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Analysis of Transformer Oil Degradation Using Dissolved Gas Analysis and Fuzzy-Based Diagnostic Assessment

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Abstract

This study aims to evaluate transformer insulating oil degradation and post-purification recovery by integrating conventional Dissolved Gas Analysis (DGA) interpretation methods with a fuzzy-logic-based diagnostic framework. The research was conducted as an in-depth case study on Transformer 1 at the Cipinang Gas Insulated Substation (GIS), where repeated DGA measurements indicated progressive thermal stress prior to maintenance intervention. Oil samples were collected at multiple observation points before and after purification and analyzed using established DGA techniques, including Total Dissolved Combustible Gas (TDCG), Roger's Ratio, Doernenburg Ratio, and the Key Gas Method. These outputs were then incorporated into a fuzzy inference system (FIS) developed in MATLAB to generate a unified oil-condition index. The results show that before purification, elevated concentrations of C_2H_4, C_2H_6, CO, and increasing TDCG values consistently indicated incipient thermal faults. After purification, combustible gas levels and TDCG values declined significantly, shifting the transformer condition to a normal operating state. While conventional ratio-based methods occasionally produced borderline or ambiguous classifications, the fuzzy-logic framework successfully consolidated multiple diagnostic outputs into a single, consistent condition assessment. The study demonstrates that integrating DGA with fuzzy inference enhances diagnostic clarity, improves post-purification evaluation, and supports more reliable transformer maintenance decision-making.

Keywords: DGA; fuzzy inference; power transformer; thermal fault; transformer oil degradation

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1. Introduction

Power transformers are essential components within the electrical power system, functioning across generation, transmission, and distribution networks to maintain efficient power delivery. In Indonesia's utility landscape, as the largest corporate that support electricity power through Indonesia coverage, PT PLN plays a crucial role in managing these systems, where transformers are used to step up voltage levels at generation stations and step them down at substations for distribution to consumers [1], [2]. The insulating oil inside these transformers provides two main functions: electrical insulation and thermal dissipation. As operating loads increase, the internal temperature of the oil also rises, accelerating oxidation processes and producing by-products such as sludge, carbon monoxide (CO), and carbon dioxide (CO_2), which indicate cellulose degradation in the paper insulation [3]. These degradation mechanisms make transformer oil a critical indicator of overall transformer health.

Dissolved Gas Analysis (DGA) is widely recognized as one of the most effective diagnostic tools for evaluating transformer oil condition [4]. DGA identifies fault-related gases generated under thermal or electrical stress, providing insights into potential internal faults such as overheating, partial discharge, or arcing. Several established interpretation methods (including the Total Dissolved Combustible Gas (TDCG) method from IEEE Std C57.104-2008,

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Roger's Ratio, Doernenburg Ratio, and Key Gas Analysis) are widely applied in the industry to classify the severity and type of faults [5], [6]. Each method analyzes specific gas ratios or concentration thresholds to determine faults categories. However, prior studies have shown that these methods may yield inconsistent interpretations when gas values fall near classification boundaries or when multiple fault signatures appear simultaneously [7], [8].

This interpretative challenge becomes more complex when assessing oil quality before and after purification. Although purification reduces moisture, acidity, and sludge content, existing DGA ratio methods do not always provide a coherent view of how purification affects residual thermal or electrical stress within the transformer [9]. As observed in Transformer 1 at the Cipinang GIS substation, elevated TDCG values signaled the need for purification, yet different diagnostic methods produced varying classifications regarding the dominant fault mechanism. This inconsistency highlights a clear gap: a unified diagnostic approach that integrates multiple DGA perspectives is needed to interpret transformer conditions more reliably across pre- and post-purification states.

To address this gap, this study combines conventional DGA methods with a fuzzy-logic-based diagnostic system developed using MATLAB. Fuzzy inference offers the flexibility to handle nonlinear, uncertain, and overlapping gas patterns, situations where ratio-based methods often struggle (related studies by Adekunle et al. [10]; and Lalitha et al. [11]). By incorporating key gases such as H_2, CH_4, C_2H_2, C_2H_4, and C_2H_6, the fuzzy system generates a more adaptive classification of transformer oil conditions. This approach not only strengthens diagnostic consistency but also provides clearer insights into how purification influences oil quality and ongoing thermal stress.

The novelty of this research lies in integrating four major DGA interpretation methods with a fuzzy inference framework to evaluate transformer oil before and after purification. Unlike traditional single-method diagnoses, the proposed hybrid approach resolves interpretative ambiguity and enhances early fault detection capability. The findings contribute a more robust diagnostic basis for transformer maintenance planning, which is crucial for utility operators such as PT PLN in ensuring reliable power system operation.

The objective of this study is to develop and validate an integrated transformer oil diagnostic framework by combining conventional DGA interpretation methods with a fuzzy inference system for assessing oil degradation and purification effectiveness. The study is conducted as a single-case investigation on Transformer 1 at the Cipinang GIS substation due to the availability of long-term DGA records, observable degradation trends, and a documented purification intervention. Although the analysis focuses on one transformer, the methodological framework is designed to be transferable to similar oil-immersed power transformers operating under comparable thermal and loading conditions.

