A Methodology for Diagnosing Faults in Oil-Immersed Power Transformers Based on Minimizing the Maintenance Cost

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ABSTRACT This article proposes a methodology for diagnosing faults in oil-immersed power transformers that considers correlation as a random variable and models the power transformer diagnosis problem as a hypothesis testing problem. Based on conventional estimation and detection theory, a novel diagnosis methodology for oil-immersed power transformer faults is developed by minimizing the maintenance cost of an oil-immersed power transformer. Unlike previous work, this is the first work to consider the optimization of the maintenance cost. Moreover, the proposed methodology is verified with a benchmark test based on 950 data sets of real historic records, and the results show that the accuracy of failure detection with this approach can reach 92.85% while the maintenance cost is minimized. Finally, the experimental results indicate that the proposed methodology displays promising performance and can be used as a tool for the diagnosis of incipient faults in oil-immersed power transformers.

INDEX TERMS Oil-immersed power transformer, electric power systems, fault detection, fault diagnosis, maintenance, minimum cost.

I. INTRODUCTION

Power transformers are some of the most critical and expensive pieces of equipment in electric power systems. The failure of power transformers inevitably has a serious negative impact on the power supply and may result in massive power blackouts and high maintenance costs. Hence, maintaining the reliability of power transformers is the most important task in an electric power system. Suitable methods for power transformer fault detection can considerably reduce the maintenance fees of power transformers and hence ensure stable and reliable energy delivery.

Among the available transformers, oil-immersed power transformers play important roles in voltage and current conversion in modern electric power systems. An oil-immersed power transformer contains a large amount of insulating oil. The goal of the insulating oil is to reduce the temperature and increase the efficiency of energy production. The purpose of the insulating oil is to isolate the insulating material from the body, suppress corona or arc, and serve as a coolant.

Insulating oil can effectively cool the temperature rise generated during the conversion of the magnetic field inside the power transformer. In other words, the insulating oil is used to block the insulation between the conductor and the shell and, by discharging the heat generated by the internal wires during operation through the operation of the cooling system, to reduce the temperature and improve the power supply capacity and efficiency. In addition to the cooling it provides through the process of the cooling power system, the insulating oil also provides some electrical insulation between the internal live parts to maintain long-term stability under the high temperature. Moreover, it is necessary to regularly sample and analyze the oil quality to determine whether the oil has latent defects for effective treatment.

Therefore, when sampled and analyzed oil quality data are misjudged due to negligence or improper analysis, the delay in processing may result in power transformer loss due to power failure. As a result, the diagnosis of insulating oil in power transformers is a very important task in electric power systems.

The insulating oil in power transformers will dissolve nine kinds of gases if the content of any combustible gas is
greater than the standard value (ANSI/IEEE C57.104). For safe operation, the power transformer must be shut down for maintenance or repair.

Additionally, dissolved gas analysis (DGA) is a popular technique for detecting incipient faults in power transformers that use oil, and some standards have been designed for DGA interpretation, such as IEEE C57.104-1991 [1] and IEC 60599.

Presently, the insulating oil in oil-immersed power transformers in the power supply operation of the Taiwan Power Company, Taiwan, follows the standard procedures in the maintenance manuals of substation equipment.

The detection results show that the gas content of hydrogen (H$_2$), methane (CH$_4$), ethane (C$_2$H$_6$), ethylene (C$_2$H$_4$), acetylene (C$_2$H$_2$), and carbon monoxide (CO) exceeds the standard value and needs to be included in tracking or performing inspections and maintenance to identify the cause of failure.

In a real case that occurred on August 13, 2012, the insulating oil in the no. 4 autotransformer (#4 ATr) of the Nanke extra-high-voltage substation (E/S) of the Taiwan Power Company, Taiwan, was sampled by the standard procedure and submitted for inspection. The inspection report of the Taiwan Power Comprehensive Research Institute showed that the gas content was compared.

The data had increased significantly compared with the previous data, especially for the content of methane, ethylene, and acetylene, which increased from 246 ppm, 276 ppm, and 0 ppm to 387 ppm, 496 ppm, and 0.8 ppm, respectively. The total combustible gas (TCG) increased from 808 ppm to 1,199 ppm; this abnormal increase might endanger the regular operation of oil-immersed power transformers.

Based on the premise of a stable power supply and equipment safety, the authorities and maintenance department of the Taiwan Power Company, Taiwan, convened relevant technical units and manufacturers to investigate, discuss, and concurrently conduct partial discharge detection for the abnormal gas content in the insulating oil to identify the cause and seek improvement methods.

