

Article

Power Transformer Component Reliability Using CIGRE Large-Scale Data Surveys

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Abstract

The probability of failure of a power transformer is difficult to quantify within a single utility because major failures are rare and operating histories are often incomplete. This paper uses large-scale CIGRE surveys (50 utilities, 26,533 transformers, 331,379 operating years) to estimate age-dependent component reliability by voltage class. In total, 1358 major failures and 991 retirements were reported for a reference period of up to 34 years. The data were treated as left-truncated and right-censored. Hazard rates were calculated for active parts, bushings, and on-load tap changers, retirements were assessed using the Kaplan–Meier estimator, and Weibull distribution models were fitted to 100–199 kV and 200–700 kV populations. The overall major failure rate was 0.41% per year. For the 100–199 kV transformers, the component hazard rates were close to constant with age ($\beta \approx 1$), and the late-life pattern was influenced by increasing retirements. For the 200–700 kV transformers, bushing hazard showed a stronger age dependency and exceeded active-part hazard at around 50 years. The results highlight the value of component-focused risk management and show that fleet reliability should be interpreted alongside retirement and condition-management practices. Key limitations include data truncation, censoring, and the lack of categorisation of failures by technology type.

Keywords: power transformer; reliability; probability of failure; hazard rate; Weibull distribution; Kaplan–Meier estimator; survival analysis; bushing; on-load tap changer; asset management

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1. Introduction

Power transformers are designed to operate reliably for decades, but when they fail, they can cause significant disruption and replacement cost. Estimating their probability of failure (PoF) is beneficial because it provides strategic support for decision making. It can be used to perform an economic analysis of when they are best to replace [1–3]. It can indicate when to conduct restoration activities before the hazard rate begins to substantially increase [4]. It is used to estimate the number of spare units which should be kept available by predicting how many units will fail within the procurement period [5]. The Australian energy regulator requires a statistical analysis of risk from different options when planning for replacement [6].

A challenge to determining PoF, however, is that one utility may not incur enough events for an analysis to be statistically rigorous. Thus, the industry has pooled data for CIGRE international reliability surveys [7–9]. The novelty of this work is the collecting, filtering, and processing of a very large volume of data that shows actual fleet transformer performance. This was performed by producing a questionnaire in Microsoft Excel and writing algorithms in Python code. A link to the questionnaire template can be found in [10]. The questionnaire was developed by reflecting on the completeness of previous surveys so that the right data was collected while minimizing respondent time and improving the disambiguation that could affect results.

Given that technology and asset management practices change, it is important to periodically revisit reliability. CIGRE publishes many materials about best practice, and thus it is expected that contemporary asset management processes will have been updated. The latest CIGRE surveys are the largest yet, enabling us to better understand failure globally, setting the benchmark for data collection [7,8]. Another advantage of such a large survey is to have sufficient failures on which to evaluate different failure locations without running into inaccuracies caused by small sample sizes. Other difficulties around obtaining enough failure data are as follows: Firstly, a transformer is normally expected to operate reliably for many decades; they are long-lasting, and so failure experience is mostly limited. Secondly, to avoid an outage, a utility can retire a transformer early, avoiding failure (although the definition of failure can be changed to reflect retirement). Thirdly, for minor failures that were then repaired, there may not be the corporate memory necessary to report these in a survey.

The first CIGRE international survey for studying probability of failure began in 1975 and resulted in a 1983 publication [11]. The objectives were to pinpoint the main causes of failure and to evaluate outage times. The actions necessary to improve reliability were then considered. In total, data on more than 1000 failures occurring between 1968 and 1978 from a population of 47,000 service-years across 13 countries were collected. Failure rates across different populations were found to be between 1 and 3% per annum. Since then, research has generally fallen into two aspects: the first is the development of statistical methods to overcome small and incomplete datasets; the second is further large-scale data collection, with a focus on strengthening standardization and processing techniques.

A common technique is to fit statistical distributions to the population and then investigate the goodness of fit. Depending on the granularity of the data, there can be several distributions present. For instance, for machines, there can be distinct early, random, and age-related failure distributions. These distributions can be subdivided further, reflecting the failure mode or location [12]. An important note is the clarification of *random*. In statistics, a random distribution has a constant failure rate, for instance, over time. The engineering definition is different, as it normally needs to be concluded from a failure investigation and implies that the cause of failure is considered to be aberrant rather than systematic.

As power transformers have long operating lives, the reliability data is often *incomplete*. When referring back to the 1968–1978 CIGRE survey [11], this means that as failures from before 1968 were not used, the data is left-truncated, and, as most of the transformers were still operating by 1978, the data is right-censored. Statistical techniques to reflect this in the analysis and also evaluate the mean life from the limited end-of-life failure data [13,14] are given in IEC standard 61649 [15], Hong [16], and Li [17].

A common statistical technique is to fit the Weibull distribution and then use its shape and scale parameters to estimate the mean and characteristic lives of the population [15]. A research group looked at the data requisites for modelling transformers and included methods to deduce the shape and scale parameters of a Weibull distribution

based on the expected fleet life [18,19]. Residual life calculations for insulation paper, such as [20], were used to estimate the characteristic life. However, there will be additional failure modes. Additionally, only one failure in the forty-four analyzed was determined to be age-related. Thus, the analysis may change as the fleet ages and wear-out failures begin.

The next CIGRE reliability survey after 1983 was conducted in 2015 [7]. Failure locations and causes were aggregated for 56 utilities from 21 countries between 1996 and 2010. The failure modes, locations, and causes were aggregated. The failure rate was determined, but not as a distribution of age, because population statistics were not collected.

Inspired by this survey was a comprehensive study of data from Australia and New Zealand for the period 2000–2015 [21–25]. This region has a history of publishing reliability statistics since 1996 [26] and later in 2004 [27]. A major update in 2015 was that the Australian government regulator had begun requiring that utilities publish the age distribution of their assets [28], and thus the collection of data was simplified. Retirements were also collected to provide a fuller picture that could impact the calculated failure rate. Data from utilities owning 5861 power transformers from 11 kV upwards were analyzed and age distributions for component reliability were presented for different voltage classes. Another aspect of this survey was determining whether there was a statistically significant difference in the probability of failure across the local distribution utilities. After a statistical analysis, none were found [23], showing the benefit of such analyses.

The CIGRE reliability survey was repeated for 2010–2020 data [8]. The questionnaire was updated to also collect the retirements and operating data so that the failure rate could be calculated as a function of age. When the failure rate of individual components is investigated, there needs to be enough failures, or else the $\pm 95\%$ confidence interval becomes excessive. For instance, in the Australian survey [21], a Weibull distribution was fitted to winding-related failures. However, no such fitting was given for other locations because there was an insufficient number of failures for acceptable $\pm 95\%$ confidence intervals. A comparison [29] was given that compared the Australian and New Zealand failure studies for events between 2000–2015 [21] and 2010–20 CIGRE data [8]. An obvious downward trend in failures was noted. It was noted that more retirements had been made that reduced the failure rate, demonstrating this relationship. This shows the benefit of continual industry efforts to improve asset management.

