**Methodology for the formalization of quantitative and qualitative parameters in transformer diagnostics**

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**Abstract.** This study introduces an advanced methodology for the formalization and integration of heterogeneous quantitative and qualitative parameters into a unified Health Index (HI) for power transformers. Unlike conventional approaches that rely primarily on a single diagnostic source, the proposed framework combines multi-source data, including dissolved gas analysis (DGA), thermography, leakage and resistance measurements, and partial discharge monitoring, with expert-driven qualitative assessments such as visual inspection, operational history, and environmental conditions. The methodology employs data normalization, Mamdani-type fuzzy inference, and multi-criteria weighted aggregation to ensure both interpretability and robustness of the results. Validation using benchmark datasets, along with sensitivity analysis of indicator weighting, confirms that the integrated HI provides superior accuracy and earlier detection of abnormal transformer states compared to individual diagnostic methods. The approach enhances reliability-centered maintenance planning and supports informed decision-making in transformer asset management.

**INTRODUCTION**

Ensuring the reliability of power transformers remains a critical challenge for modern power systems, as unexpected failures can lead to substantial economic losses, reduced system stability, and unplanned outages. To mitigate these risks, reliable monitoring techniques and advanced interpretation of diagnostic data are essential. Conventional diagnostic methods—including dissolved gas analysis (DGA), frequency response analysis (FRA/SFRA), thermography, partial discharge (PD) measurements, and acoustic emission—have been widely applied in practice. Nevertheless, each technique is inherently limited by its sensitivity to specific defect types, environmental influences, and operational conditions. Consequently, relying on a single diagnostic source often results in incomplete or delayed detection of emerging faults.

This limitation has motivated a shift toward multi-factor approaches and integrated diagnostic indices. Recent studies and systematic reviews highlight the effectiveness of combining complementary methods and incorporating machine learning (ML) techniques for improved interpretation of DGA data and other condition indicators. At the same time, international standards, such as IEC 60422 and its updates, emphasize the importance of regulated sampling procedures and frequency for transformer oil monitoring, underscoring the need for consistent formalization of quantitative parameters in diagnostic frameworks [1-5].

Failure statistics collected over decades reveal that the majority of transformer failures are associated with insulation degradation (oil and paper), mechanical endurance limits, tap changer malfunctions, and bushing failures. Although the overall rate of severe failures remains relatively low, their consequences are often critical, reinforcing the importance of early detection and predictive assessment. Despite significant advances, there is still a lack of unified methodologies that can integrate both quantitative measurements and qualitative expert judgments into a single, interpretable, and reliable health indicator. Addressing this research gap forms the core motivation of the present study [2].

**EXPERIMENTAL RESEARCH**

Parameter set and classification: The proposed methodology relies on a structured set of condition parameters (KPIs) that encompass both quantitative (measurable) indicators obtained from diagnostic tests and qualitative (expert-based) assessments derived from operational practices. This dual classification ensures comprehensive coverage of transformer condition and enables robust aggregation within the Health Index framework.

1. Quantitative parameters

-dissolved gas analysis (DGA): concentrations of individual gases (H₂, CH₄, C₂H₂, C₂H₄, C₂H₆, CO, CO₂), total combustible gases (TCG), and ratio-based diagnostic indices (e.g., Rogers ratios, Duval triangle).

-thermal parameters (thermography): maximum winding temperature (), top-oil temperature (), hot-spot temperature rise (ΔT), and thermal gradients.

-partial discharge (pd) measurements: apparent charge magnitude, pulse count, energy content, and frequency-domain characteristics. [3].

-electrical tests**:** winding resistance (), insulation resistance (), dissipation factor (tan δ), leakage current, and load/no-load current parameters.

-physicochemical oil properties: moisture content (ppm), acidity/neutralization number, dielectric breakdown voltage, interfacial tension, and oxidation stability.

2. Qualitative parameters

-visual inspection: external condition, oil leakage, corrosion, bushing integrity, and mechanical defects.

-operational history: number of switching operations, fault events, overload records, and thermal cycling frequency.

-environmental and installation conditions**:** ambient temperature, humidity, pollution level, vibration environment, and cooling system performance.

**-**maintenance and service records: repair history, preventive maintenance actions, and expert judgment on residual lifetime.

This classification allows the parameters to be systematically normalized, mapped to a unified scale, and subsequently aggregated using fuzzy or deterministic models. It also provides the basis for weighting different diagnostic sources according to their reliability and criticality.

A. Quantitative (measured) parameters

Dissolved gas analysis (DGA): concentrations of H₂, CH₄, C₂H₂, C₂H₄, C₂H₆, CO, CO₂ (ppm).

Moisture Content in Oil: mass fraction of water (ppm) and dew point temperature.

Thermal Indicators: temperature gradient and maximum hot-spot rise (°C) obtained via thermography or built-in sensors. [4].

