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A Survey of Prognostics and Health Management for Transformers: From Statistical Analysis to Condition-Based Diagnostics

Jiaxiang Cheng[1], Sungin Cho[2], Yap-Peng Tan[3], and Guoqiang Hu[4]

[1,3,4] *Nanyang Technological University, 639798, Singapore*
jiaxiang002@e.ntu.edu.sg
eyptan@ntu.edu.sg
gqhu@ntu.edu.sg

[2] *SP Group, 349277, Singapore*
chosungin@spgroup.com.sg

Abstract

Power transformers are one of the key network components for reliable and efficient operation of power grids. Over the past few decades, there have been growing research efforts in improving the prognostics and health management (PHM) for transformers, including failure analysis using time-to-event data and condition-based diagnostics for both single and multiple components. In this paper, we survey recent literature and relevant works, focusing on widely used statistical models and advanced diagnostic techniques that leverage on condition data and maintenance history. Additionally, we examine the role of artificial intelligence (AI) applications in PHM for power transformers. Finally, we summarize the current limitations and future opportunities to support new research efforts for improving the monitoring of power transformers.

1. Introduction

Power transformers play a crucial role in the operation of power grids. Any malfunction can have severe impacts on the grid, resulting in significant costs. Therefore, research on accurate failure analysis and fault diagnosis for transformers is essential. To mitigate potential hazards, condition-based assessments have been proposed using monitoring techniques such as frequency response analysis (FRA), dynamic resistance measurement (DRM), and dissolved gas analysis (DGA), etc. In addition, utilities operators have conducted failure analysis to gain insights into the general lifetime and failure modes of transformers with statistical modeling (Martin, Marks, Saha, Krause, & Mahmoudi, 2018), which helps develop strategic plans.

By understanding the major root causes of failures and performance characteristics of different transformer models, utilities operators can better plan for maintenance and replacement, reducing costs and improving grid reliability. Statistical analysis and condition-based diagnostics methods can enable better prognostics and health management (PHM) practices at different implementation stages. This paper presents a review of the applications of statistical analysis and condition-based diagnostics to power transformers, as well as trends of research in the past two decades. The study identifies current challenges and future directions to improve PHM applications to power transformers.

The remainder of paper is structured as follows. Section 2 presents the problem of failure analysis, including different statistical models and relevant research. Section 3 covers the research trends of component-level diagnostics and comprehensive assessment tools for transformers, focusing on novel work from the past decade. Section 4 discusses the remaining challenges, and Section 5 concludes the paper.