For a power transformer, the reliability of key components, such as the active part (windings, core insulation), bushings, and on-load tap changers (OLTCs), are core to determining the overall failure. Thus, the CIGRE survey also collected data on these types of failures. These are shown in Figure 1, with their proportion reported in [8]. One quarter of these failures was in the bushings, notably because these are replaceable parts. A further statistical analysis would be beneficial to provide guidance as to when these occur at an unacceptable probability of failure and should be replaced. The tap changer undergoes regular maintenance, which should be revisited if the probability of failure elevates significantly after a specific age. Not all of this data was used in this article because not every utility provided the age distribution of their operating assets and the data containing unknown failure locations were omitted. However, the outcome is expected to be similar because of the commonality of failure. The electrical and dielectric components can be combined into an overall “active parts” population where there are a large number of failure points to analyze statistically. In this paper, the reliability of these subcomponents is explored further to improve decision-making in maintenance and renewal planning.

In this paper, the statistical datasets from both CIGRE surveys were merged when age distribution and failure location data were available, followed by a detailed

investigation of the component hazard rates. In summary, this study provides new insights into the age-dependent failure patterns of transformer components at different voltage levels, investigates the impact of retirements, and proposes a framework to reduce the hazard rate based on other CIGRE brochures. The nomenclature used is given in Table 1.

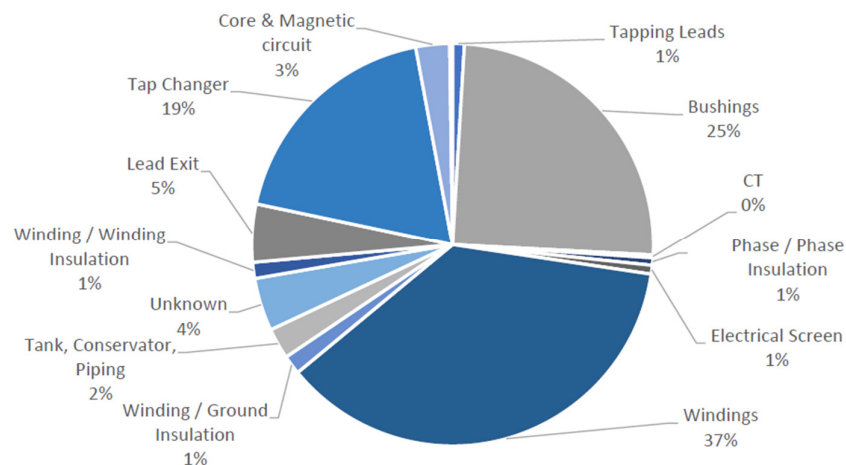


Figure 1. Failure location analysis for 848 major failures, collected only for the A2.67 survey, as given in the CIGRE brochure [8].

Table 1. Nomenclature used in the article.

Quantity	Definition	Unit	Interpretation	Relationship
PoF/ Unreliability $F(t)$	$F(t) = P(T \leq t)$	-	Cumulative probability that failure has occurred by time t	$PoF(t) = F(t) = 1 - S(t)$
Failure rate	$\lambda = \frac{\text{failures}}{\text{population} \times \text{time}}$	1/time	Empirical or average frequency of failures over a time interval	Equals the hazard rate only when defined as an instantaneous conditional rate; otherwise represents an empirical or averaged quantity.
Hazard rate	$h(t) = \frac{f(t)}{S(t)}$	1/time	Instantaneous conditional rate of failure at time t , conditional on survival to t	$h(t) = -\frac{d}{dt} \ln S(t)$
Survival function	$S(t) = P(T > t)$	-	Probability that the asset remains in service beyond time t	$S(t) = 1 - F(t)$

2. Materials and Methods

2.1. Materials

A questionnaire was developed by the working group to help us to simplify collection. Terminology was standardized to reduce ambiguity; for instance, a major failure was defined as any situation that required the transformer to be removed from service for longer than a week for investigation, remedial work, or replacement. This was chosen to remove short-time trips or fast repairs. Previously used definitions include the repair cost exceeding 2% of the replacement value of the failed transformer [26] or the subsequent scrapping of the transformer [21].

The age distribution of the operating units was collected so that the failure rate could be analyzed across the population and the random and wear-out periods could be investigated.

A definition for retirement was included because it was noted in the 2015 survey that many transformers are retired rather than run to failure [8]. The consequence of this is that the failure rate will appear low. In another paper, survival was estimated by assuming an age of five or ten years post disposal age when a transformer had been withdrawn with an unknown cause or when the withdrawal was preventative [30].

As a large amount of data was expected, the spreadsheets were designed to be easily correlated, such as by using drop-down boxes being to describe the failure location and mode. This prevented spelling errors, which might not be picked up in the analysis.

Both Microsoft Excel and Python code were used to collate operational data from these spreadsheets, collected by CIGRE WG A2.37 [7] and WG A2.62 [8]. The Python source code used for the reliability calculations is provided in Supplementary File S1. The A2.37 survey only collected data on the failures but not the age distribution of the operating transformers. The A2.62 survey did collect data on operational units, and so when a utility responded to both surveys with the failure location, its failure series could be combined. Data was collected from fifty utilities for a reference period up to 34 years. In total, 1358 major failures and 991 retirements were reported from a pool of 26,533 transformers and 331,379 operating years (Figure 2). These transformers had a voltage of at least 100 kV, with the highest being 700 kV. A major failure was defined as where the transformer was offline for at least a week awaiting repair or was scrapped. The repair could be either performed on site or the transformer could be returned to the factory. The overall failure rate was 0.41% annually.

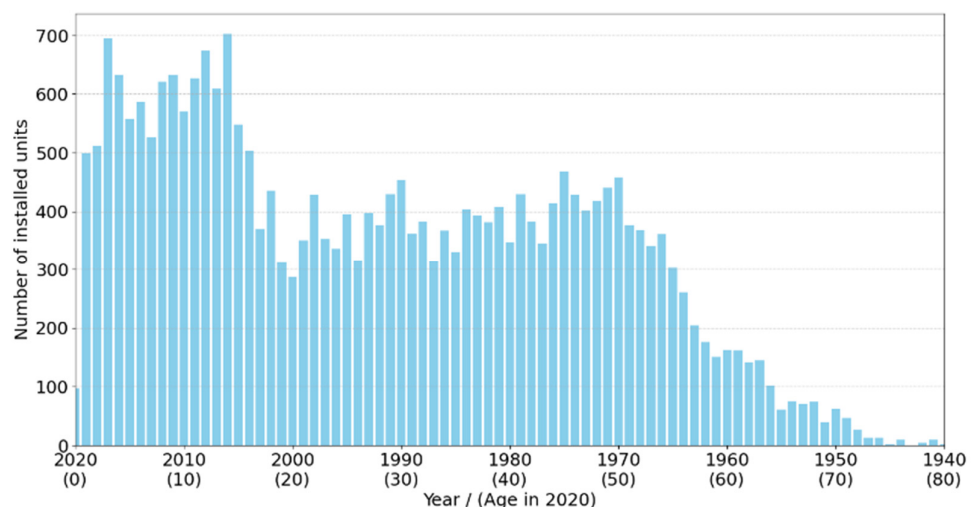


Figure 2. Age distribution of the transformer population investigated in this survey.