2. Research Method

The research was conducted using transformer oil samples taken from Transformer 1 located at the Cipinang Gas Insulated Substation (GIS) operated under PT PLN Indonesia Corporation. The study followed a diagnostic workflow that combines conventional Dissolved Gas Analysis (DGA) interpretation methods with a fuzzy-inference-based evaluation model. All procedures were carried out in accordance with IEEE Std C57.104-2008 and IEC 60599 guidelines, which define measurement thresholds, diagnostic limits, and recommended interpretation rules for fault-related gases [5], [6].

2.1 Data Collection and Laboratory Testing

Oil samples were collected at six observation points between 2019 and 2024, consisting of four measurements before purification and two measurements after purification. The sampling interval ranged from 6 to 12 months, depending on operational conditions and maintenance schedules. This temporal coverage allows trend-based evaluation of gas evolution and post-purification recovery, ensuring that the diagnostic assessment reflects both degradation progression and maintenance impact. These gases represent dominant indicators of thermal and electrical decomposition, cellulose degradation, and insulating oil deterioration [3], [12]. The sampling was conducted twice: before purification and immediately after the purification process, allowing comparative evaluation of oil condition.

2.2 DGA Interpretation Methods

The diagnostic evaluation of transformer oil in this study relies on four established Dissolved Gas Analysis (DGA) interpretation techniques that are widely applied in industrial transformer maintenance. First, the Total Dissolved Combustible Gas (TDCG) method from IEEE Std C57.104-2008 provides an overall indication of oil condition by categorizing the cumulative concentration of combustible gases into severity levels that correspond to normal operation, incipient faults, or critical deterioration [5]. In addition, Roger's Ratio Method offers a more detailed fault characterization by analyzing gas ratios such as CH_4/H_2, C_2H_2/C_2H_4, and C_2H_4/C_2H_6 to distinguish between low-temperature overheating, high-temperature overheating, partial discharge, and arcing events [7], [13]. The Doernenburg Ratio Method further supports fault identification by examining

inter-gas relationships, namely C_2H_2/C_2H_6, C_2H_2/CH_4, C_2H_4/C_2H_6, and CH_4/H_2 to determine whether thermal or electrical stresses dominate the degradation process [8]. Complementing these ratio-based approaches, the Key Gas Method interprets transformer oil condition by associating specific gases with typical fault mechanisms, such as hydrogen for partial discharge, acetylene for arcing, and ethylene for thermal degradation, as outlined in IEC 60599 [6]. Together, these four interpretation frameworks provide a comprehensive foundation for assessing the transformer's internal condition both before and after purification.

2.3 Oil Purification Process

The purification process followed industry standards for restoring transformer oil quality by reducing moisture, acidity, and particulate contamination. The process includes degassing, vacuum dehydration, and filtration to remove sludge and stabilize dielectric properties. Purification effectiveness was evaluated by comparing gas concentrations, TDCG levels, and ratio-based classifications before and after treatment. A notable decrease in moisture and dissolved gases is generally associated with improved dielectric strength and reduced thermal stress within the transformer [3].

2.4 Fuzzy Inference System Development

To address ambiguity and nonlinear gas behavior that often limit traditional DGA methods, this study incorporates a Fuzzy Inference System (FIS) developed using MATLAB. In computational intelligence, fuzzy logic is widely applied for modeling systems where variable boundaries are not strictly defined [14], making it suitable for transformer diagnostics where dissolved gas concentrations frequently fall into overlapping or uncertain ranges [15]. The fuzzy system in this research follows the classical Mamdani architecture, which represents knowledge through linguistic rules and membership functions to approximate expert reasoning.

The fuzzy model begins by defining input variables representing the key DGA gases: hydrogen (H_2), methane (CH_4), acetylene (C_2H_2), ethylene (C_2H_4), and ethane (C_2H_6). Each gas is assigned membership functions categorized into linguistic terms such as low, medium, and high, based on concentration limits from IEEE Std C57.104-2008 and IEC 60599 [5], [6]. A typical membership function $\mu(x)$ maps a gas concentration x into a value between 0 and 1, within the following Equation 1.

$$\mu(x): x \rightarrow [0,1] \tag{1}$$

These membership functions were modeled using triangular and trapezoidal shapes, which are commonly used due to their simplicity and suitability for real-time implementation [15]. Next, a set of fuzzy rules was constructed to emulate expert interpretation of DGA patterns. Examples include:

- IF C_2H_2 is high AND C_2H_4 is medium THEN fault level is arcing,
- IF H_2 is high AND CH_4 is low THEN fault level is partial discharge.

The fuzzy inference process consists of four main steps:

1) Fuzzification: transforming numeric gas concentrations into fuzzy membership grades.
2) Rule Evaluation (Inference): applying logical operators (*AND, OR*) to compute rule activation using min/max fuzzy operators.
3) Aggregation: combining outputs of all activated rules into a unified fuzzy set.
4) Defuzzification: converting the aggregated fuzzy output into a crisp diagnostic value using the centroid method, represented mathematically as Equation 2.

$$y^{\backslash^*} = \frac{\int y \cdot \mu(y)\, dy}{\int \mu(y)\, dy} \tag{2}$$

The crisp output represents the fault severity index, which is mapped to categories such as normal, incipient thermal fault, moderate thermal fault, or severe electrical fault. This approach enhances the interpretive clarity of DGA by capturing complex interactions among gases and reducing the diagnostic inconsistencies often observed in ratio-based methods. The final fuzzy output provides a unified assessment of oil condition both before and after purification, allowing a more comprehensive understanding of transformer health.