The final decision was to shut down on October 25th, 2012, for internal inspection of the transformer body. It was found that one of the four screws of the S-phase on-load tap changer (OLTC) selection switch leading to the no-load tap and position tap 6 (NTAP T6) contact terminal board had melted and a large amount of copper rust slag had adhered to the surrounding surface.

The gas analysis process is performed to analyze and inspect the insulating oil. It is necessary to refer to the specification guidelines of oil-immersed power transformer fault diagnosis and the manufacturer’s literature information. If we want to be more productive and accurate, we can decompose the content of each gas in the oil and follow the various standard test methods or graphs that are used as the basis for interpretation and comparison.

However, most of them are still drawn manually based on the judgment and experience of each technician and may be affected by human error or a lack of experience, which will cause misunderstanding and increase the number of power outages and substantial maintenance costs.

Therefore, it is necessary to rely on high-quality technologies and experience to diagnose oil-immersed power transformers. For this purpose, an innovative diagnostic methodology is developed from a large amount of data, correlation coefficient theory and classical detection/estimation theory in this article. Big data are used to establish two sets of probability density functions (PDFs) from the experimental data sets. The diagnostic methodology for the minimization of the maintenance cost is based on classical detection/estimation theory, and minimizing the cost is regarded as the criterion of diagnosis.

The remainder of this article is organized as follows. Related works are reviewed and introduced in Section II. The proposed methodology is introduced in Section III. The experimental design and a performance evaluation of the proposed methodology are described in Section IV. Finally, we conclude this work in Section V.

II. RELATED WORKS

Generally, the insulation system of an oil-immersed power transformer consists of insulation oil and solid insulation (such as paper, insulation board, or rubber). Hence, based on certain measurements and analyses of the oil, many diagnostic techniques for power transformers have been proposed in the literature [2]–[6]. Morais and Rolim [2] developed and applied oil power transformers and performed gas analysis.

Through integrated calculations of the standard specifications of the content of each gas in the oil by an artificial neural network (ANN) and fuzzy logic system, the system stability and reliability were assessed, with reliability and accuracy values greater than 80%.

Malik et al. [3] used artificial intelligence (AI) to compile diagnostic technology, and a fuzzy logic method was adopted to diagnose multiple fault conditions for the same power transformer. This work was shown to yield substantial results. Rozga et al. [4] proposed a multilevel detection procedure to ensure the accuracy of abnormality detection for power transformers.

Sarkar et al. [5] designed an optimized model based on traditional and new technologies as well as expert experience to test the insulation of power transformer equipment, especially the moisture content of insulating paper. IEEE Std. 62-1995 (R2005) [6] was used as a guide to assess the pros and cons of different decomposed gas levels in oil, and these levels were divided into four stages, namely, normal, attention required, abnormal, and dangerous, for the reference of maintenance personnel for power system equipment.

The Rogers ratio, Doernenburg ratio, Duval triangle [7]–[10], and linear support vector machine (SVM)-based methodologies [11], [12] are well-known conventional fault recognition methodologies for power transformers.

Piotrowski et al. [7] analyzed the excess hydrogen in the gas content of oil; it was confirmed by the IEC 60599 ratio methodology and the Duval triangle methodology that a
partial discharge phenomenon occurred in the power transformer, but the case described in CIGRE manual 2965 may be caused by the incompatibility between the material and the oil.

Mansour [8] noted that the Duval triangle methodology cannot be used to effectively diagnose low overheating and corona discharge. Therefore, a pentagonal diagnosis methodology was developed by incorporating the content of ethane and hydrogen gas. Compared with those of the diagnostic methodology of the ratio method, the results of a fault case indicated that the proposed diagnosis method was more accurate.

Sumari and Ahmad [9] proposed a smart knowledge growth system in which future phenomena are predicted from real-life data for decision makers. An advantage of this system is that it encompasses the new idea mechanisms of AI established by human thinking and receives information from various sensors as inputs to improve the accuracy of the output.

Li et al. [10] adopted the proportion of each gas concentration in oil and an SVM; the initial fault diagnosis method used a genetic algorithm for a power transformer. Kečman and Melki [11] used MATLAB software to implement a linear SVM and an optimization algorithm from an SVM solver; this approach was effective for large and very large data sets.