2.2. Methods

The number of transformers and operating years falls as the voltage increases, which is expected, as globally there are fewer high-voltage networks than lower-voltage ones. Thus, the population was split into two voltage classes, with nearly equal observations: one was 100–199 kV and the other was 200–700 kV.

The empirical hazard rate in (1) is an estimate of the theoretical hazard $\hat{h}(t) = f(t)/S(t)$, where $S(t)$ is the survival function:

$$\hat{h}(t) = \frac{f(t)}{n(t)} \quad (1)$$

where $f(t)$ is the number of failures in the interval $[t, t + 1)$ and t is in years. The number of transformers operating in this interval is $n(t)$. The data are both left-truncated and right-censored. Transformers typically operate for several decades; a survey often only covers a proportion of the overall life, and so the data is statistically incomplete. For instance, the 2024 survey [8] collected data from 2010 to 2020. The early reliability of transformers installed before 2010 is unknown, and the reliability after 2020 is similarly uncertain. In terms of statistics, this dataset is both left-truncated and right-censored, and so appropriate analysis techniques are required [16].

The collected dataset for operational units was arranged as a table with year of manufacture (YOM) and the number installed that year. Processing was required to determine $n(t)$ by correctly counting the operational experience for each utility within their different reference periods. Equation (2) aggregates operating exposure across utilities and years of manufacture. The calculation for operational units was performed separately for each utility because they had varying reference periods. Therefore, the first sum in (2) is taken over all utilities u .

The reference period is given in (2) by $t_{u,end} - t_{u,start}$, referring to the end and start years of utility u . Function $I_u(\cdot)$ returns the number of transformers of utility u that were manufactured in year $(\cdot)$. The summation operates by sequentially counting the transformer age backwards from the end of the reference period. For example, suppose that the reference period ended in 2020. To find the number of operating transformers that are t years old, $I_u(t_{u,end} - t - i)$ finds the YOM for transformers installed in 2020 minus t years. The counter i is used to cycle through the reference period. Initially, it is set to 0 and then increments; for instance, when it is equal to 2, the algorithm uses YOM data from 2018. A two-year-old transformer in 2019 would have been installed in 2017. Counter i increments until the start of the reference period, $t_{u,start}$, is reached. This method retains left-truncation and right-censoring because no data from outside the reference period is used. This method was also used in [31,32].

$$n(t) = \sum_{u \in \text{Utilities}} \sum_{i=0}^{t_{u,end} - t_{u,start}} I_u(t_{u,end} - t - i) \quad (2)$$

Another statistical technique to analyze survival for left-truncated and right-censored populations is the Kaplan–Meier estimator (3) [33]. This has the benefit of not assuming that a particular distribution is valid. This calculates $\hat{S}(t)$, the probability that a unit remains in service (i.e., not retired) beyond time t . It is useful to compare with the hazard rate; for instance, if the hazard rate falls with age, it may be because the retirement rate has increased. $r(t)$ represents the number of retirements at time t .

$$\hat{S}(t) = \prod \left(1 - \frac{r(t)}{n(t)} \right) \quad (3)$$

A common statistical technique is the Weibull distribution, where the shape and scale parameters provide interpretations of the population [34]. This distribution has been used by Zhou et al. [18,19] and Awadallah et al. [20], who investigated the reliability of UK transmission utility transformers, finding good agreement when a large-enough population was used.

The two-parameter Weibull distribution is defined by the cumulative distribution function (CDF), which describes the failed fraction of the population:

$$F(t) = 1 - e^{-(t/\hat{\eta})^{\hat{\beta}}} \quad (4)$$

where

- $\hat{\beta} > 0$ is the shape parameter, determining the failure rate behaviour. $\hat{\beta}$ is a dimensionless number and determines the shape of the density function.
- $\hat{\eta} > 0$ is the scale parameter, representing the characteristic life or scale parameter. It corresponds to the time when 63.2% of units have failed, i.e., $F(\eta) \approx 0.632$. $\hat{\eta}$ has the same units as t , for example, year.

The probability density function (PDF) is

$$f(t) = \frac{\hat{\beta}}{\hat{\eta}} \cdot (t/\hat{\eta})^{\hat{\beta}-1} \cdot e^{-(t/\hat{\eta})^{\hat{\beta}}} \quad (5)$$

The hazard rate (instantaneous failure rate) is

$$h(t) = \frac{\hat{\beta}}{\hat{\eta}} \cdot (t/\hat{\eta})^{\hat{\beta}-1} \quad (6)$$

Interpretation of $\hat{\beta}$:

- $\hat{\beta} < 1$: Decreasing hazard rate (early-life failures).
- $\hat{\beta} = 1$: Constant hazard rate (random failures).
- $\hat{\beta} > 1$: Increasing hazard rate (wear-out failures).

The cumulative hazard $H(t)$ accumulates the hazard rate over time:

$$H(t) = \left(\frac{t}{\hat{\eta}}\right)^{\hat{\beta}} \quad (7)$$

The approach taken to fit Weibull distributions to the component reliability followed that used by the IEC standard for Weibull analysis [15]. This was

- Take the hazard rate $h(t)$, calculated using (1).
- Calculate the cumulative hazard rate $H(t)$.
- Determine $\ln(t)$.
- Plot $\ln(H(t))$ against $\ln(t)$.

If the points follow a straight trend line, then the Weibull distribution is accurate for modelling the failure data. The gradient and y-intercept of the trend line are used to estimate the $\hat{\beta}$ and $\hat{\eta}$ coefficients of the Weibull distribution, where

- The $\hat{\beta}$ parameter is equal to the line gradient.
- $\hat{\eta} = \exp\left(\frac{-y \text{ intercept}}{\hat{\beta}}\right)$.

Confidence intervals can be calculated for the β and η values using regression in Excel or the method by Bain and Engelhardt [35,36].

3. Results

The age distribution for operating transformers was processed according to (2), so the hazard rate was estimated from left-truncated and right-censored data. This method calculates the number of transformers observed to survive each year of age, which are shown in Figures 3 and 4.