2.5 Integration of DGA Methods into the Fuzzy Inference System

The integration of conventional DGA methods into the fuzzy inference system is performed by mapping the outputs of TDCG, Roger's Ratio, Doernenburg Ratio, and Key Gas Analysis into fuzzy linguistic variables representing fault severity. Gas concentrations (H_2, CH_4, C_2H_2, C_2H_4, and C_2H_6) serve as primary numerical inputs, while the diagnostic conclusions derived from ratio-based methods guide the construction of fuzzy rules.

Specifically, each DGA gas concentration is converted into membership grades (low, medium, high) based on IEEE C57.104 and IEC 60599 thresholds. The fuzzy rules emulate expert reasoning by combining gas patterns commonly associated with thermal faults, partial discharge, or normal conditions. The outputs of traditional DGA interpretations are therefore not replaced, but embedded as knowledge constraints within the fuzzy rule base, allowing the fuzzy system to resolve ambiguities arising from overlapping ratio classifications.

3. Results and Discussion

3.1 DGA Results Before Purification

The initial DGA results for Transformer 1 at the Cipinang GIS substation indicate a significant presence of combustible gases associated with thermal decomposition. Prior to purification, hydrogen (H_2), methane (CH_4), ethylene (C_2H_4), and ethane (C_2H_6) were observed at elevated concentrations, suggesting ongoing thermal stress within the insulating oil. The Total Dissolved Combustible Gas (TDCG) value exceeded the threshold for normal operation based on IEEE Std C57.104-2008 (see Fig. 1), placing the transformer in a condition categorized as requiring maintenance attention [5]. According to IEC 60599, the relative increase of hydrocarbon gases signifies cellulosic degradation as well as thermal strain associated with hotspot formation [6]. These observations align with findings reported by Badaruddin and Firdianto [12], who noted that elevated CO and CO_2 levels further reinforce the presence of thermal aging within the insulation system.

3.2 DGA Results After Purification

Following purification, the DGA results shows in Fig. 2 indicate a notable decrease in combustible gas concentrations. Moisture content, TDCG levels, and total hydrocarbon gas concentrations declined, consistent with expected improvements in dielectric quality [3]. The reduction in H_2 and CH_4 indicates a decrease in thermal stress, while decreased CO and CO_2 concentrations demonstrate a reduction in paper insulation degradation. The TDCG value decreased into the IEEE *Condition 1* zone, confirming the effectiveness of the purification process.

3.3 TDCG Trend Analysis

The TDCG trend before and after purification shows a clear downward trend (Fig. 3). Prior to purification, the TDCG level indicated that continued operation without intervention could accelerate aging and increase fault probability [5]. After purification, TDCG values fell into a safer operational zone, enabling continued transformer operation under normal monitoring protocols.

3.4 Ratio-Based Diagnosis (Roger & Doernenburg)

Application of Roger's Ratio and Doernenburg methods yielded consistent indications of low-to-medium thermal faults before purification. The CH_4/H_2 ratio suggested low-energy thermal decomposition, while the C_2H_4/C_2H_6 ratio was indicative of overheating below 300°C (see Fig. 4). These results are consistent with the Key Gas method, which identified C_2H_4 as the dominant thermal indicator, aligning with similar findings in IEC 60599 [6] and the studies of [7], [13].

Post-purification ratio interpretations shifted toward normal or marginal conditions, reflecting reduced thermal stress and confirming successful removal of dissolved gases. However, some ratios remained near diagnosis boundaries, demonstrating the inherent ambiguity of conventional ratio-based interpretation, one of the key motivations for employing fuzzy logic.

The interpretation of Roger's diagnostic ratios (see Fig. 5) suggests that the transformer predominantly experienced low-temperature thermal faults prior to purification, consistent with the observed increases in hydrocarbons such as CH_4 and C_2H_6. The absence of acetylene across all periods further indicates that high-energy electrical faults were not present. While Roger's method provides valuable insight into fault type classification, its reliance on discrete threshold-based decision rules may lead to interpretive ambiguity, especially when gas concentrations lie near classification boundaries. This limitation motivates the need for complementary ratio-based diagnostics, which are addressed in the subsequent Doernenburg analysis.

The Doernenburg ratio method was applied to evaluate the presence of thermal or electrical faults by examining the relationships among key dissolved gases, specifically the ratios CH_4/H_2 (R1), C_2H_2/C_2H_4 (R2), C_2H_4/C_2H_6 (R3), C_2H_2/CH_4 (R4), and C_2H_6/C_2H_2 (R5). Based on Fig. 6, the results indicate that, prior to purification, the transformer exhibited ratio patterns characteristic of mild to moderate thermal degradation. The R1 (CH_4/H_2) ratio, for instance, consistently showed values above 13 in several measurement periods (28 May 2019, 28 August 2019, and 20 March 2020), which is typically associated with low-temperature thermal faults. This aligns with the elevated concentrations of hydrocarbon gases found in the DGA results, suggesting that partial overheating or localized thermal stress affected the insulation or oil during these intervals. Meanwhile, R3 (C_2H_4/C_2H_6) also presented nonzero values (particularly 0.0158, 0.0126, and 0.0061 in the years before purification) further reinforcing the presence of early-stage thermal deterioration.