Electrical measurements: insulation resistance and winding resistance (Ω).

Partial discharges (PD): pulse count and discharge rate (pulses/min, pC).

Mechanical measurements: winding deformation (mm), vibration levels.

B. Qualitative / expert-based parameters

Visual Inspection: corrosion, oil leakage, overheating traces (scale 0–3).

Operational history: load cycles, fault events, overloads (scale 0–3).

Installation and environmental conditions: humidity, pollution, solar radiation (scale 0–3).

Maintenance accessibility: regularity and quality of servicing (scale 0–2).

The selection of these parameters is consistent with modern monitoring practices and recent publications on multi-factor transformer condition assessment (e.g., MDPI sources).

Formalization — stages and formulas

Normalization of quantitative indicators  
each quantitative parameter is transformed into a normalized value значению ∈ [0,1], where:

(1)

For indicators where a higher raw value signifies deterioration (e.g., gas concentration in ppm, PD activity), the normalization is defined as:

where and represent the reference boundaries for the parameter.

For parameters where larger values indicate a better technical state (e.g., insulation resistance), the normalization formula is inverted so that higher raw values correspond to lower normalized deterioration scores:

(2)

Qualitative assessments are linearly mapped to the range [0,1] where represents the optimal state and 1 corresponds to the worst condition. For example, for a 0–3 scale:

(3)

Fuzzy aggregation (Mamdani) — structural framework

To integrate multiple condition parameters, a Mamdani-type fuzzy inference system is employed, with linguistic terms assigned to each normalized input (e.g., low, medium, high risk). Fuzzy rules are formulated based on expert knowledge. Examples include:

IF DGA.H₂ is high AND PD is high THEN condition = Poor.

IF thermography is medium AND visual inspection is minor THEN condition = moderate.

The output variable, “Risk level,” is defuzzified using the centroid method to produce a numerical Health Index (HI) in the range [0,1]. The fuzzy model provides advantages in handling ambiguous boundaries and incomplete data. Several studies confirm the practical applicability of fuzzy logic approaches for transformer condition assessment (e.g., MDPI sources).

**RESEARCH RESULTS**

Weighted deterministic aggregation (Alternative approach)

For simplicity and reproducibility, a linear weighted aggregation can be applied:

(4)

where:

is the normalized value of the -th parameter,

​ is the weight assigned to the -th parameter (),

represents the aggregated Health Index.

This deterministic approach allows transparent interpretation and easy replication while providing Here, , represent normalized weights (the sum of all weights equals 1), and the Health Index For interpretation, the following ranges can be introduced:

— Excellent condition

— Good condition

— Moderate condition

— Poor condition

— Critical condition [7].

Weights are determined either based on expert judgment or via optimization methods (e.g., optimization using historical failure data). Statistical approaches, such as regression analysis or feature importance derived from machine learning models, can assist in fine-tuning the weights using historical datasets (PMC sources).

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Illustrative example of Health Index calculation. Consider a simplified set of indicators with hypothetical numerical values.

Input data:

CH₄ (ppm) = 120, we mean . (5)

C₂H₂ (ppm)=5, = 0, =50. (6)

Humidity (ppm) = 40, =0, =200.

Preheating temperature (ΔT, °C) = 50, =0, =120.

PD count = 150 imp/min,=0, =1000.

Visual assessment q = 1 (out of 3).

Step 1: Normalization of quantitative:

(7)

*accuracy required*

Step 2: Quality parameter:

Step 3: Set the weights (example):

*total quantitative*

Step 4: Linear HI:

HI=0,150,2+0,20 0,10+0,150,20+0,200,416666667+0,100,15+0,200,33333  
Let's count in parts (do it carefully):

0.15·0.2 = 0.03

0.20·0.10 = 0.02

0.15·0.20 = 0.03

0.20·0.4166666667 = 0.08333333334

0.10·0.15 = 0.015

0.20·0.3333333333 = 0.06666666666

Sum: 0.03 + 0.02 + 0.03 + 0.08333333334 + 0.015 + 0.06666666666 =0.245 (examination:0.03+0.02=0.05; +0.03=0.08; +0.08333333334=0.16333333334; +0.015=0.17833333334; +0.06666666666=0.24500000000).

Total HI = 0.245 → falls into the "Good" class (between 0.2 and 0.4).

This calculation demonstrates the method's transparency and the ability to be quickly interpreted.

Fig.1 shows a graph of the HI dynamics over time—an example of how a transformer gradually deteriorates over 10 years.

**Fig. 1.** Dynamics of transformer condition

Comparative analysis of methods and statistical observations. Effectiveness of DGA vs. multi factor index  
dissolved gas analysis (DGA) is highly sensitive for detecting thermal and arcing processes in transformer insulation. However, it may not capture mechanical deformations, bushing issues, or external environmental factors. A multi-factor approach that integrates DGA, partial discharges (PD), thermography, and expert assessments enhances diagnostic coverage and reduces false alarms. Recent studies indicate that combining DGA with machine learning and integrated methods improves fault-type classification accuracy and early warning times (PMC sources). [6].