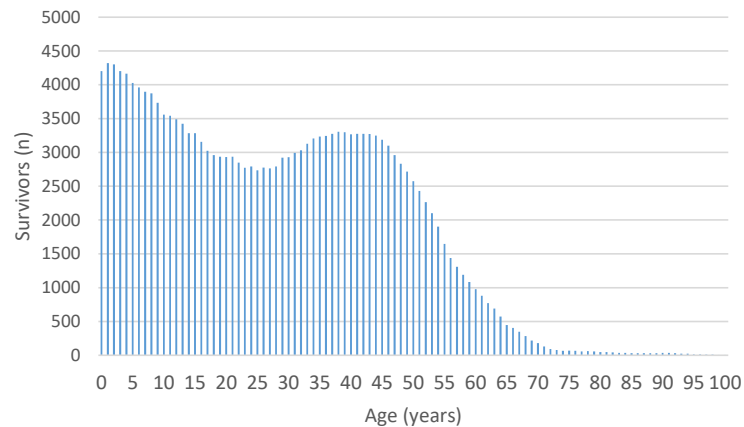


Figure 3. Age distribution of 100–199 kV assets surviving each year of operation under the observation window. The age distribution of operating units has been adjusted for left-truncation and right-censoring.

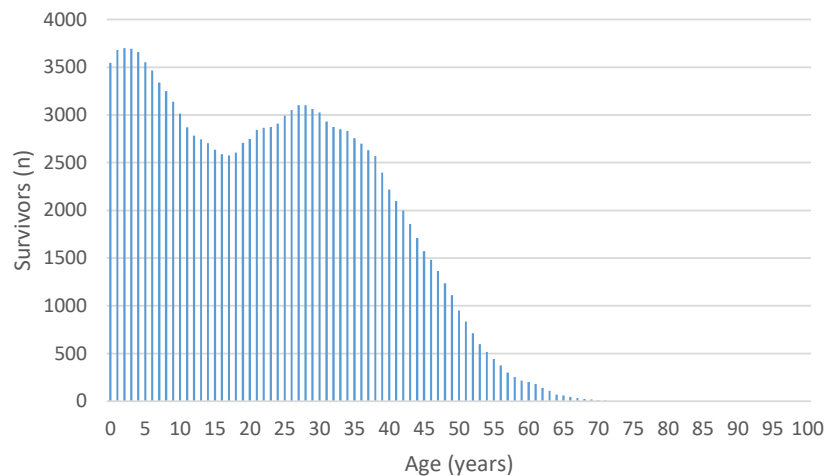


Figure 4. Age distribution of >200 kV assets surviving each year of operation under the observation window. The age distribution of operating units has been adjusted for left-truncation and right-censoring.

The cumulative probability of retirement, $1 - S(t)$, was estimated using the Kaplan–Meier estimator calculated in (3). This is shown in Figure 5. The retirement distribution shows a continuous increase with age rather than a sharp cutoff, which indicates the absence of strict, across-the-board, age-based replacement policies. Failure, retirement, and survival populations were used to generate hazard rates (Figures 6–11).

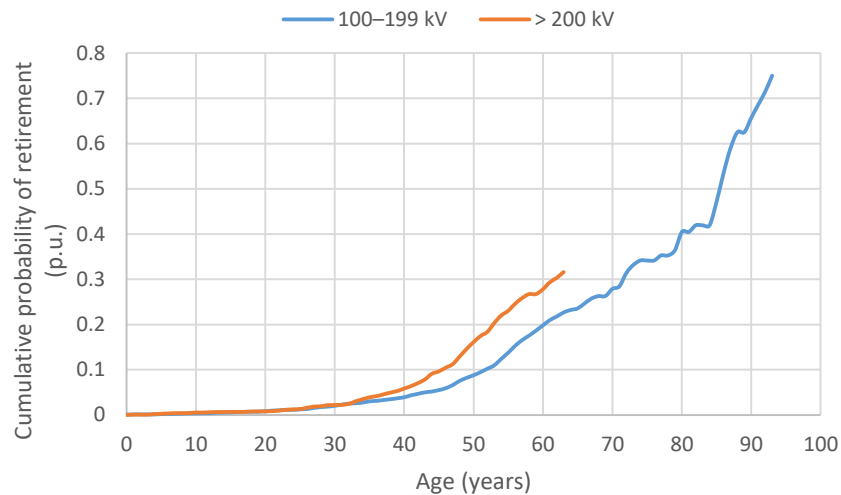


Figure 5. Cumulative probability of retirement $1 - S(t)$ estimated using the Kaplan–Meier estimator. For >200 kV, this finishes at 62 years because no transformers older than this have been retired yet (although they can still be operating or have failed). For the 100–199 kV population, the respective oldest retirement was 93 years.

Failures for both populations are shown in Figures 6 and 7. Their numbers fall after forty to fifty years, as there are fewer transformers operating after this age (Figures 3 and 4) and the number of retirements increases.

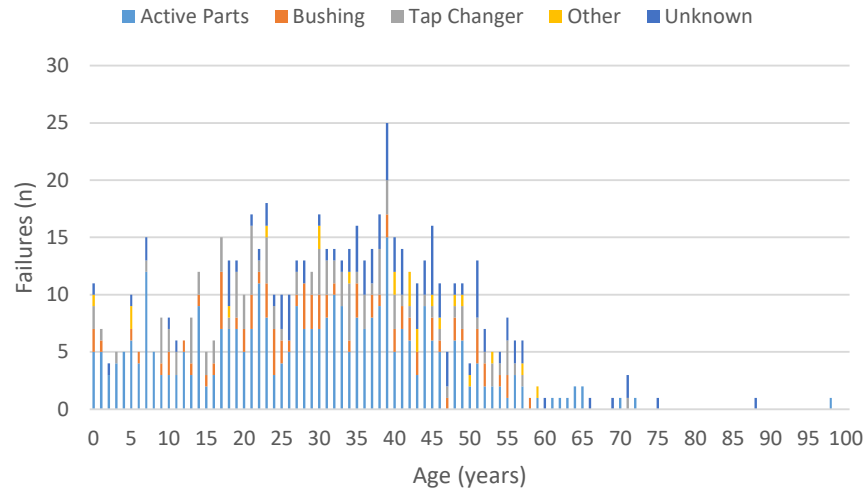


Figure 6. Major failures for power transformers 100–199 kV by fault location.

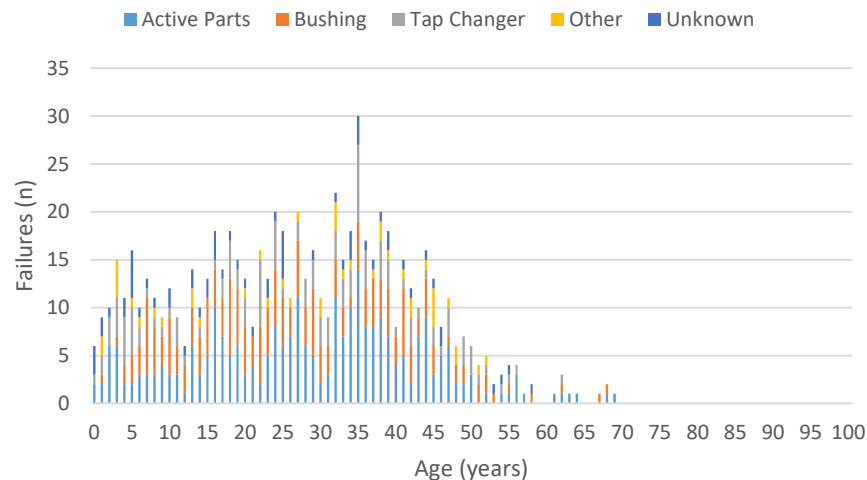


Figure 7. Major failures for power transformers >200 kV by fault location.