The remaining ratios, particularly R2 (C_2H_2/C_2H_4) and R4 (C_2H_2/CH_4), consistently yielded zeros during the pre-purification period, suggesting the absence of high-energy electrical discharges such as arcing. This aligns with the simultaneous absence of acetylene (C_2H_2) in the DGA dataset, indicating that the transformer was not experiencing severe electrical faults despite showing thermal anomalies.

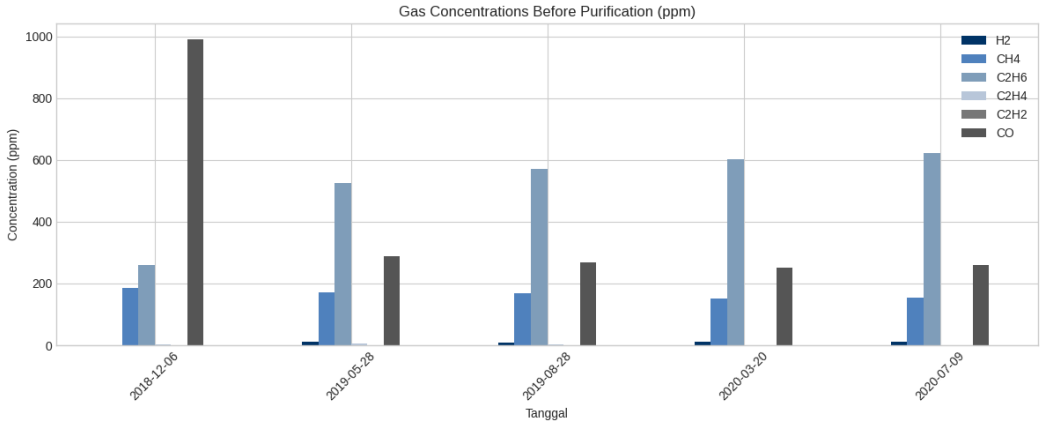

Fig. 1. Dissolved gas concentrations before purification for Transformer 1, showing dominant hydrocarbon gases and CO indicating early thermal stress.

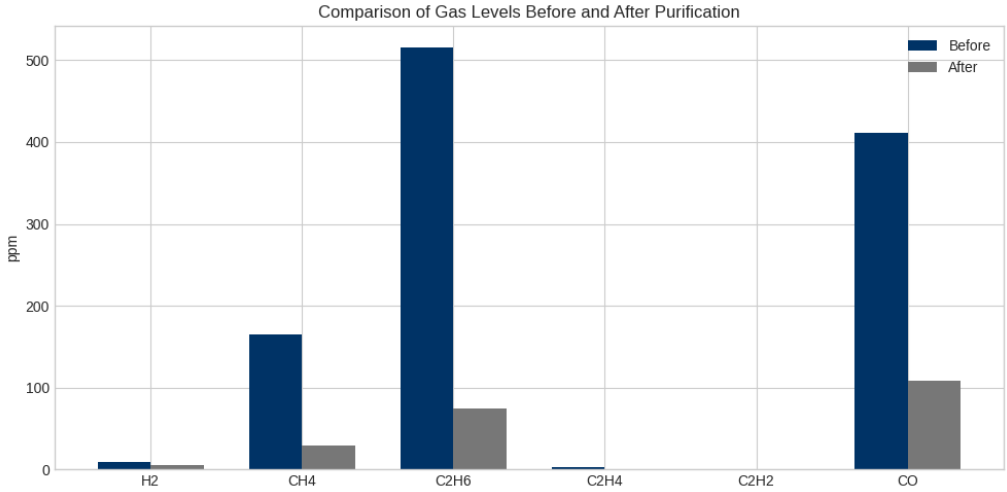

Fig. 2. Comparison of dissolved gas concentrations before and after purification, illustrating reductions across major hydrocarbon gases and CO.

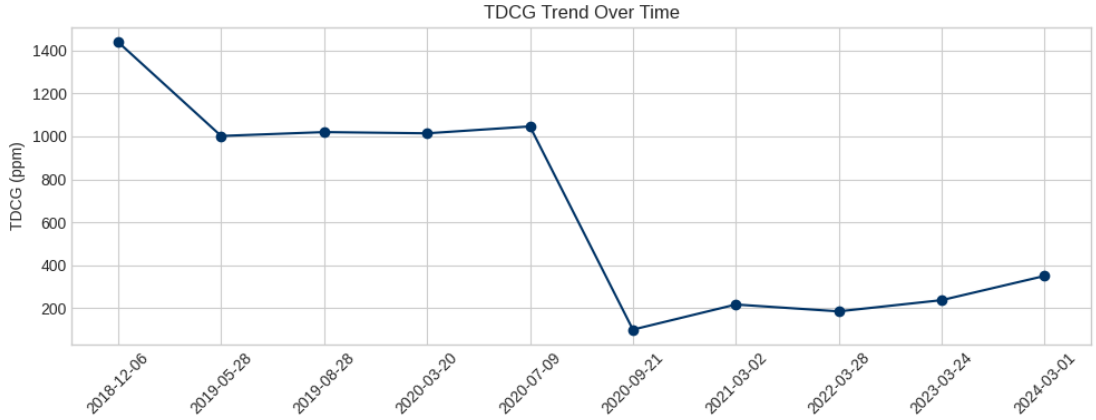

Fig. 3. Trend of Total Dissolved Combustible Gas (TDCG) over time, highlighting the reduction following the purification process.

