



AI Based Fault Detection In Power Transformer

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Abstract: Power transformers are vital components of electrical power systems, and their failure can result in serious economic losses and power interruptions. Conventional fault detection techniques, such as differential protection and threshold-based dissolved gas analysis (DGA), often fail to identify incipient and complex faults at an early stage. This work presents an **Artificial Intelligence (AI)-based fault detection approach** for power transformers to enhance reliability and operational safety. The proposed method employs machine learning and deep learning techniques to analyze transformer condition data, including dissolved gas concentrations, temperature variations, and electrical parameters. After data preprocessing and feature extraction, AI models are trained to detect and classify different electrical, thermal, and mechanical faults accurately. Compared to traditional methods, the AI-based system provides improved fault detection accuracy, early warning capability, and reduced false alarms. This approach supports predictive maintenance, minimizes downtime, and extends transformer service life, making it suitable for modern smart grid and condition monitoring applications.

Index Terms –AI fault detection, power transformer, Condition Monitoring, Predictive maintenance.

INTRODUCTION

Power transformers are among the most critical and expensive components in electrical power systems, playing a vital role in power generation, transmission, and distribution networks. Their reliable operation is essential to ensure uninterrupted power supply and system stability. Transformer failures can lead to prolonged outages, equipment damage, fire hazards, and significant economic losses. Therefore, effective fault detection and condition monitoring techniques are necessary to maintain transformer health and enhance operational reliability.

Conventional transformer protection and diagnostic methods, such as differential protection, Buchholz relays, and threshold-based dissolved gas analysis (DGA), are widely used in practice. Although these methods are effective in detecting severe faults, they often fail to identify incipient and evolving faults at an early stage due to their dependence on fixed rules and predefined limits. Additionally, the increasing complexity of modern power systems and variable operating conditions reduce the accuracy of traditional approaches.

Recent advancements in Artificial Intelligence (AI) have opened new possibilities for transformer fault detection and condition assessment. AI-based techniques, including machine learning and deep learning algorithms, can analyze large volumes of operational data and identify complex, nonlinear relationships among fault parameters. By enabling early fault detection and accurate fault classification, AI-based methods support predictive maintenance strategies, reduce downtime, and extend transformer service life. This paper focuses on the application of AI techniques for efficient fault detection in power transformers.

I. LITERATURE REVIEW

Transformer condition monitoring and fault detection have been the subjects of extensive research over the last few decades due to their critical role in power systems. Traditional diagnostic approaches, such as Dissolved Gas Analysis (DGA), partial discharge monitoring, thermal monitoring, and protection relays, have been widely employed. IEC standards and diagnostic codes (e.g., Duval Triangle, Rogers Ratio Method) provide guidelines for interpreting DGA results; however, these rule-based methods often fail to detect early and complex faults in real-world operating conditions due to fixed thresholds and simplistic correlations among fault gases.

With the advancement of data-driven techniques, researchers have turned to Artificial Intelligence (AI) and Machine Learning (ML) to enhance fault detection accuracy. **Artificial Neural Networks (ANN)** have been used for classifying transformer faults based on DGA data, demonstrating higher accuracy compared to conventional methods (Ghorbani et al., 2010). Similarly, **Support Vector Machines (SVMs)** have been investigated for pattern recognition in gas concentration datasets, yielding promising results in differentiating fault types.

Hybrid models combining ML algorithms with optimization techniques have also shown improvements. For instance, **Genetic Algorithm (GA)-based feature selection coupled with SVM** enhances classification performance by selecting the most relevant fault indicators. Recent studies have explored **Deep Learning (DL)** architectures such as **Convolutional Neural Networks (CNN)** and **Long Short-Term Memory (LSTM)** networks for time-series analysis of transformer data, enabling robust detection of thermal and electrical abnormalities.

Fuzzy logic approaches and expert systems have been proposed to handle uncertainties inherent in transformer operating conditions. Fuzzy-based DGA interpretation and neuro-fuzzy systems provide flexible decision boundaries and greater resilience to noisy inputs.

Despite these advancements, challenges remain, such as the requirement for extensive labeled datasets, imbalanced fault categories, and the need for real-time implementation in smart grid environments. Recent research emphasizes hybrid AI frameworks, integration of multi-sensor data (temperature, vibration, acoustic, electrical), and the development of explainable AI (XAI) models to improve interpretability and operational acceptance.

II. PROBLEM STATEMENT

Power transformers are critical and high-value components of electrical power systems, and their failure can lead to severe economic losses, prolonged power outages, and safety hazards. Conventional transformer fault detection and protection techniques, such as differential relays, Buchholz relays, and rule-based dissolved gas analysis (DGA) methods, are primarily designed to detect severe faults and often fail to identify incipient or slowly developing faults at an early stage. These traditional approaches rely on fixed thresholds and predefined rules, which limits their accuracy under varying operating conditions and complex fault scenarios.

With the increasing integration of smart grids and real-time monitoring systems, large volumes of transformer operational data are being generated. However, the effective utilization of this data for accurate and early fault diagnosis remains a significant challenge. Existing methods lack adaptability, predictive capability, and robustness to noise and uncertainty. Therefore, there is a need for an intelligent, data-driven fault detection system that can analyze transformer condition data in real time, accurately detect and classify different fault types, and support predictive maintenance to enhance transformer reliability and service life.