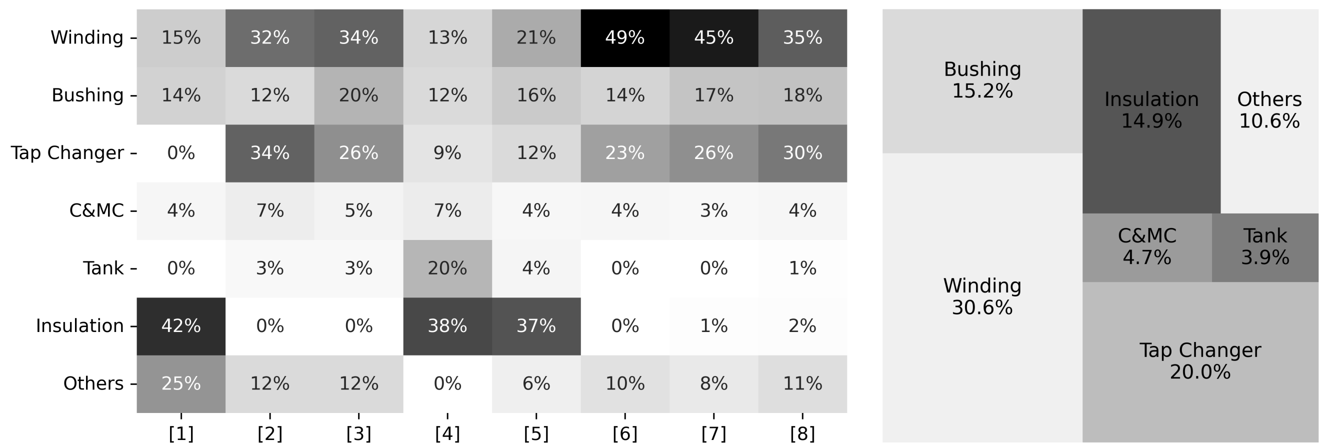
2. Statistical Analysis for Transformer

Statistical modeling of failure rate or reliability is a crucial task across various sectors, including power industry, which has received considerable attention in recent decades. Reliable estimation of transformer survivability is essential for strategic decisions such as optimizing maintenance and replacement plans (Jürgensen, Nordström, & Hilber, 2016). It provides valuable insights into the costs associated with potential failures of either an individual transformer or a certain fleet. By accurately estimating failure rates, utilities operators can make informed decisions that optimize performance and minimize costs, improving the reliability of the power grid.

In survival analysis, assume the cumulative distribution function ($c.d.f$) of the lifetime random variable ($r.v.$) τ is repre-

Table 1. Comparison of two-parameter Weibull models estimated by different studies using diverse data sources.

Source	η	β	Population	Failures	Observation	Voltage Class
Hong et al. (2009)	32.75	4.09	167	4	*from* 1980	-
Cota-Felix et al. (2009)	33.54	7.02	100	16	1975 - 2008	13.8 kV
Chmura et al. (2011)	71.15	3.20	$\sim$200	$\sim$16	1951 - 2011	110 & 150 kV
Zhou (2013)	79	3.3	$>$800	$\sim$70	10 *years*	-
Martin et al. (2018)	112	3.49	$<$5,861	$<$198	2000 - 2015	$\leq$66 kV



(a) Failure statistics of power transformers from various sources.

(b) Failure statistics in average per component.

Figure 1. Failure statistics of power transformers from [1] Singh et al. (2019), [2] Kalbfleisch and Prentice (2011), [3] Koch and Kruger (2012), [4] Murugan and Ramasamy (2015), [5] Murugan and Ramasamy (2019), [6] Yasid et al. (2019), [7] Tenbohlen et al. (2012), [8] Vahidi and Tenbohlen (2014). C&MC stands for Core & Magnetic Circuits.

sented by $F(t)$, while the probability density function (*p.d.f*) is represented by $f(t)$, which is differentiated from $F(t)$. The reliability or survival function, denoted as $R(t)$, is equal to $1-F(t)$, representing the probability of survival after a given time t. The failure or hazard rate, $\lambda(t)$, can be defined as,

$$\lambda(t) = \frac{f(t)}{R(t)}, \tag{1}$$

where $\lambda(t)$ is sometimes referred to as $h(t)$, corresponding to the hazard rate. Many statistical models have been proposed for survival analysis, among which, Weibull distributions are the most commonly used parametric models for estimating lifetimes (Weibull, 1961), and the Cox proportional hazards model is a popular semi-parametric model for identifying the covariates' effects to the hazard rate (Cox, 1972). When prior information on the distribution of failure probability is uncertain, the Kaplan-Meier estimator is a useful model for approximation (Kaplan & Meier, 1958).

The two-parameter Weibull model is most commonly used for failure analysis of power transformers. Table 1 provides a summary of its applications. Variants of Weibull distribution have been proposed to enhance the regression performance (Jiang, 2013; A. M. Sarhan, 2013). A study by Martin et al. (2017) demonstrated that using separate Weibull distributions to model early-stage failures and aging-related failures can improve the fitting performance.

The accuracy of parameter estimation in statistical analysis of transformers depends on data quality. Due to the long lifespan of transformers, the available data are often highly left-truncated and right-censored. The Weibull distribution is popular due to its efficiency in handling censored data (Cota-Felix et al., 2009). To ensure data quality, Zhou, Wang, Jarman, and Li (2014) proposed using Monte Carlo simulation to generate samples with pre-set Weibull distributions and employing maximum likelihood estimation (MLE) to estimate the parameters, establishing criteria for total sample sizes and censoring rates. However, data quality still remains an major issue, and researchers have explored various approaches. For example, Hong et al. (2009) marked rare failure events occurring within the early phase as right-censored data to avoid misleading model regression.

The estimation of failure rates of an individual transformer has been studied by incorporating the relative measurements of condition variables among transformers. Jürgensen et al.