A key finding of the WG A2.62 survey was that the distribution for major failures was now nearly random [8], although in the context that transformers are retired instead of being run to failure. The age distributions in Figures 10 and 11 are nearly random, as shown in Tables 2 and 3, where $\hat{\beta}$ is nearly 1 and η has long characteristic lives. The hazard rate is an outcome of the owners' asset management system. Over the years, much guidance has been given by CIGRE in brochures to improve the life cycle management of assets, and when best practice is followed, it is unsurprising that failures are avoided. The relationship between retirement and failures can clearly be seen in Figures 5 and 10, where the retirement rate increases instead of the failure rate. In Figure 8, there is a dip in the active-part failure distribution after forty years, coinciding with the increase in retirements, showing that this has been caused by the decreasing population. In Figure 6, the population size after sixty years falls, and so the hazard rate looks significant, with a small number of failures.

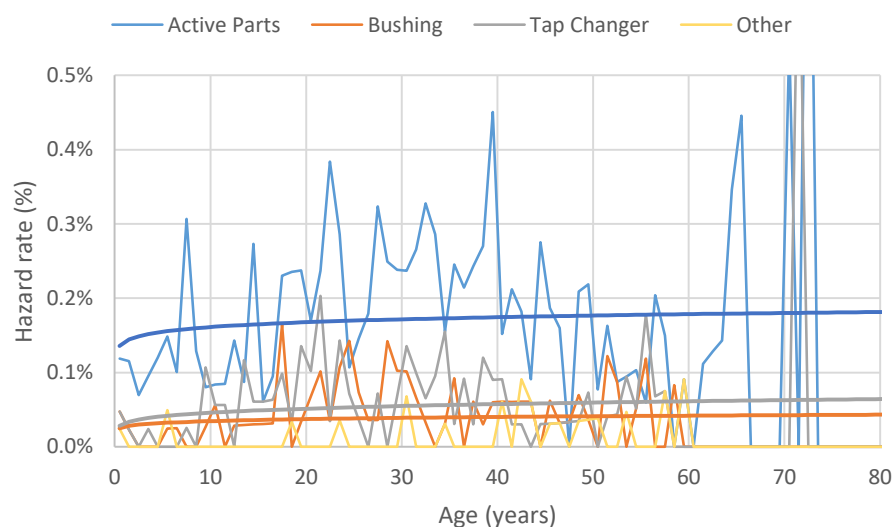


Figure 8. Hazard rate for 100–199 kV transformer failures using both non-parametric and Weibull distribution methods.

In contrast, for power transformers > 200 kV, there is more of an age dependency, and the bushing hazard rate passes that of the active part around fifty years. When investigating the type of bushing technology recorded causing the failure, the oil-impregnated paper types can be seen dominating the population (Table 4). Both shunt reactors and power transformers use the same types of bushing. While it is not possible to calculate the failure rate of OIP bushings because the fleet size was not collected, the histograms in Figures 12 and 13 show that failures still occur at relatively early ages. For instance, failures occur after ten years for the 100–199 kV units and five years for the >200 kV units. OIP bushings have been noted to be the single largest cause of fires [37]. A survey from Australia and New Zealand [25] analyzed fire safety practices and noted the various replacement programs undertaken by the local utilities. Bushing service lives of 30–40 years have been mentioned [38–42]. Seals on the OIP bushings have been found to fail, allowing for moisture ingress and deterioration. Careful condition monitoring is advised [43].

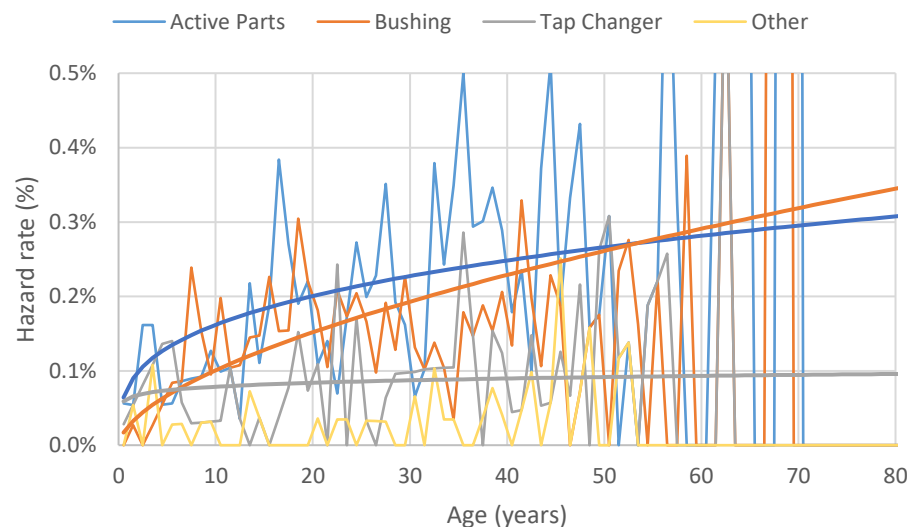


Figure 9. Hazard rate for >200 kV transformer failures using both non-parametric and Weibull distribution methods.

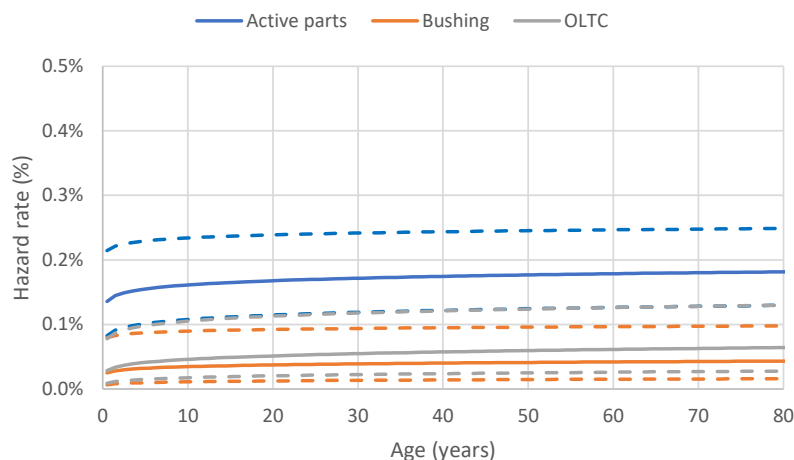


Figure 10. Hazard rate for 100–199 kV transformer failures using the Weibull distribution along with $\pm 95\%$ confidence intervals (dashed lines).