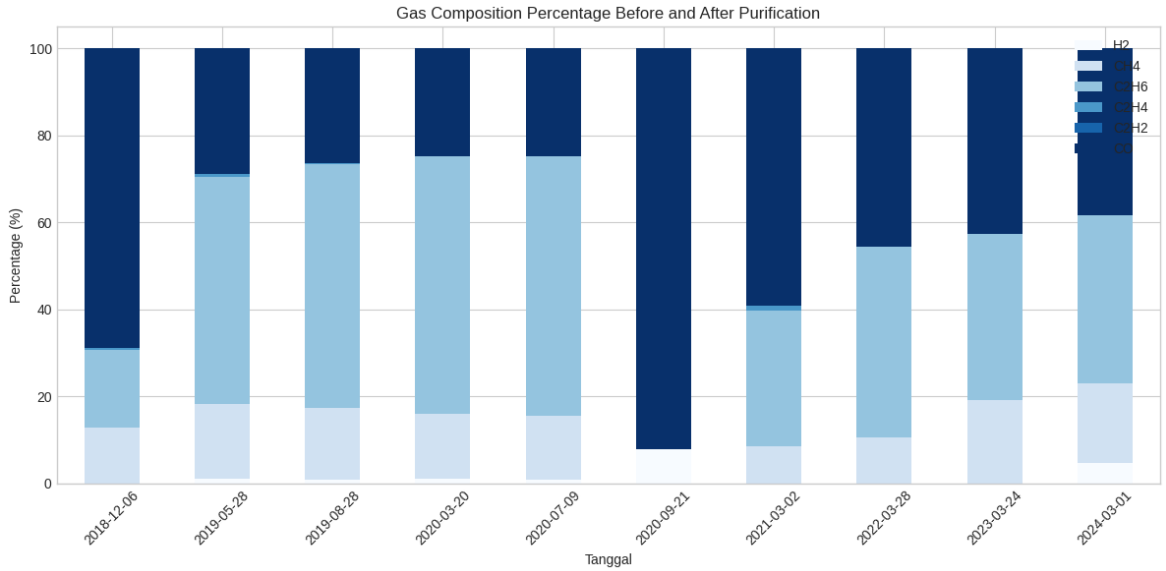

Fig. 4. Percentage composition of dissolved gases before and after purification, illustrating shifts in dominant fault-related gas contributions.

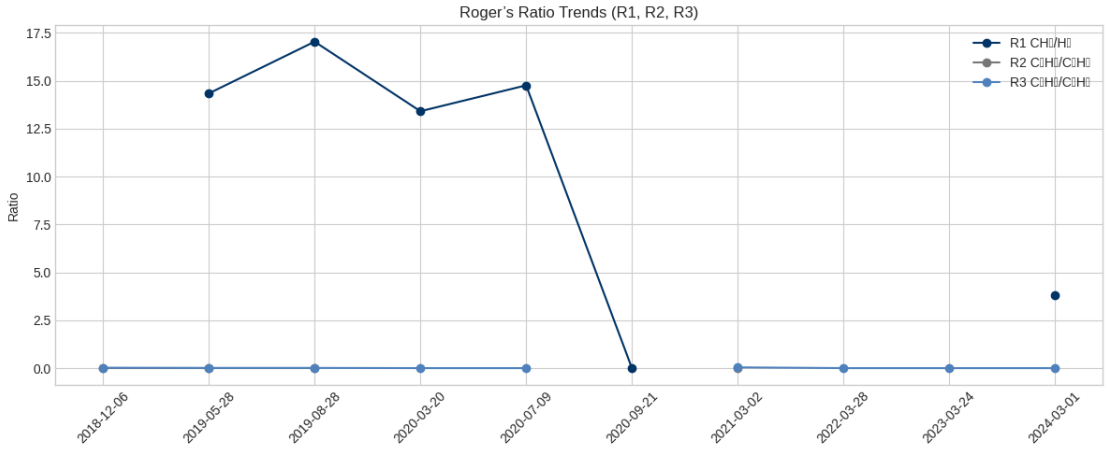

Fig. 5. Trends of Roger's diagnostic ratios (R1: CH_4/H_2, R2: C_2H_2/C_2H_4, R3: C_2H_4/C_2H_6) before and after oil purification, showing shifts in thermal fault indicators.