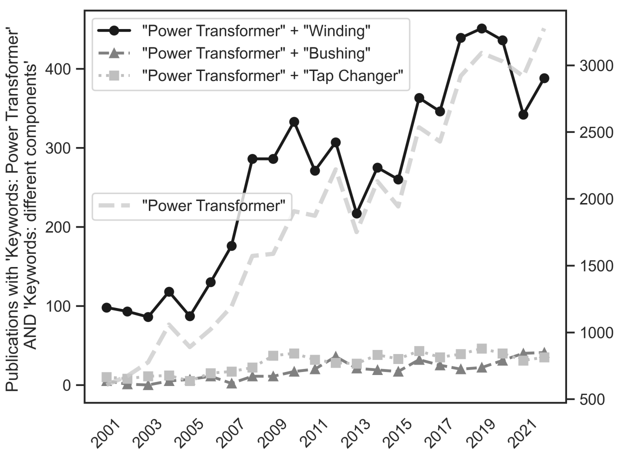


Figure 2. Trend of the number of publications retrieved from Scopus using the search criteria 'Keywords: Power Transformer' AND 'Keywords: *different components*'. The number of publications with the search criteria 'Keywords: Power Transformer' is shown as the benchmark for comparison.

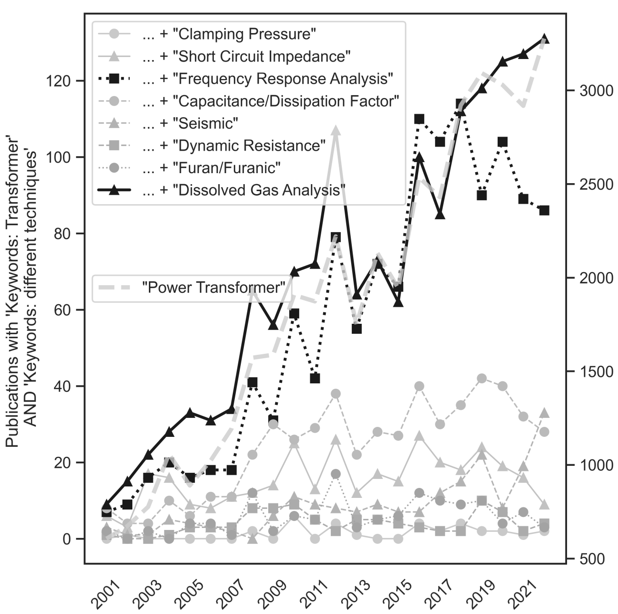


Figure 3. Trend of the number of publications retrieved from Scopus using the search criteria 'Keywords: Transformer' AND 'Keywords: *different techniques*'. The number of publications with the search criteria 'Keywords: Power Transformer' is shown as the benchmark for comparison.

(2016) proposed a method to calculate the relative condition measurements, which can be paired with corresponding fault locations or failed components to derive individual failure rates. This method provides a clear view of priority for maintenance and replacement. It was further improved by using the *ARIMA* model for predicting trends of each covariate, enabling the estimation of future failure rates within a certain horizon (Jurgensen, Nordstrom, & Hilber, 2019).

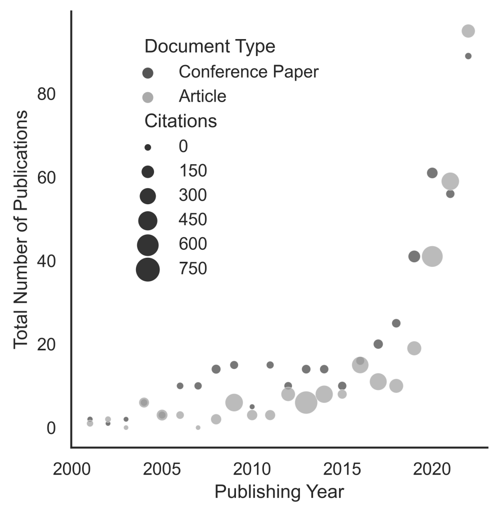


Figure 4. Trend of the number of publications and citations retrieved from Scopus using the search criteria 'Keywords: Power Transformer' AND ('Keywords: Artificial Intelligence' OR 'Keywords: Machine Learning' OR 'Keywords: Deep Learning').