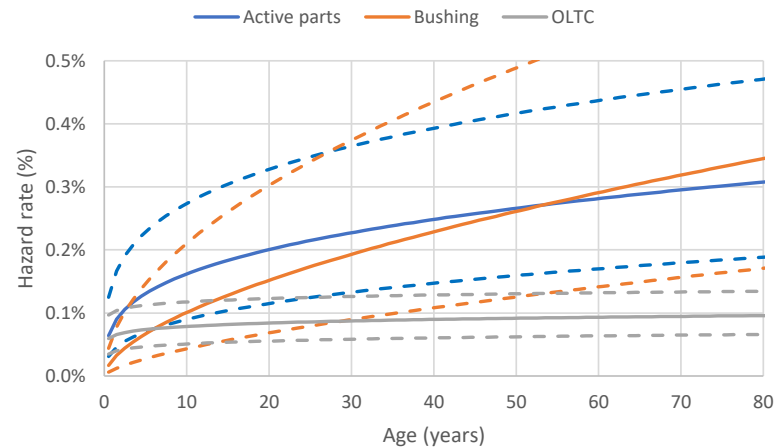


Figure 11. Hazard rate for >200 kV transformer failures using the Weibull distribution along with $\pm 95\%$ confidence intervals (dashed lines).

Table 2. Weibull distribution coefficients for 100–199 kV transformers. Extremely high characteristic life values are indicative of random failure distributions within this age range.

Location		Weibull Distribution Coefficients			
Active parts	$\hat{\beta}$	1.06	$\hat{\eta}$	520	
	$-95\% \hat{\beta}$	1.03	$-95\% \hat{\eta}$	690	
	$+95\% \hat{\beta}$	1.09	$+95\% \hat{\eta}$	400	
Bushing	$\hat{\beta}$	1.11	$\hat{\eta}$	1830	
	$-95\% \hat{\beta}$	1.04	$-95\% \hat{\eta}$	960	
	$+95\% \hat{\beta}$	1.17	$+95\% \hat{\eta}$	3700	
OLTC	$\hat{\beta}$	1.16	$\hat{\eta}$	1200	
	$-95\% \hat{\beta}$	1.10	$-95\% \hat{\eta}$	680	
	$+95\% \hat{\beta}$	1.22	$+95\% \hat{\eta}$	2100	

Table 3. Weibull distribution coefficients for transformers with voltages > 200 kV. Extremely high characteristic life values are indicative of random failure distributions within this age range.

Location		Weibull Distribution Coefficients			
Active parts	$\hat{\beta}$	1.31	$\hat{\eta}$	290	
	$-95\% \hat{\beta}$	1.26	$-95\% \hat{\eta}$	210	
	$+95\% \hat{\beta}$	1.36	$+95\% \hat{\eta}$	400	
Bushing	$\hat{\beta}$	1.59	$\hat{\eta}$	240	
	$-95\% \hat{\beta}$	1.52	$-95\% \hat{\eta}$	170	
	$+95\% \hat{\beta}$	1.66	$+95\% \hat{\eta}$	360	
OLTC	$\hat{\beta}$	1.10	$\hat{\eta}$	900	
	$-95\% \hat{\beta}$	1.06	$-95\% \hat{\eta}$	690	
	$+95\% \hat{\beta}$	1.13	$+95\% \hat{\eta}$	1200	

Table 4. Distribution of bushing failure and technology using both shunt reactors and power transformers.

Technology	100–199 kV	>200 kV
OIP	49	89
RBP	3	3
RIS	1	0
RIP	3	4
Cable Box	3	1
Oil SF6 bushing	-	8
Total	59	105

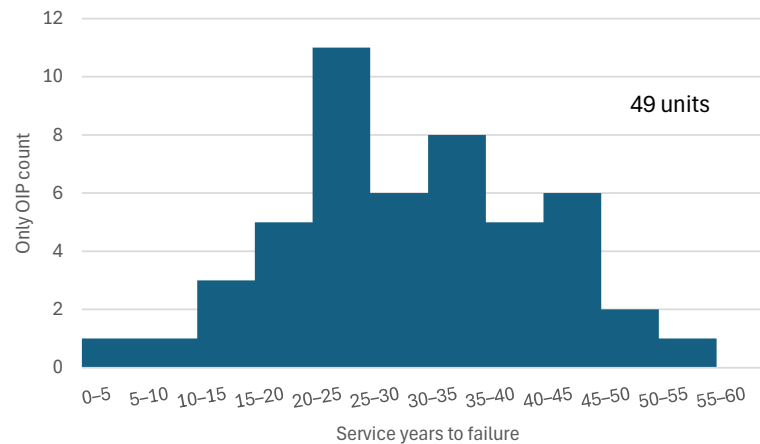


Figure 12. Histogram of OIP bushing failures for 100–199 kV transformers, 49 units.

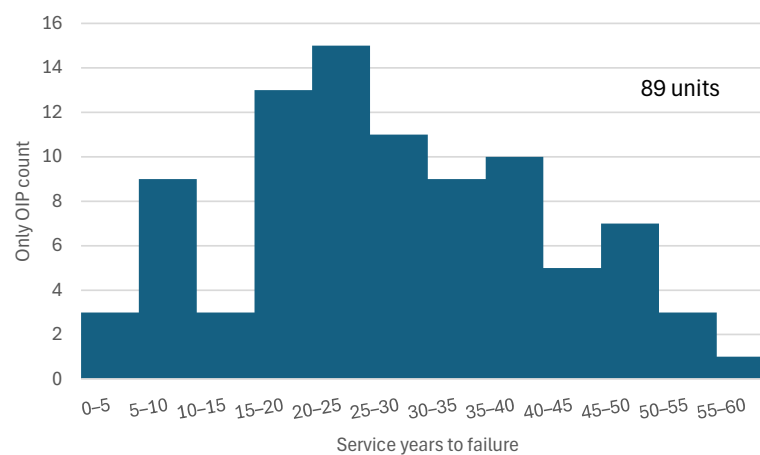


Figure 13. Histogram of OIP bushing failures for >200 kV transformers, 89 units.

4. Discussion

4.1. Statistical Distributions

A bathtub curve is frequently used to describe the early, random, and wear-out regions of an asset's failure rate, although not all sections might be present. For example, an early-failure distribution is not pronounced in Figures 10 and 11 because of the effort to deliver a quality transformer fit for purpose. This includes effective design, specification, manufacture, testing, and initial operation [8,37,44–49]. In use, the operational stresses should be managed to prevent early failure or wear-out. Over time, the materials and transformer will eventually age and life-extension activities can be carried out [50–71]. The water content of insulation can increase over time, caused by ingress and chemical reactions [72], which can cause failure at elevated load [73–78].