Khan et al. [12] applied a fuzzy logic and adaptive neural fuzzy inference system to analyze the internal initial faults of power transformers for oil-in-gas analysis. This method is stable and highly accurate and can overcome the limitations of traditional diagnostic methods such as the IEC 60599 standard, Rogers ratio, and Doernenburg ratio methods.

In these diagnostic methodologies, the key gas ratios are first computed and then mapped to predefined fault patterns. The above traditional DGA ratio schemes have been widely used for power transformer diagnosis. However, some limitations exist in these methods; for example, an interpretation for every possible combination of ratios may not be provided.

Therefore, several more sophisticated power transformer fault diagnosis technologies have been developed to improve the diagnostic capability using SVM, fuzzy neural network (NN) [13], AI [14], [15] and related machine learning-based methods [16].

Miranda et al. [13] developed a set of autoassociative NN autoencoders to identify faulty and nonfaulty conditions. This method uses two sets of parallel models. When the vector data are input, the autoencoders compete with each other and use the latest recognition result as the diagnostic result. This method has been verified with actual data to achieve high accuracy.

Chamandoust et al. [14] adopted a dual optimization method for the development and design of a hybrid system, with the goals of optimizing the net cost and operating cost. Moreover, this method incorporated many considerations, such as wind turbine, solar cell, and fuel cell characteristics.

Gill and Sharma [15] developed a gesture recognition method in human-computer interaction free mode, and the method involved four algorithms: image number, spike value, object counting, and template matching. This method displayed high robustness and yielded effective results in a cluttered and noisy background.

Puth et al. [17] adopted a GARCH-Copula sequence comparison-based algorithm to develop a novel four-stage algorithm to measure the correlation coefficient for the rankings of financial time series. The proposed method was verified by practical data, and its advantages over other methods were illustrated.

In general, these newly developed fault diagnosis technologies for power transformers have improved fault identification accuracy. Most of the above conventional and advanced fault diagnosis methods for power transformers aim to categorize the fault type and increase the diagnostic accuracy. However, these developed diagnostic methods are not directly linked to the maintenance cost as a design criterion. Other recent related works include [21]–[32].

Notably, modern deep learning techniques are used in power transformer diffident protection [31] and fault diagnosis [32]. Machine learning-based techniques (such as deep learning techniques) require massive amounts of data (patterns) for training data sets and test data sets to increase the accuracy of faults diagnosis. If real historic oil-immersed power transformer fault data can be obtained, deep learning technology may be applied to the proposed problem. However, fault data are very limited in real situations.

Through correlation analyses among the content patterns of gases dissolved in power transformer oil when the power transformer is operating in normal and abnormal conditions, we consider the correlation a random variable and then model the power transformer diagnosis problem as a hypothesis testing problem [20]. Based on conventional estimation theory and detection theory, a novel detection method for oil-immersed power transformer faults is developed in this article by minimizing the power transformer maintenance cost. In theory, maintenance cost minimization is an optimal solution.

Therefore, the incipient failure detection problem for oil-immersed power transformers is investigated in this article, and a novel diagnosis methodology for minimizing the maintenance cost of an oil-immersed power transformer is proposed. Compared to previous work, this is the first work to consider the optimization of the maintenance cost.

Moreover, the proposed diagnostic methodology is applied in a test case of 950 sets of real historic record data provided by Taiwan Power Company, Taiwan. The proposed diagnostic methodology is introduced in detail in the next section.

III. THE PROPOSED DIAGNOSTIC METHODOLOGY
A. PRELIMINARY INFORMATION

As mentioned earlier, based on the information associated with the gases dissolved in power transformer oil, many incipient fault detection methods for power transformers have been developed in the literature.
Based on this approach, we note that the content patterns of dissolved gases (DGs), e.g., H₂, CH₄, C₂H₂, C₂H₄, C₂H₆, and CO, in power transformers operating under normal and abnormal conditions are different. Intuitively, the correlation between two measured DG contents in normal and abnormal working conditions will be relatively low.

However, two measured DG contents in normal working condition should be highly correlated. This correlation may play a crucial role in determining whether a power transformer is operating in normal or abnormal conditions.

Hence, our idea is first to identify the typical DG content pattern from collecting DG measurements from a power transformer working in a normal state.

Then, the correlation between the tested DG in the power transformer and the typical DG pattern is considered as a random variable \( r \), and two hypotheses can be defined. One is hypothesis \( H_1 \), which represents the tested power transformer being in a good working condition.

