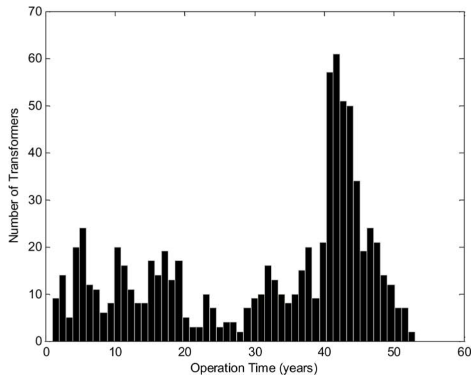

Fig. 8. Age profile of a group of operating transformers in a utility company.

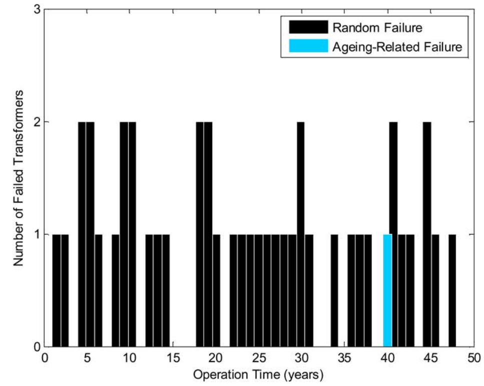

Fig. 9. Age profile of historically failed units in the group of transformers.

Through the comparison of these two cases, it is clear that a larger sample size or a lower censoring rate is expected for accurately modelling random failures than aging-related failures.

IV. Case Study to Simulate a Utility's Transformer Fleet Data and the Importance of Postmortem Analysis

Lifetime models for the cases of random and aging-related failures can be used through the competing risk model [24], to form a database which represents the failure characteristics of a transformer fleet. In this case study, a lifetime database, whose composition is similar to a utility's transformer survival and failure data collected since the 1960s, is simulated.

First, the random failure is represented by the Weibull distribution with the two parameters $\eta = 500$ (the scale parameter) and $\beta = 1$ (the shape parameter). This reflects the utility's current understanding on the level of random failure rate, which is around 0.2% per transformer per year. This is equal to a mean time to failure (MTTF) of $1/0.2\% = 500$ years. Then, the aging-related failure is assumed to follow the Weibull distribution of $\eta = 100$ and $\beta = 5$, which also reflects the utility's current understanding on the transformer aging-related failures. Finally a set of 800 lifetime data, whose age profile is provided in Fig. 8, is generated to mimic the real-life situation for the utility's transformer fleet.

Among the 800 lifetime data, 44 transformers failed at various ages and the failure data are generated. The number of failed transformers at each age is presented in Fig. 9. It is known through postmortem analysis that 43 are random failures and only 1 belongs to the type of aging-related failure.

Postmortem analysis plays an important role in helping distinguish different failure modes so that the lifetime model for each failure mode can be estimated separately. By separating the failure modes, the scale parameter and shape parameter of the two-parameter Weibull distributions for both random failure and aging-related failure are estimated separately using survival and failure data through the maximum-likelihood method. The estimated Weibull parameters are listed in Table II.

As presented in Table II, both random failure and aging-related failure models can be successfully derived. The shape parameter of the random failure model and aging-related model are estimated as $1.28 \cong 1$ and $7.91 > 1$, respectively.

For the random failure model, the relative bias of the estimated scale parameter, 37.2%, is larger than the relative bias of the estimated shape parameter, 28%. For the aging-related failure model, the relative bias of the estimated shape parameter, 58.6%, is much higher than the relative bias of the estimated scale parameter of 4%. These correspond well to the simulation results presented in Table I, that is, that the accuracy level of the estimated β is generally higher than the estimated η for the random failure model; whereas the accuracy level of estimated β is generally lower than the estimated η for the aging-related failure model.

TABLE II
Comparison of Estimated Weibull Parameters of Both Random and Aging-Related Failure Modes

Distribution	***Random Failure***		***Ageing-Related Failure***	
	Shape Parameter	***Scale Parameter***	***Shape Parameter***	***Scale Parameter***
Assumed	1	500	5	100
Estimated	1.28	314	7.91	96
Conventionally Estimated	1.26	345	--	--

The very large bias of estimated β in the aging-related failure model can be attributed to the limited number of failures. The extremely high censoring rate of 99.875% results with only 1 aging-related failure in 800 samples. By looking up Table I, it is known that 20 or more aging-related failures are expected for the estimated β value to reach the desired accuracy level.

When postmortem analysis results are not available, which is common for most utilities, failure modes cannot be distinguished and all of the data are used to estimate the parameters of one Weibull distribution. The estimated parameters, hereafter referred to as conventionally estimated results, are also presented in Table II and this means that the mode of aging-related failure is concealed under the random failures.