III. OBJECTIVES

The primary objectives of this work are as follows:

- To study conventional transformer fault detection and condition monitoring techniques and identify their limitations in detecting incipient faults.
- To develop an Artificial Intelligence (AI)-based fault detection model for power transformers using operational and condition monitoring data.
- To preprocess and extract relevant features from transformer data such as dissolved gas concentrations, temperature, and electrical parameters.
- To train and evaluate machine learning and deep learning algorithms for accurate fault detection and classification.
- To compare the performance of the proposed AI-based approach with traditional diagnostic methods in terms of accuracy and reliability.
- To enable early fault detection and predictive maintenance, thereby reducing transformer downtime and extending service life.

IV. METHODOLOGY

A. Types of Transformer Faults:

Transformer faults can be broadly classified as:

Electrical Faults

- i. Inter-turn winding fault
- ii. Phase-to-phase fault
- iii. Phase-to-ground fault
- iv. Core insulation failure

Thermal Faults

- I. Hot spots
- II. Overloading
- III. Cooling system failure

Mechanical Faults

- i. Winding displacement
- ii. Core deformation

B. Conventional Fault Detection Techniques (Limitations)

Method	Limitation
Differential Protection	Cannot detect incipient faults
Buchholz Relay	Works only for oil-filled transformers
DGA Threshold Method	Depends on fixed gas limits
Periodic Testing	Not real-time

AI overcomes these limitations through adaptive learning and prediction.

C. AI techniques used for transformer fault detection

● Machine learning(ML)

1. Support Vector Machine(SVM)- fault classification
2. Random Forest(RF)- Decision based diagnosis
3. K-nearest Neighbor (k-NN)- pattern matching

● Deep Learning(DL)

- i. Artificial Neural Networks(ANN)
- ii. Convolution Neural Networks (CNN)- image based thermal fault detection
- iii. Long Short-Term Memory(LSTM)-time-series sensor data analysis

● Hybrid AI Models

- a. ANN+ Fuzzy Logic
- b. Genetic Algorithm(GA) +SVM
- c. PSO-optimised Neural Networks

D. AI-Based Fault Detection Methodology(Step by Step Process)

1. Data Acquisition:

- i. Dissolved Gas Analysis(DGA)
- ii. Temperature Sensors
- iii. Current and Voltage Signals
- iv. Acoustic emission data

2. Data Pre-Processing

- a. Noise Filtering
- b. Normalization
- c. Feature extraction (FFT, Wavelet Transform)

3. Feature Selection

- a) Gas ratios (H_2 , CH_4 , C_2H_2)
- b) Temperature Rise
- c) Harmonic Components

4. AI Model Training

- Supervised Learning using labeled fault data
- Training-validation-testingsplit

5. Fault Detection and Classification

- Healthy/incipient/severe fault
- Fault type identification

6. Decision and Alarm Generation

- Early Warning
- Maintenance recommendation

V. SYSTEM ARCHITECTURE

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Sensors → Data Acquisition Unit → Preprocessing Module
    → AI Model (ANN / SVM / LSTM)
    → Fault Diagnosis & Classification
    → Alarm / SCADA / Maintenance System
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VI. ROLE OF DISSOLVED GAS ANALYSIS (DGA) WITH AI

AI enhances DGA by:

- Learning non-linear gas relationships
- Avoiding fixed threshold limitations
- Predicting future fault severity

Common AI-based DGA methods:

- ANN based DGA
- Fuzzy-logic DGA
- Deep learning based gas pattern recognition

VII. ADVANTAGES OF AI BASED FAULT DETECTION

- Early fault detection
- Reduced false alarms
- Predictive maintenance
- Improved transformer life
- Real-time monitoring
- Reduced down time and cost

VIII. CHALLENGES

- Requirement of large labeled datasets
- Model Interpretability
- Data Imbalance
- Cybersecurity concerns in smart substations

IX. APPLICATIONS

- Smart Substations
- Condition based maintenance(CBM)
- Utility-scale transformers
- Industrial power systems
- Renewable energy integration

X. FUTURE SCOPE

- Digital Twin of Transformers
- Explainable AI (XAI)
- Edge-AI-based monitoring
- AI-driven self-healing power systems

CONCLUSION

AI-based fault detection significantly enhances the reliability and safety of power transformers. By integrating AI with real-time sensor data and traditional protection systems, utilities can shift from **reactive maintenance to predictive maintenance**, ensuring uninterrupted power supply and extended transformer lifespan.

REFERENCES

- [1] M. Duval, "A review of faults detectable by gas-in-oil analysis in transformers," *IEEE Electrical Insulation Magazine*, vol. 18, no. 3, pp. 8–17, May–June 2002.
- [2] T. K. Saha, "Review of modern diagnostic techniques for assessing insulation condition in aged transformers," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 10, no. 5, pp. 903–917, Oct. 2003.
- [3] A. Abu-Siada and S. Islam, "A new approach to identify power transformer criticality using dissolved gas analysis," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 19, no. 3, pp. 1007–1012, June 2012.
- [4] J. R. Macedo et al., "Artificial neural networks for fault diagnosis in power transformers using dissolved gas analysis," *Electric Power Systems Research*, vol. 81, no. 7, pp. 1442–1449, July 2011.