The other is hypothesis \( H_0 \), which represents the power transformer experiencing incipient failure. Thus, the power transformer diagnosis problem can be modeled as a hypothesis testing problem [20]. The optimal decision rule is developed by minimizing the power transformer maintenance cost as follows.

### B. CONDITIONAL PROBABILITY DENSITY FUNCTIONS

Here, let \( x \) and \( y \) be the two data sets of the six DGs (including H₂, CH₄, C₂H₂, C₂H₄, C₂H₆, and CO). These gases were extracted from power transformer insulation oil under abnormal and normal conditions. Please note that \( x \) is the abnormal group (condition) and \( y \) is the normal group (condition).

The correlation of \( x \) and \( y \) is computed based on Pearson’s correlation coefficient (PCC) (1), also referred to as Pearson’s \( r \) [17], where \( n \) is the sample size and \( x_i \) and \( y_i \) are the individual sample points indexed with \( i \). The result can be considered a variable that reflects the similarity of the corresponding data patterns between the two data sets [18], [19].

\[
\rho = \frac{n \sum x_i y_i - \sum x_i \sum y_i}{\sqrt{n \sum x_i^2 - (\sum x_i)^2} \sqrt{n \sum y_i^2 - (\sum y_i)^2}}
\]

(1)

Without loss of generality, \( n \) is the number of gas types and is set to 6 in this article, and the index \( i \) ranges from 1 to \( n \). One example of the computation is shown in Table 1.

This formulation will yield a value in the range of \(-1 \leq \rho \leq 1\). Since we want to use the correlation \( \rho \) to determine whether a power transformer is working normally, we have to know the conditional PDFs of the correlation \( \rho \) under hypotheses \( H_1 \) and \( H_0 \), namely, \( p(\rho | H_1) \) and \( p(\rho | H_0) \).

However, we do not theoretically know the conditional PDFs. Fortunately, based on the empirical data, we can obtain estimated conditional PDFs, denoted as \( \hat{p}(\rho | H_1) \) and \( \hat{p}(\rho | H_0) \).

In this article, we create the estimated PDFs of the correlation \( r \) from the empirical data. The empirical distributions are used for hypothesis testing [20] to assess the performance of the proposed scheme.

### C. THE POWER TRANSFORMER DIAGNOSIS MODEL

The power transformer fault diagnosis problem is treated as a binary hypothesis testing problem. Hence, when we conduct a hypothesis test, there are a couple of things that could go wrong.

There are two kinds of errors, namely, type-I and type-II errors, which cannot be avoided by design. A type-I error involves falsely inferring the existence of something that is not present, and a type-II error involves falsely inferring the absence of something that is present. These errors may affect the power transformer maintenance cost. Here, we adopt classical detection and estimation theory [20] to express the possible maintenance cost in terms of the conditional probabilities and the corresponding decision regions as follows:

\[
C = P(H_1) C_{11} \int_{z_1} \hat{p}(\rho | H_1) d\rho + P(H_1) C_{01} \int_{z_0} \hat{p}(\rho | H_1) d\rho + P(H_0) C_{10} \int_{z_1} \hat{p}(\rho | H_0) d\rho + P(H_0) C_{00} \int_{z_0} \hat{p}(\rho | H_0) d\rho
\]

(2)

where \( P(H_1) \) and \( P(H_0) \) are the probability values in the previous period and represent that the power transformer is operating under normal or abnormal conditions, respectively; \( C_{11}, C_{01}, C_{10} \) and \( C_{00} \) are the costs of the four decisions, where the first subscript indicates the hypothesis chosen and the second subscript indicates the true hypothesis.

Additionally, \( z_1 \) and \( z_0 \) are the decision regions corresponding to the chosen hypotheses \( H_1 \) and \( H_0 \), respectively.

It is reasonable to assume that the cost of a wrong decision is higher than the cost of a correct decision. In a Bayes test [20], we can find the decision regions \( z_1 \) and \( z_0 \) such that the cost is minimized. Therefore, we can obtain the following alternative expression, which is the well-known likelihood ratio test [20]:

\[
\frac{\hat{p}(\rho | H_1) H_1}{\hat{p}(\rho | H_0) H_0} \geq \frac{p(H_0)(C_{10} - C_{00})}{p(H_1)(C_{01} - C_{11})}
\]

(3)

By employing the above likelihood ratio test, a detection method for oil-immersed power transformer faults can be designed based on the empirical data of the target power transformer. The usage of the proposed methodology is illustrated by the following experimental design based on real data collected from Taiwan Power Company, Taiwan.