A striking feature of Figures 10 and 11 is that the hazard rate is nearly constant until retirements and scraps occur (and also because the $\hat{\beta}$ coefficient is slightly higher than 1). While there is no obvious start to the age-related distribution apparent in Figures 10 and 11, transformers are eventually retired, removing them from the population. This indicates the effective management and removal of transformers to prevent failure. This can include active condition assessment and timely intervention, such as using the

transformer assessment indices for evaluation and the determination of when to conduct maintenance.

Figure 14 provides a commentary on the typical bathtub of failure and observations of this data. The lack of early failures can be attributed to the reasons mentioned earlier. Random failures are currently very low. Network protection can help us to prevent stochastic failure causes like lightning and surges. While there is no significant increase in hazard rate, even for >200 kV units, the $\hat{\beta}$ is still one. However, the retirement rate does increase, inferring a preference to not incur a failure and retire instead.

Failure distribution	Comments	Observations in data
Early	Managed by specification, quality manufacture, appropriateness for application, reviews, testing, etc.	Early distribution not pronounced.
Random	Unusual events and also lightning and surges, animals, weather, unexpected influences, etc.	Traces flat.
Wear-out	Materials age with use over time. Successive stresses over time weaken the system. Apply condition monitoring and take action. May run asset to failure if minimal impact on community.	Retirement and scrapped distributions show increasing hazard rate and can mask hazard behaviour.

Figure 14. Description of different failure distributions.

While the previous figures show the failure location, a breakdown of failure causes is shown in Figure 15. Whereas external short circuits and lightning are stochastic and difficult to predict, many of the other causes appear to be deterministic, such as ageing, overloads, loss of clamping pressure, corrosive sulphur, etc., because these can cause the wear-out of insulation that leads to eventual failure. Monitoring schemes detect many of these problems.

Active condition monitoring and assessment can help us to detect or mitigate these problems, ensuring timely intervention such as using the transformer assessment indices [79] for evaluation and deciding when to conduct maintenance.

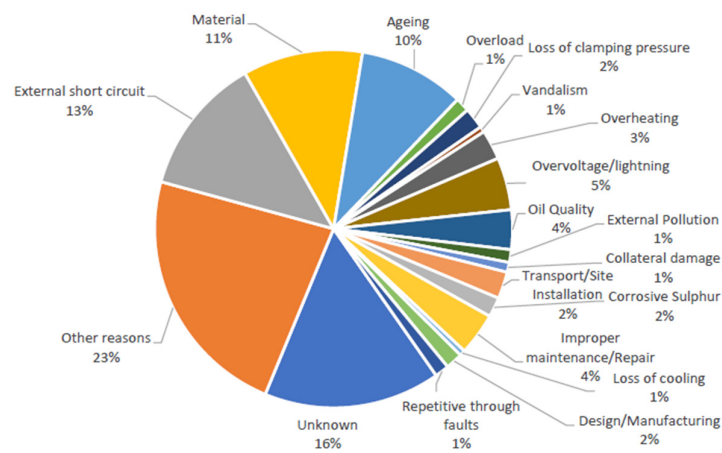


Figure 15. Failure cause analysis for 783 failures [8] (data does not sum to 100 % due to rounding).

A transformer could already be in a poor condition, yet not fail until an overstress happens, which could be years later. Thus, there can be a lag between condition becoming poor and the actual failure on a surge or through-fault. Successive stochastic faults may worsen condition such as causing movement or partial discharge until failure occurs, and this might not be detected in testing.

4.2. Conceptual Model to Assess Condition

CIGRE materials discuss the use of monitoring and condition assessment to evaluate when to plan intervention or retirement [79]. This allows for utilities to take action before failure occurs.

An early systematic use of condition assessment was in the reliability-centred maintenance [80] of aircraft, where many failures were considered to be caused by the wear-out of components. The term “potential failure” was introduced to describe a worn component requiring overhaul or replacement. Extensions to this philosophy have described how to detect worn components using testing and the definition of numerical limits. CIGRE provides such a methodology with a scoring matrix using definitions such as “de-energize as soon as possible ... component is at end of life” or “very poor condition—high likelihood of failure ... Component is near end of life” [79]. Measurement limits are given that are based on various IEC, IEEE, and CIGRE sources.

An advantage of identifying potential failures using condition scoring and test measurements is that numerical limits are easy to follow. However, failure is still probabilistic, and it is difficult to ascertain the onset of the potential failure period. It might be unclear whether an identified change is reflective of normal ageing or indicative of a section wearing out and a potential failure emerging. Examples of expected changes in the condition of normally ageing units are given [50]. A poor-condition transformer may still operate for a while until it experiences the stress that finally causes failure (which could be stochastic). Transformers may have the same score in the CIGRE condition assessment matrices [79], but different degradation modes are responsible.

For normally ageing units, the random statistical nature implies the limited use of the condition to determine the hazard rate because this does not increase significantly. Instead, the focus should be on using the condition to detect life-limiting factors and plan retirement or life extension, for instance, if the solid insulation has reached end of life. Transformers can develop faults from excessive wear or unusual external stress like overvoltage or short circuits. Such faults may eventually lead to a major failure, and thus, when a fault is detected, either directly or by a change in condition, then further analysis is recommended to decide how to proceed. Some problems can be either the change in condition happening faster than the interval of the testing, a change in a measurement being insufficient to diagnose a fault, or the right test not being performed.

A suggested management model is shown below in Figure 16. The two streams function as follows: normal ageing and fault establishment.