3. CONDITION-BASED DIAGNOSTICS

The contributions of different components to transformer failures are summarized in Figure 1 based on various studies. The results indicate that winding, bushing, and tap changer are the main components responsible for failures, with insulation systems also showing a significant percentage of failures in some studies (Singh et al., 2019; Murugan & Ramasamy, 2015, 2019). However, the definitions of insulation systems vary among studies, making the causes of failures ambiguous. Futhermore, windings and insulation systems are closely related, further complicating the analysis of failure causes.

In this study, we used different combinations of keywords to extract relevant publications from the *Scopus* database and analyze the research trends. Figures 2 and 3 show the number of publications related to different components and diagnostic techniques in the past two decades. Figure 2 reveals that research on winding has consistently contributed to a significant proportion of power transformer studies, consistent with the finding in Figure 1 that winding is the major cause of transformer failures. Figure 3 highlights that FRA and DGA are the main diagnostic techniques studied for power transformers over the years, with FRA mainly used for diagnosing winding in various studies (Aljohani & Abu-Siada, 2014, 2016, 2017). DGA is a comprehensive diagnostic tool that can be used to analyze the health condition of power transformers by examining different indicators (Duval, 1989).

We also conducted an analysis of publications on both power transformers and artificial intelligence (AI). To highlight the trends in AI-related studies on power transformers, we present Figure 4, which shows the number of publications and

Table 2. Application of DGA gas ratio for various fault detection.

Fault Type	CH_4/H_2	C_2H_2/CH_4	C_2H_2/C_2H_4	C_2H_4/CH_4	C_2H_4/C_2H_6	C_2H_6/C_2H_2	CO_2/CO
Thermal Faults	[1]-[4]*	[1]†	[1]-[4]*	[3]	[1]-[4]‡	[1]†	
Partial Discharge	[2]-[4]	[1]†,[2]	[1]‡,[3],[4]		[3],[4]	[1]‡,[2]	[1]†
Arcing	[2],[4]	[1]†	[1],[4]		[1]‡,[4]	[1]†	
Discharges of Low Energy	[2],[3]		[2],[3]		[2],[3]		
Discharges of High Energy	[2],[3]		[2],[3]		[2],[3]		

Ref.: [1] *Doernenburg Ratio & Rogers Ratio* (IEEE PES Transformers Committee et al., 2019), [2] *IEC Ratio* (Duval, 2008), [3] Kim et al. (2013), [4] *NBR7274 Method* (IEEE PES Transformers Committee et al., 1992);

* Not significant for thermal faults $< 300^{o}$C in [2] *IEC Ratio* (Duval, 2008);

† Only Doernenburg Ratio in [1] *Doernenburg Ratio & Rogers Ratio* (IEEE PES Transformers Committee et al., 2019) included; ‡ Only Rogers Ratio in [1] *Doernenburg Ratio & Rogers Ratio* (IEEE PES Transformers Committee et al., 2019) included.

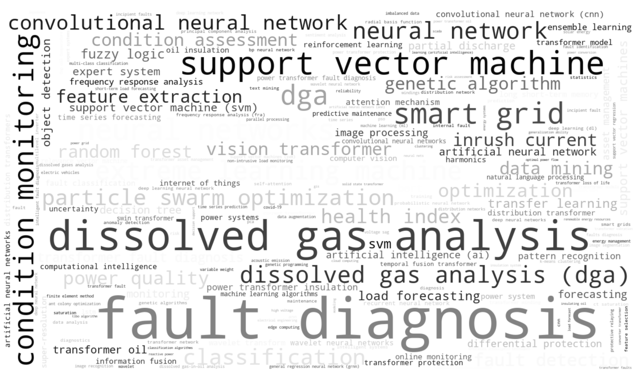


Figure 5. Word cloud of author keywords extracted from publications retrieved from Scopus using the search criteria 'Keywords: Power Transformer' AND ('Keywords: Artificial Intelligence' OR 'Keywords: Machine Learning' OR 'Keywords: Deep Learning'). The searched keywords in the criterion are not included in the word cloud. The size of each phrase corresponds to its frequency of occurrence among the author keywords.

their corresponding citations, thereby indicating the extent to which they have been cited. Notably, we observe a clear and significant increase in the number of studies on power transformers with AI-related keywords, particularly after 2015. It is to be noted that as more citations are expected with increasing years of exposure, it may take longer time to show the actual trending of citations for publications in recent years. Nevertheless, the trend underscores the growing importance of AI in the domain of power transformers, and the increasing emphasis on harnessing AI-based solutions to address the challenges associated with these systems.