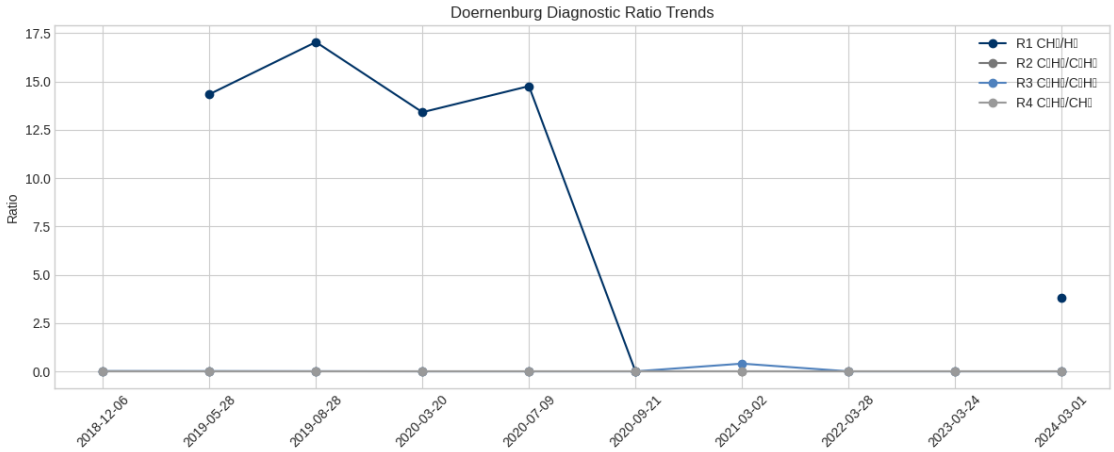

Fig. 6. Trends of Doernenburg's diagnostic ratios before and after purification, showing variations in thermal and electrical fault indicators across operational years.

3.5 Key Gas Interpretation

The Key Gas method was applied to identify the dominant fault-related gases and to determine the corresponding fault types present in the transformer. Prior to purification, the DGA profile showed that ethylene (C_2H_4) consistently appeared as the dominant hydrocarbon gas, indicating thermal overheating in the range of approximately 150–300°C. Elevated ethane (C_2H_6) further suggested overheating of the cellulose-based insulation, while hydrogen (H_2) exhibited moderate fluctuations that may reflect low-energy partial discharge activity [16], [17]. Throughout the entire observation period, acetylene (C_2H_2) remained at 0 ppm, confirming the absence of arcing or other high-energy discharges. High levels of CO and CO_2 strengthened the indication of long-term thermal degradation within the insulation system. After the purification process, concentrations of C_2H_4 and C_2H_6 dropped to near-zero values, CO declined substantially, and H_2 returned to levels consistent with normal operating conditions. These patterns collectively demonstrate strong agreement between the Key Gas method and the Roger's and Doernenburg ratio analyses, all of which point to thermal fault activity before purification and a recovery to normal operation afterward. Besides, the following Fig. 7 shows the key gas dominance before and after purification.

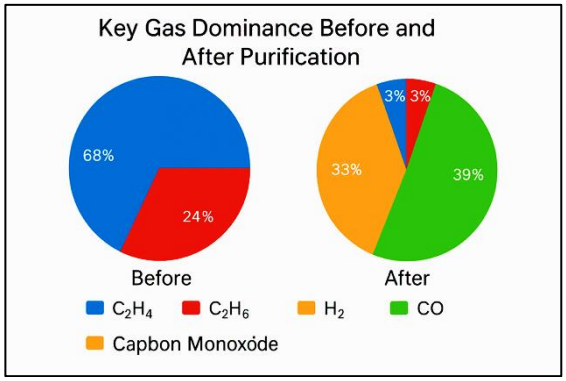

Fig. 7. Key Gas dominance before and after purification showing ethylene (C_2H_4) as the primary overheating indicator prior to purification and near-zero hydrocarbon levels after purification.

3.6 Purification Effect on Thermal Performance

The oil purification process effectively restored the chemical and dielectric stability of the insulating oil by reducing moisture, hydrocarbons, and carbon monoxide. Post-purification, gas concentrations across all primary DGA parameters declined sharply, as shown in Fig. 8. The removal of dissolved gases and moisture allowed the transformer to dissipate heat more efficiently, stabilizing winding temperatures during high-load conditions [17].

Field observations indicated that before purification, a loading of approximately 1,390 A resulted in a winding temperature of ~80°C. After purification, the transformer tolerated loads up to ~1,610 A with temperatures remaining around 77°C, confirming improved cooling performance. The purification therefore not only reduced chemical stressors but also enhanced thermal management, supporting its role as a preventive maintenance action [18].

3.7 Fuzzy Logic-Based Integrated Diagnosis

To obtain an integrated and more practical assessment of transformer oil condition, the four diagnostic methods namely TDCG, Roger's Ratio, Doernenburg Ratio, and Key Gas Analysis, were combined using a fuzzy logic system implemented in MATLAB. In this framework, the DGA indicators are mapped into linguistic variables representing fault severity levels and oil condition categories. The fuzzy inference engine then produces a single condition index, which is consistent with the condition classification defined in IEEE C57.104 and the condition table adopted in this study.