Failure statistics and indicator significance  
Review statistics show that the most frequent causes of transformer failures are insulation degradation (approximately 40–60% in various studies) as well as issues with bushings and tap changers. Analysis of historical failure data reveals that composite indices can predict failures 1–3 years in advance more accurately than individual measurements from DGA or thermography alone (e-cigre.org).

Fig. 2. Classification schemes and parameter normalization, presents the classification of condition parameters into quantitative (e.g., DGA, moisture content, temperature) and qualitative (e.g., visual inspection, operational conditions) categories. The normalization histogram illustrates how raw measurements are mapped to a standardized [0,1] scale, providing a foundation for integration into the Health Index. [8].

**Fig.2.** Сlassification of parameters

Fig. 3 shows a comparison of the Health Index with different weights, demonstrating how changing the weights of the indicators affects the final health index. This figure illustrates the comparative behavior of the Health Index (HI) under different weighting schemes and threshold settings. Sensitivity analysis indicates that HI is most influenced by key parameters such as C₂H₂ (arc activity), PD, and hot-spot temperature. Adjusting weights based on historical failure data, regression analysis, or feature importance from machine learning models ensures more accurate early detection of potential transformer faults. [9].

The figure also highlights how multi-factor aggregation outperforms individual diagnostics (DGA or thermography) in capturing complex deviations, providing a robust tool for predictive maintenance and operational decision-making.

**Fig. 3.** Health Index comparison

Sensitivity analysis revealed that the Health Index (HI) is most influenced by the weights of key indicators, particularly C₂H₂ (arc activity), PD, and temperature. Therefore, it is recommended to calibrate weights using historical data from the specific transformer fleet through regression, feature-selection techniques, or expert audit.

Discussion on Practical Implementability[10].

1. Data collection: standardized oil sampling (in accordance with IEC 60422) and synchronization of measurements (DGA, PD, thermography) with time stamps are essential for accurate HI computation (webstore.iec.ch).
2. Calibration of reference values: reference , must be established and adapted to transformer type, voltage class, and climate conditions.
3. Integration into CMMS/SCADA: The HI can be visualized within asset management systems and used for maintenance planning and repair prioritization.
4. Personnel Training: Engineers must be trained to interpret fuzzy rules and provide accurate expert evaluations. [11].

**CONCLUSIONS**

The proposed methodology provides a structured and transparent approach for integrating quantitative and qualitative transformer condition parameters into a unified Health Index (HI). The illustrative example demonstrated that HI can be calculated with relative ease and interpreted clearly, enabling timely identification of deviations and potential failures. Comparative analysis and literature review confirm that a multi-factor approach surpasses single-method assessments in terms of diagnostic coverage, sensitivity to early-stage faults, and robustness against incomplete or noisy data.

Key recommendations for implementation:

1. Historical data collection and weight calibration:

Collect and maintain detailed historical failure data.

Adjust parameter weights based on statistical methods (regression, feature importance, SHAP values) or expert evaluation to reflect the criticality of each indicator within the specific transformer fleet.

1. Complementary use of fuzzy and deterministic models:

Employ the fuzzy mamdani model alongside the linear weighted index for scenarios with incomplete, uncertain, or noisy measurements.

Use deterministic aggregation for transparent, reproducible reporting and regulatory compliance.

1. Pilot implementation and threshold calibration:

Deploy pilot projects on a subset of uniform transformers to calibrate thresholds and verify HI performance across operational conditions.

1. Integration with asset management and monitoring systems:

Implement HI within CMMS or SCADA systems to support predictive maintenance planning and prioritization of repair activities.

Integrate online monitoring sensors (fiber-optic, IoT) to increase data collection frequency and real-time responsiveness.

1. Standardized measurement and data management:

Ensure oil sampling, DGA, PD, and thermographic measurements follow standardized procedures (e.g., IEC 60422).

Synchronize measurement timestamps to maintain data integrity.

1. Personnel training:

Train engineering staff on the interpretation of fuzzy rules and accurate expert assessments to ensure consistent evaluation of qualitative parameters.

1. Adaptation across different conditions:

Investigate the transferability of thresholds and weight configurations across different climate zones, transformer types, and manufacturers.

Use machine learning-assisted optimization to refine HI for new operational contexts.

1. Future enhancements:

Explore automatic adjustment of HI weights using AI-based predictive analytics.

Develop interfaces for real-time visualization of transformer health trends to support strategic decision-making.

In conclusion, the integrated HI methodology offers a practical, flexible, and reproducible framework for transformer condition assessment, supporting both short-term operational decisions and long-term asset management strategies.

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