Figure 5 presents a word cloud generated from the keywords of the same set of AI-related publications, which reveals the most frequent keywords found in relevant studies. It can be noticed that *fault diagnosis* and *dissolved gas analysis* emerge as the most frequently included terms. The application of AI in traditional diagnostics has been widely adopted thanks to advances in data collection and storage techniques. Meanwhile, DGA data are easy to collect within power utilities, which has prompted researchers to apply diverse AI/ML methodologies to obtain insights for diagnosis and to undertake more comprehensive analyses (Lu et al., 2018; Lin et al., 2018; Zeng et al., 2020). Table 2 summarizes the most commonly used gas indicators from DGA for checking health conditions at a general level, which can serve as the reference for feature selection when applying AI with DGA data.

4. Challenges for Transformer Diagnostics

4.1. Limited Failure Data for Statistical Analysis

The lifespan of a transformer typically ranges from 20 to 50 years. As a result, there are limited failure data available within a fleet of transformers, which can be noticed from Table 1. This poses significant challenges for researchers in building feasible survival models. Therefore, for the foreseeable future, a major focus and challenge will be on the treatment of highly censored and unbalanced data. Although Monte-Carlo simulation methods have been proposed for preliminary assessments of data usability (Zhou et al., 2014), techniques for data augmentation and optimizing statistical model estimation are expected to handle cases with poor data quality and limited failure data.

4.2. Study on Critical Components Besides Winding

The windings, bushings, and tap changers are widely considered the most critical components of power transformers and are responsible for a significant portion of failures, as shown in Figure 1. Research on windings and associated diagnostic techniques have been developing with the research on power transformers, but less attention has been paid to bushings and tap changers, as presented in Figures 2 and 3. It also worths focusing more on other critical components, such as the bushings, which are more vulnerable due to their unique structure (Johnson & Iliev, 2012). To closely monitor the health condition of bushings, diagnostic techniques involving capacitance, dissipation factor, and thermal analysis can be further studied (Stih & Mikulecky, 2013; Mariprasath & Kirubakaran, 2018).

4.3. Feasible Application of Artificial Intelligence (AI)

The use of AI holds promise for condition monitoring of transformers. Recent research demonstrates that advanced ML techniques have already been applied in various areas, including survival analysis, DGA, etc. Traditional methods, e.g., Weibull distribution for survival analysis, can provide reliable insights with the ability to handle truncated and censored data, while advanced techniques, especially end-to-end methods, require further development and validation to generate more interpretable outcomes. Rather than replacing traditional methods, ML techniques can also serve as auxiliary tools to improve the performance of conventional techniques. For instance, they can aid in data pre-processing and dimensionality reduction. Therefore, it is essential to explore the potential benefits of ML techniques while also acknowledging the strengths of traditional methods.

5. Conclusion

This paper provides a review of the relevant work on failure analysis and diagnosis of transformers. From survival analysis to component-level diagnostics, the health profiles of transformers can be illustrated from various aspects. Potentials can be seen that the condition information from different diagnostic techniques can be combined with the traditional way of statistical modeling, to help utilities operators monitor the health condition of individual assets more accurately.

Challenges remain for both improvements on conventional methods and implementation of advanced techniques as discussed in the previous section. Some possible future work is provided below:

1. The questions remain for statistical analysis of transformers including how various models perform for different cases; how to select the best model for a given case with clear criteria; how to properly define the remaining useful life based on the estimated models; and how the models help make better maintenance or replacement plans for transformers;

2. Advanced condition-based monitoring techniques can be combined with semi-parametric statistical models to achieve a clear view of how different condition variables impact the lifetime trending of transformers;

3. The AI/ML techniques can potentially be applied to many tasks including early prediction of failure rate, data processing for modeling, analysis of the data obtained from different diagnostic techniques, etc.

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