For the pre-purification dataset, the fuzzy logic system classified the transformer oil as being in Condition 2, indicating that the transformer was operating with a moderate level of thermal and dielectric stress (see Fig. 9). The fuzzy output also identified the simultaneous presence of thermal faults, cellulose degradation, and partial discharge activity, consistent with the elevated concentrations of hydrocarbon gases and CO/CO_2 observed in the DGA results. In practical terms, this classification suggests that continued operation without corrective action would increase the likelihood of accelerated aging and potential fault development inside the transformer.

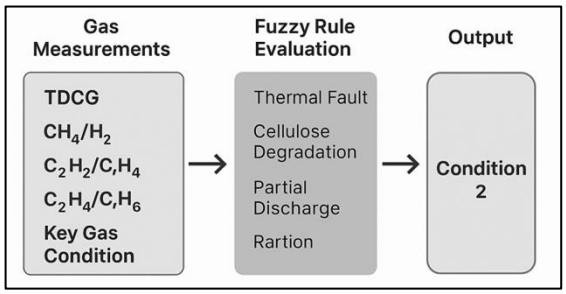

Fig. 8. Fuzzy interpretation results before purification showing Condition 2 classification, with indications of thermal fault, cellulose degradation, and partial discharge activity derived from DGA-based fuzzy rule evaluation.

After purification, the fuzzy diagnosis shifted to Condition 1 (Fig. 10), which corresponds to a normal operating state requiring only routine monitoring. This change is in line with the post-purification DGA profile, where combustible gas levels and TDCG values were significantly reduced, and moisture and thermal indicators returned to acceptable ranges. The fuzzy logic output therefore

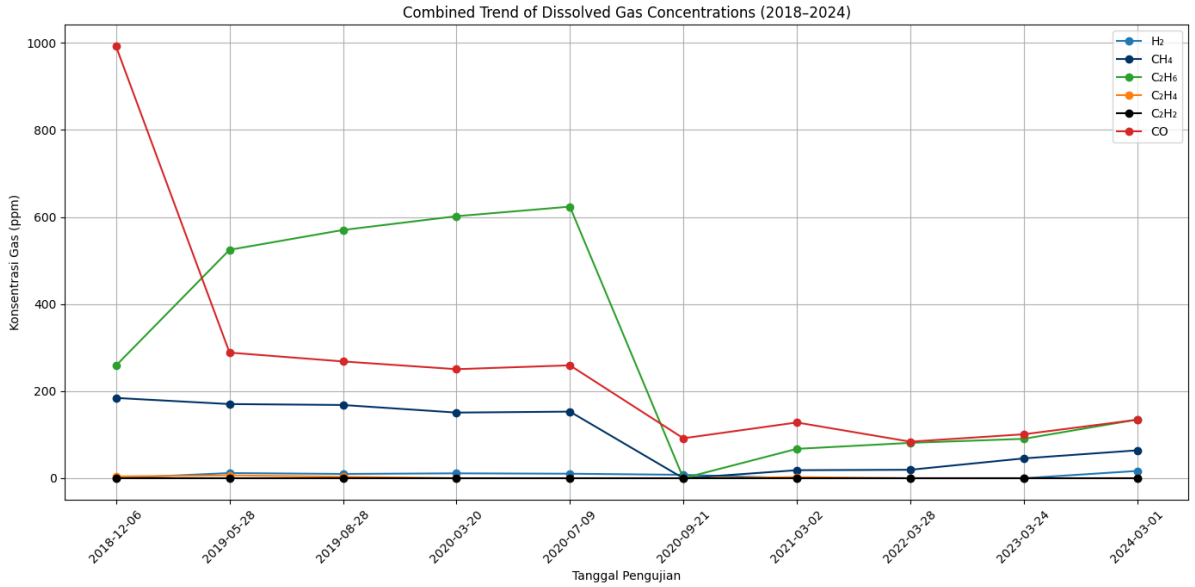

Fig. 9. Combined trend of dissolved gas concentrations (H_2, CH_4, C_2H_6, C_2H_4, C_2H_2, CO) from 2018 to 2024, illustrating the reduction in hydrocarbon and carbon monoxide content following the oil purification process and the stabilization of thermal-fault indicators.

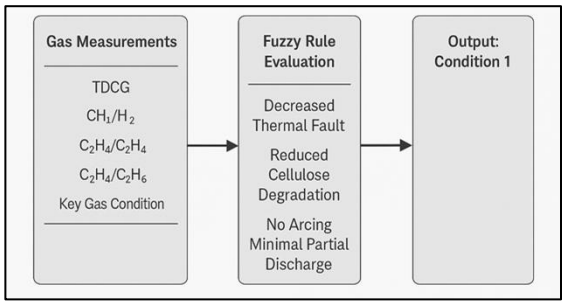

Fig. 10. Fuzzy interpretation results after purification showing a shift to Condition 1, indicating normal operating state with reduced thermal stress, minimal partial discharge activity, and no evidence of arcing, as derived from DGA-based fuzzy rule evaluation.

provides a concise and unified representation of the improvement in oil condition. By summarizing the combined effect of all four DGA interpretation methods into a single diagnostic label, the fuzzy system simplifies decision-making for maintenance planning while preserving consistency with established standards and field measurements.