### IV. EXPERIMENTAL DESIGN AND PERFORMANCE EVALUATION

In this article, we collect 1,000 sets of DG data for the target power transformer in normal situations and another 100 sets of data for the power transformer under normal and abnormal conditions.
conditions to estimate the conditional PDFs $\hat{p}(r | H_1)$ and $\hat{p}(r | H_0)$.

Based on maintenance experience, we set the values of the probabilities in the previous periods $P(H_1)$ and $P(H_0)$ and the four kinds of maintenance costs $C_{11}$, $C_{01}$, $C_{10}$ and $C_{00}$. The performance and validity of the developed power transformer fault detection method were assessed with benchmark testing data obtained from Taiwan Power Company and the abovementioned literature.

### A. EXPERIMENTAL DESIGN

Based on the 1,000 normal and 100 normal DG data sets collected, by using (9), we obtained $1,000 \times 100 = 100,000$ data samples of $r$ for the power transformer in a normal status. Similarly, based on the 1,000 normal and 100 abnormal DG data sets collected, we obtained $1,000 \times 100 = 100,000$ data samples of $r$ for the power transformer under incipient failure.

The probability histograms of the correction $r$ for these two cases are shown in Fig. 1 and Fig. 2. Based on the probability histograms, the correlation between the two measured DG content patterns under normal and abnormal working conditions is low. However, the correlation between the two measured DG content patterns under normal working conditions is high with high probability. This result is consistent with our intuition.

Based on the empirical data, the estimated conditional PDFs of $r$, denoted $\hat{p}(r | H_1)$ and $\hat{p}(r | H_0)$, are obtained, and the corresponding expressions are given in (4) and (5) by using a PDF estimation method. In other words, formulas (4) and (5) are derived from Figs. 1 and 2, respectively, which show the experimental results of the empirical data compiled and estimated by the MATLAB software tool. Moreover, these estimated PDFs for the normal and abnormal status groups are drawn in Fig. 3 and Fig. 4.

![FIGURE 1. The histogram for the normal status group.](image1)

![FIGURE 2. The histogram for the abnormal status group.](image2)

![FIGURE 3. The estimated probability density function for the normal status group.](image3)

\[
\hat{p}(r | H_1) = \begin{cases} 
8.6r^9 + 8.51r^8 - 9.76r^7 - 8.82r^6 \\
+ 4.51r^5 + 2.32r^4 - 1.67r^3 \\
+ 0.31r^2 + 0.98r + 0.25, & -0.34 \leq r \leq 1 \\
0, & -1 \leq r < -0.34 
\end{cases} 
\]  

(4)

\[
\hat{p}(r | H_0) = 21.32r^9 - 1.74r^8 - 40.19r^7 + 35r^6 \cdot 21.36r^5 \\
- 21.36r^4 + 0.38r^3 + 4.42r^2 - 1.6r + 0.49, \\
-1 \leq r \leq 1 
\]  

(5)

Without loss of generality, the probability values in the previous year $P(H_1)$ and $P(H_0)$ and the values of the four kinds of maintenance costs $C_{11}$, $C_{01}$, $C_{10}$ and $C_{00}$ are assigned as listed in Table 2. For convenient computation, we can set $C_{01}$ as any constant, and the values of $a$, $b$ and $\alpha$ are set according to user experience with the target power transformer being evaluated.

Based on the estimated conditional PDFs and parameter values, the likelihood ratio test of (3) can be directly used for diagnostic purposes. By substituting these values and the estimated conditional PDFs into (2) and minimizing the cost
function, we can also obtain the diagnostic rule, which is expressed as (6); this equation is equivalent to (3), and the threshold $\eta$ is obtained at the same time as the parameters in (3).

The resulting decision regions $z_1$ and $z_0$ corresponding to the chosen hypotheses $H_1$ and $H_0$ are assigned based on $r > \eta$ and $r < \eta$, respectively. The diagnostic rule and the decision regions are depicted in Fig. 5.

In practice, the proposed detection scheme presented in (6) will be implemented, as shown in Fig. 6, where an average process is used, i.e., $r$ will be replaced by $\bar{r}$. The data processor computes the correlation values between one new measured data vector and 1,000 presaved normal DG data sets and then takes the average of the 1,000 correlation values.

The obtained average value $\bar{r}$ is compared with the threshold $\eta$ to make a decision. Note that the number of presaved normal DG values does not have to be equal to 1,000. Statistically, the larger the number is, the better the result, but values may be limited by the computing power of the system used to run the algorithm and the available data sets.