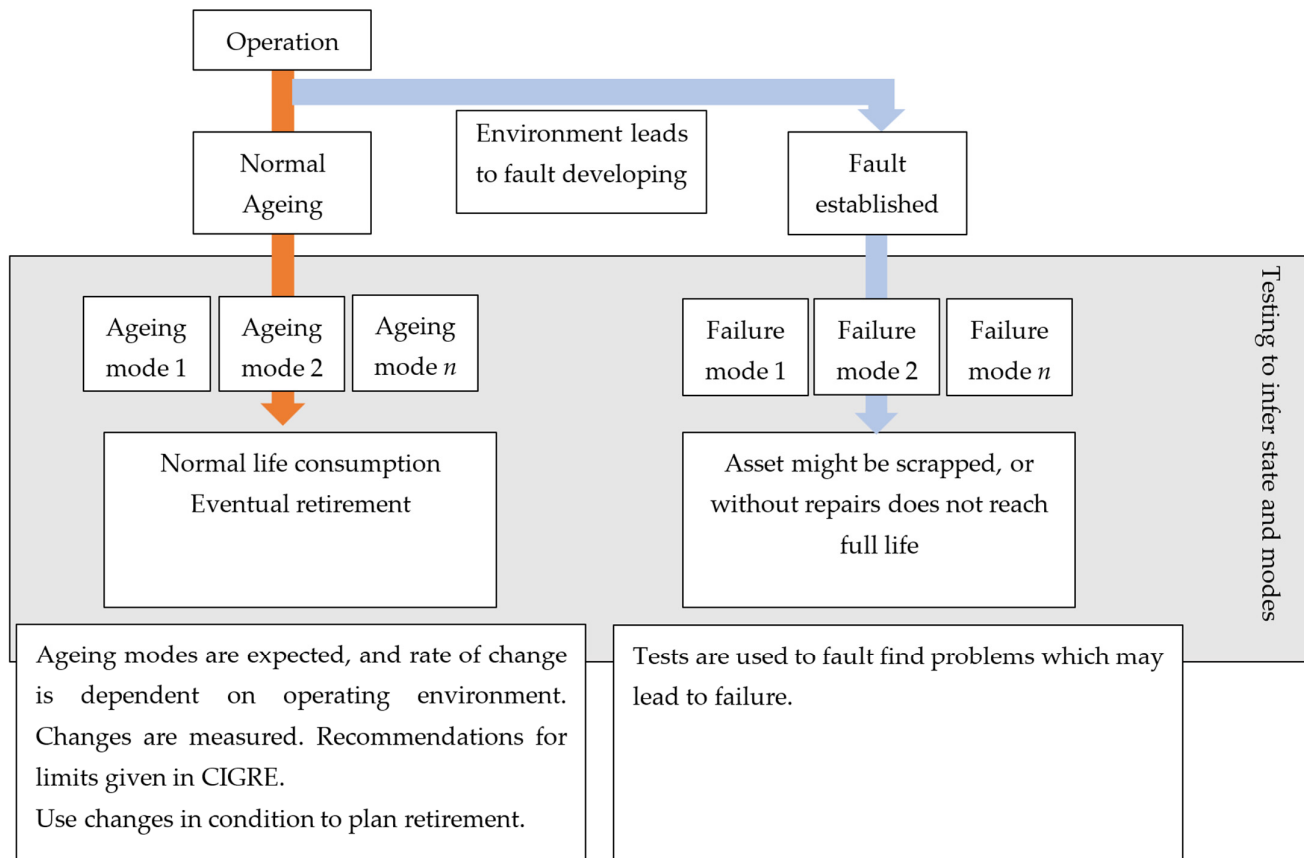


Figure 16. Normal ageing and fault-forming processes. One arrow signifies that in operation the transformer will age normally according to different ageing modes, and then it is retired once its life is consumed. An example is insulation wear and degradation. The other arrow shows a fault is occurring which then leads to failure. An example could be a downstream fault damaging the electrical insulation of a transformer leading to a failure. Testing may identify that this fault has occurred before failure.

The normal ageing stream seeks to estimate the remaining life of the transformer, assuming that it is ageing as expected. For instance, paper degree of polymerization can be used to estimate life remaining under different operating scenarios. The wear of the various parts of a transformer is measured and their condition is tracked. Life extension and maintenance can be performed to keep the asset in good condition. The insulation should be kept dry to prevent flashover failures or accelerated paper ageing. The work of CIGRE WG A2.62 shows that there is not a strong relationship between the age and hazard rate as long as the units are eventually withdrawn from service. At some point, condition is used to recommend retirement.

The fault-developing stream seeks to detect the likelihood of the different failure modes that are not caused by normal ageing, for instance, lightning, external short circuits, etc. Surges can cause sections of insulation to move, and then partial discharge or overheating may occur. DGA also falls into this stream, where, if there is an unexplained increase in dissolved gases, then a further analysis is performed to ascertain the fault. DGA in itself can detect electrical or thermal faults, but does not indicate their location; instead, the engineer is required to deduce this. The probability of the failure of a transformer with a particular fault was not investigated by the WG A2.62 survey. The focus is therefore recommended to be on monitoring the condition of a transformer and taking action when required. Early failures are not considered in this chart. These failures

can either be factory defects, improper installations, or incorrect and unsuitable asset specifications. These can be managed separately.

5. Conclusions

This paper analyzed major power transformer component reliability using the latest large-scale CIGRE survey dataset (50 utilities, 26,533 transformers, 331,379 operating years, 1358 major failures, and 991 retirements) and applied non-parametric hazard estimation together with Weibull modelling to compare age-dependent behaviour across two voltage classes (100–199 kV and > 200 kV). The results show that the observed hazard rates are strongly shaped by both component behaviour and retirement practices, which reinforces the notion that the fleet hazard rate should be interpreted within the context of asset management decisions rather than as an ageing curve alone.

- The overall major failure rate for the surveyed population was 0.41% per year over the observation window.
- For 100–199 kV transformers, the estimated hazard rates for active parts, bushings, and OLTCs were close to random over age ($\beta \approx 1$), with long characteristic lives from Weibull fitting, indicating no pronounced wear-out behaviour within the observed window.
- Retirements increased steadily with age and influenced the apparent late-life failure behaviour by reducing the number of older units remaining in service.
- For > 200 kV transformers, bushing hazard showed stronger age dependence than for the lower voltage class and exceeded the active-part hazard at approximately 50 years, highlighting bushings as a key life-limiting component at higher voltages.
- OIP bushings dominated the reported bushing failures, and failures were observed at relatively early ages in both voltage classes, supporting proactive bushing risk management.

From an asset management perspective, these findings support using component-level hazard information to prioritize interventions (e.g., targeted bushing replacement programs and review of OLTC maintenance practices) rather than assuming an inevitable transformer-level wear-out curve. The conceptual model proposed in this paper provides a practical method to apply the survey statistics: (i) a normal-ageing stream in which condition assessment and remaining-life estimation guide life extension or planned retirement, and (ii) a fault-developing stream in which monitoring and diagnostics aim to detect emerging defects and manage the short-term risk of major failure. The near-random hazards observed for much of the fleet should therefore be interpreted as consistent with effective condition management and selective withdrawal, not as evidence that ageing mechanisms are absent.

The key limitations of this paper are that the survey data set is both left-truncated and right-censored and that retirements can mask wear-out behaviour by removing high-risk units before failure. In addition, some sub-population denominators were not captured (e.g., bushing fleet counts by technology), limiting the extent to which technology-specific failure rates can be quantified. Future surveys and studies would benefit from collecting component population counts (particularly bushing technology), linking condition and monitoring indicators to subsequent failures to quantify the change in hazard rate given a detected defect and further separating the effects of ageing, maintenance, and retirement decisions on the observed hazard behaviour.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/en19133197/s1>. Supplementary File S1: Python script used to process left-truncated and right-censored reliability data.

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Abbreviations

The following abbreviations are used in this manuscript:

CDF	Cumulative distribution function
CIGRE	Comité International des Grands Réseaux Électriques
DGA	Dissolved gas analysis
kV	Kilo volts
OIP	Oil-impregnated paper (bushing)
OLTC	On-load tap changer
PDF	Probability density function
PoF	Probability of failure
RBP	Resin-bonded paper (bushing)
RIS	Resin-impregnated synthetic (bushing)
SF6	Sulphur hexafluoride
YOM	Year of manufacture

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