V. Proposed Approach That Combines the Random and Aging-Related Failure Models

A combined lifetime model, representing the failure characteristics of a transformer fleet in the entire lifetime cycle, can be built up with the competing risk model once the distributions of random and aging-related failure models are derived.

The competing risk model holds due to the fact that power transformers are replaceable units having two main failure modes, that is, random failure and aging-related failure. As

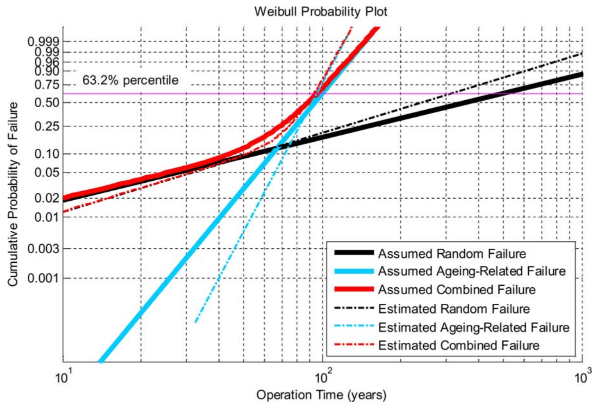

Fig. 10. Comparison of estimated distributions and the assumed ones.

defined in Section II, the two failure modes are independent of each other. A transformer will fail whenever one of the two failure modes first occurs to the transformer. The same concept is applied by Schijndel in formulating an integral transformer reliability model [25], in which a transformer is considered as a series system consisting of separate subcomponents, and the system fails when either of the subcomponents fails.

Therefore, the reliability, the CDF, and the instantaneous failure rate of transformers (i.e., the combined lifetime model) are denoted as $R_C(x)$, $F_C(x)$, and $h_C(x)$, respectively, and hold the following relationships as:

$$R_C(x) = R_R(x) \times R_A(x) \tag{5}$$

$$F_C(x) = 1 - (1 - F_R(x)) \times (1 - F_A(x)) \tag{6}$$

$$h_C(x) = h_R(x) + h_A(x) \tag{7}$$

where

x	failure time, expressed as a variable;
$R_R(x)$, $F_R(x)$ and $h_R(x)$	reliability, the CDF, and the instantaneous failure rate for random failure, respectively;
$R_A(x)$, $F_A(x)$ and $h_A(x)$	reliability, the CDF, and the instantaneous failure rate for aging-related failure, respectively.

With (5)–(7), the combined lifetime model can therefore be derived based on the random and aging-related failure models. The CDF for each failure mode and its corresponding originally assumed distributions are presented in Fig. 10, along with the derived combined lifetime model.

It is observed from Fig. 10 that the actual transformer lifetime model, that is, the combined lifetime model, can be easily derived by combining the separate lifetime models of each failure mode. The accuracy of the lifetime model is greatly improved with the correct identification of the failure modes through postmortem analysis.

The mean lifetime and the median lifetime of the combined lifetime model and the conventionally estimated lifetime model are listed together with the two values of the originally assumed lifetime model in Table III.

TABLE III
COMPARISON OF THE COMBINED LIFETIME MODELS

Combined Distribution	*Mean Lifetime (yrs)*	*Median Lifetime (yrs)*
Assumed	83	88
Estimated	82	88
Conventionally Estimated	321	258

In the present case, the median lifetime is found to be around 88 years instead of the unreliable conventionally estimated result of 258 as listed in Table III. The derived mean lifetime of the combined lifetime model is found to be around 82 years instead of the value of 321 years when the failure modes are unidentified. The mean lifetime of 82 years then provides asset managers some confidence to say that it might be reasonable to allow transformers to be operated beyond the original assumed design lifetime of 40 years, although more failure data are still needed for further verification.

VI. CONCLUSION

Accurate lifetime modelling for power transformers is crucial for planning the future replacement of aging transformer populations. Since most of the transformer fleets have not yet completed their first life cycle, there is a lack of transformer failure data, and survival data are therefore as important as failure data in developing lifetime models.

Through a series of Monte Carlo simulations, the data requisites for lifetime modelling have been analyzed for both random failure and aging-related failure models. It is shown that censoring rate and the sample size of the collected lifetime data will unavoidably affect the modelling accuracy; the random failure model tends to require a larger sample size with a lower censoring rate than the aging-related failure model.

The transformer life-cycle failure model can be represented by the combination of the random and aging-related failure models. Postmortem analysis, as the proposed approach to distinguish the two failure modes, helps improve the accuracy of transformer statistical life modelling; the case study which mimics a utility's transformer lifetime data indicates that through distinguishing the failure modes, the lifetime modelling gives the mean lifetime of 82 years which provides asset managers some confidence to allow transformers to be operated beyond the original assumed design lifetime of 40 years.

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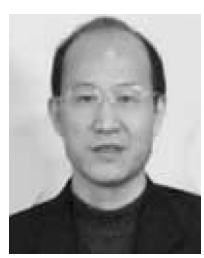

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