To assess the performance of our fault detection method for oil-immersed power transformers, we first used the data presented in Section III to estimate the conditional PDFs $\hat{p}(r | H_1)$ and $\hat{p}(r | H_0)$, as shown in Fig. 5. Additionally, we set the values of the parameters shown in Table 2 based on experience to determine a threshold $\eta$ of 0.46, and the minimized maintenance cost was 0.6141$C_0$, as shown in Fig. 7.

Note that the experience values are not given here for business confidentiality reasons.

### B. VALIDITY VERIFICATION AND PERFORMANCE

We employed a chromatography instrument (ASTM D3612) to collect another 950 sets of data for a power transformer with insulating oil; data from the target power transformer of Taiwan Power Company were used as the benchmark for testing. The benchmark data consisted of 900 sets of values obtained under normal conditions and 50 sets obtained under abnormal conditions.

The novel detection method proposed in this paper for oil-immersed power transformer faults was developed based on minimizing the power transformer maintenance cost. Based on the abovementioned estimation theory and detection theory, minimization of the maintenance cost can be ensured if the proposed scheme is adopted. Therefore, for comparison, the probability of obtaining a detection error can be computed with the proposed method.

In statistical hypothesis testing [20], a type-I error is the rejection of a true null hypothesis $H_0$, and a type-II error fails to reject a false null hypothesis. Here, the diagnostic rule presented in (6) is used, and the probabilities of these two types of detection errors are expressed as shown in (7) and (8), respectively. The probability of obtaining a detection error can therefore be obtained as shown in (9).

$$P_m = \int_{z_1}^{\eta} \hat{p}(r | H_0) \, dr$$

$$P_f = \int_{0}^{\eta} \hat{p}(r | H_1) \, dr$$

$$P_e = P(H_1) \int_{0}^{\eta} \hat{p}(r | H_1) \, dr + P(H_0) \int_{z_1}^{\eta} \hat{p}(r | H_0) \, dr$$

To assess the performance of our fault detection method for oil-immersed power transformers, we first used the data presented in Section III to estimate the conditional PDFs $\hat{p}(r | H_1)$ and $\hat{p}(r | H_0)$, as shown in Fig. 5. Additionally, we set the values of the parameters shown in Table 2 based on experience to determine a threshold $\eta$ of 0.46, and the minimized maintenance cost was 0.6141$C_0$, as shown in Fig. 7.
Furthermore, using the proposed power transformer fault detection procedure shown in Fig. 6, the resulting detection error was 7.15%. Through the benchmark test, we found that the developed diagnostic method also has a satisfactory detection accuracy with a low complexity of implementation, comparable to those of some related works, as summarized in Table 3. Note that the proposed method can only detect if the transformer is going to have a fault, but it cannot carry out the classification of the transformer’s faults. Nevertheless, our scheme will be very suitable for online diagnostic tools because it is easy to implement in a monitoring system. This scheme can also be used as the first stage to detect if the transformer is going to have a fault; then, the existing transformer’s fault classification methods can be employed to determine what types of faults to expect, or the transformer can be shut down for manual inspection.

V. CONCLUSION
In this paper, a detection method for oil-immersed power transformer faults is developed by minimizing the maintenance cost. The novelty of this method is that it considers the maintenance cost as a design criterion instead of the detection error. This approach is believed to be directly linked to a company’s operating cost because it guarantees a minimized maintenance cost. Because the maintenance cost is highly related to the detection error, the performance of the proposed method can also be verified by the detection accuracy.

The proposed methodology was applied in a benchmark test of 950 sets of historical data, and the results showed that the failure detection accuracy was 92.85% with minimized maintenance costs. The experimental results indicated that the proposed methodology displayed promising performance and can be used as a tool for the diagnosis of incipient faults in power transformers.

Additionally, the proposed detection procedure is very straightforward and can be implemented with software or hardware. Therefore, this method is very suitable for real-time online fault detection for oil-immersed power transformers. Moreover, the proposed scheme can also be used as the first stage to detect if an oil-immersed...
power transformer is going to have a fault; then, the existing fault classification approaches for oil-immersed power transformers can be employed to determine which kinds of faults to expect, or the transformer can be shut down for manual inspection. In conclusion, the proposed methodology provides insight into the ability to minimize maintenance costs in the diagnosis of oil-immersed power transformers, thus improving the accuracy of detection and reducing maintenance costs.

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