3.8 Discussion

The combined analysis of DGA, ratio-based diagnostics, fuzzy logic interpretation, and purification evaluation provides a coherent picture of the health status of Transformer 1 at the Cipinang GIS substation. Before purification, the DGA results showed increased concentrations of hydrocarbon gases and CO/CO_2, indicating thermal stress and cellulose degradation within the insulation system. TDCG values exceeded the normal range, and both Roger's and Doernenburg's ratios pointed to low- to medium-level thermal faults rather than high-energy arcing. These findings are consistent with IEEE C57.104 and IEC 60599, which associate elevations in C_2H_4, C_2H_6, CO, and CO_2 with overheating and aging of the insulating oil and paper [5], [6]. The absence of acetylene across all measurement periods further supports the conclusion that no severe electrical discharge had occurred [16].

Unlike classical DGA methods, which produced some conflicting diagnoses at threshold boundaries, the fuzzy system generated a single, unified condition index by processing overlapping gas values through rule-based inference. This demonstrates the advantage of fuzzy logic in handling uncertainty and diagnostic ambiguities [8].

The fuzzy logic interpretation reinforces and synthesizes these observations by mapping the multi-method DGA inputs into a single condition index. Prior to purification, the fuzzy system classified the transformer oil in Condition 2, with an indication of thermal faults, cellulose degradation, and partial discharge activity. After purification, the fuzzy output shifted to Condition 1, confirming that the maintenance action successfully reduced fault-related stress and restored oil quality. This transition demonstrates the strength of the fuzzy approach in handling borderline and overlapping gas values that may cause interpretive inconsistencies in ratio-based methods alone. Rather than replacing conventional diagnostics, fuzzy logic in this context serves as an integrative layer that consolidates the results of

TDCG, Roger's Ratio, Doernenburg Ratio, and Key Gas Analysis into a practical decision-making tool.

In addition to improving oil quality, the purification process also enhanced the cooling performance of the transformer. Prior to purification, field data showed that a peak load of approximately 1,390 A on the low-voltage side resulted in a winding temperature of around 80°C, and extrapolation suggested that loading the transformer up to its nominal current of 1,732 A could have driven the temperature close to 99°C, approaching an overheating condition. After purification, the highest observed load increased to about 1,610 A while the temperature remained near 77°C. Simple proportional analysis indicated that, at the nominal current of 1,732 A, the expected temperature would be approximately 82°C, still within a safe operating margin. This comparison confirms that purification not only improves dielectric properties but also restores effective heat dissipation capability, allowing the transformer to operate closer to its rated capacity without exceeding thermal limits.

Furthermore, predictive analysis of future TDCG values was carried out using MATLAB to estimate when the next purification action might be required. By extrapolating the historical TDCG trend and using the previously observed ethane threshold (around 623 ppm) as a reference for initiating purification, the model suggests that, under similar operating conditions, the transformer oil would likely require the next purification around the year 2030. While this prediction should be validated against future operating data and periodic DGA measurements, it provides a useful planning tool for asset managers by linking diagnostic results with long-term maintenance scheduling. Overall, the integration of DGA, purification assessment, fuzzy logic interpretation, and predictive analysis offer a comprehensive framework for transformer condition monitoring and supports more informed maintenance and operational decision-making.

4. Conclusion

This study demonstrated that the integration of conventional Dissolved Gas Analysis (DGA) methods, oil purification assessment, and a fuzzy inference system provides a comprehensive and reliable framework for evaluating transformer health. The pre-purification DGA results showed elevated concentrations of key combustible gases, indicating incipient thermal faults and degradation within the insulation system. Following purification, substantial reductions in hydrocarbon gases, moisture content, and TDCG levels confirmed the effectiveness of the treatment in restoring dielectric performance. While traditional ratio-based diagnostic methods offered valuable insights, they also exhibited interpretive inconsistencies when gas values were near threshold boundaries. The fuzzy inference system successfully addressed these ambiguities by generating a unified diagnostic output that aligned with both laboratory measurements and physical transformer conditions. Overall, the combined diagnostic approach enhances early-fault detection capabilities, improves accuracy in assessing post-purification transformer health, and provides a more dependable basis for maintenance planning and asset-management decisions within high-voltage power systems.

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Author Contributions

T.H. contributed to the conception and design of the study, conducted the data collection at PLN GIS Cipinang and ULTG Cawang, performed the dissolved gas analysis (DGA), S.W. carried out the fuzzy logic interpretation using MATLAB. Both also prepared the initial draft of the manuscript, A.O.P. and R.S. contributed to the structuring of the analytical framework, refinement of the research methodology, manuscript editing, visualization development, and overall technical validation of the results. She also provided substantial guidance in transforming the original thesis into a publishable journal manuscript. All authors reviewed, revised, and approved the final version of the manuscript.

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AI Usage Policy

The authors declare that no artificial intelligence (AI) tools were used in the data analysis, interpretation, or

development of the research methodology presented in this study. All experimental procedures, dissolved gas analysis (DGA) evaluations, and diagnostic interpretations were performed manually using standard engineering methods and established computational tools.

AI-assisted tools were used only for linguistic refinement and formatting during manuscript preparation, without generating or altering any scientific content, datasets, or research conclusions. The responsibility for the accuracy and integrity of the scientific results remains entirely with the authors.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability Statement

All data that support the findings of this study are included within the article (and any supplementary files).

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