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Transformer Fault Detection System Based On Vibration Pattern Using ML

Vineeth VV[1], Rejiv Elshan Nify J[2], Rathika P[3], Sharath k[4], Suriya Prasath NS[5]

[1]Assistant professor
[1,2,3,4,5]Department of EEE
Sri Krishna college of engineering and technology
Coimbatore,India
[1]vineethvv@skcet.ac.in, [2]rejivelshannify@gmail.com, [3]rathikp0311@gmail.com, [4]smartsharath10@gmail.com, [5]Suriya.ns1206@gmail.com

Abstract

The project focuses on transformer fault detection by integrating vibration, current, and voltage sensors. Utilizing machine learning techniques, specifically K-Nearest Neighbors (KNN) and Random Forest algorithms, the system aims to identify and classify various faults such as short circuit, overvoltage, undervoltage, and high vibration. The sensors provide real-time data, which is used to train the models for accurate fault prediction. KNN leverages proximity-based classification, while Random Forest utilizes an ensemble of decision trees to enhance accuracy. The trained models enable quick and precise identification of transformer faults, contributing to early detection and prevention of potential damage. This integrated approach harnesses the power of machine learning to improve the reliability and efficiency of transformer systems in power distribution networks.

Keywords—Transformer Fault Detection, Machine Learning Analysis, Edge Computing, Real-Time Monitoring, Proactive Maintenance

1. INTRODUCTION

The power grid infrastructure plays a pivotal role in ensuring the seamless distribution of electricity, and transformers are integral components in this network. However, transformers are susceptible to various faults that can lead to operational inefficiencies, downtimes, and even catastrophic failures. Timely detection of these faults is crucial for maintaining the reliability and performance of power distribution systems. This project introduces an innovative approach to transformer fault detection by integrating vibration, current, and voltage sensors with machine learning algorithms, specifically **K-Nearest Neighbors (KNN) and Random Forest.**

OBJECTIVES

The primary goal of this project is to design and implement a reliable and efficient transformer fault detection system using machine learning algorithms.

The Specific Objectives Include:

Data Collection and Integration: Gather data from vibration, current, and voltage sensors installed on the transformer to create a comprehensive dataset. Integrate this data for a holistic view of the transformer's operational parameters.

Feature Engineering: Extract relevant features from the sensor data to provide meaningful input for the machine learning algorithms. Feature engineering is crucial for enhancing the models' ability to discern patterns indicative of different faults.

Algorithm Selection: Evaluate and choose suitable machine learning algorithms for fault detection. KNN is employed for its simplicity and efficiency in proximity-based classification, while Random Forest is chosen for its ability to handle complex datasets through an ensemble of decision trees.

Training and Validation: Train the machine learning models using historical data and validate their performance to ensure accurate fault classification. This involves refining the models to achieve optimal results in detecting short circuits, overvoltage, undervoltage, and high vibration faults

Real-time Implementation: Implement the trained models in a real-time monitoring system connected to the transformer. This integration allows the system to continuously assess the transformer's condition and promptly identifying any emerging faults.

2. LITERATURE SURVEY

The study on transformer fault detection via Frequency Response Analysis (FRA) explores how transformer faults can be promptly identified and mitigated to prevent serious damage to power systems. By comparing the frequency response of healthy and faulty transformers, FRA aids in identifying fault type, severity, and location. Advanced methods are proposed to address limitations in traditional FRA, making it a more comprehensive diagnostic tool. The paper concludes with suggestions for further research in this area [1].

In a paper on transformer fault on-line diagnosis, a system based on multi-source information fusion is developed to improve fault detection in mine transformers exposed to interference. LabVIEW is used as a platform for feature extraction and neural network- based diagnosis, ensuring high accuracy, real-time monitoring, and stability. This system caters to the unique needs of coal mines, enhancing transformer reliability. The solution is robust and meets operational demands in harsh environments [2].

Another study employs Rough Set Theory and Support Vector Machine (SVM) to improve power transformer fault diagnosis. These methods address uncertainties in transformer fault data, providing more accurate results than traditional approaches like neural networks. By using rough set theory, the amount of fault data required is reduced, improving efficiency and diagnostic precision. This model enhances the reliability of the power system [3].

Dissolved Gas Analysis (DGA) is a chemical tool for diagnosing incipient transformer faults through the detection of gas decomposition in transformer oil. Early detection of such gases helps identify developing faults before they become severe. Data from over 5000 transformers show that one in four transformers has an operational fault, proving the method's effectiveness. DGA has become a critical tool for power engineers over three years of practical application [4].

A study on winding fault models in transformers presents a method compatible with EMTP software for simulating internal faults. The model allows for accurate fault simulation between turns or between a turn and the earth. The method simplifies the evaluation of leakage factors between transformer coils, contributing to accurate fault modeling. Experimental validation confirms the model's accuracy in real-world applications [5].

EXISTING SYSTEM

Oil-Dissolved Gas Analysis (DGA):

Disadvantages:

- Late detection: It requires frequent sampling of oil, which delays a fault sighting.
- Subjective interpretation: The interpretation pertaining to gas-in-oil ratios would be subjective and often expertise-based.
- Environmental implication: Oil sampling and analysis has environmental implications.

Dissolved Gas Relay (DGR):

Disadvantages:

- Limited sensitivity: May not detect minor faults in their early stages.
- Calibration: It is not easy to calibrate and for accurate operation.
- Low-diagnostic capability: Gives less information about the nature and exact location of the fault.

Monitoring Temperature:

Disadvantages:

- Only for thermal faults: It cannot detect faults of other types, like internal flashover or insulation breakdown.
- Less emphasis on diagnostic information: Gives information about temperature and not about the cause of the fault.

Partial Discharge (PD) Monitoring:

Disadvantages:

- High Initial Investment Costs: Requires specific equipment and experience to be installed and analyzed in place.
- Susceptibility to noise interference: External electrical noise normally always crosses PD measurements.

PROPOSED SYSTEM

This innovative transformer fault detection system utilizes a combination of sensors (gyroscope, voltage, and current) and advanced Machine Learning (ML) techniques to proactively identify potential issues.

The system employs the K-Nearest Neighbors (KNN) algorithm for accurate fault classification. Built upon a cost-effective foundation of Arduino (NodeMCU) and IoT integration, it enables real-time monitoring, remote access, and on-site feedback through an LCD display. GPS integration facilitates precise location tracking of faulty transformers. Python-based data analysis provides valuable insights for continuous model improvement. This system offers a reliable and efficient solution for ensuring the safe and reliable operation of power transformers.

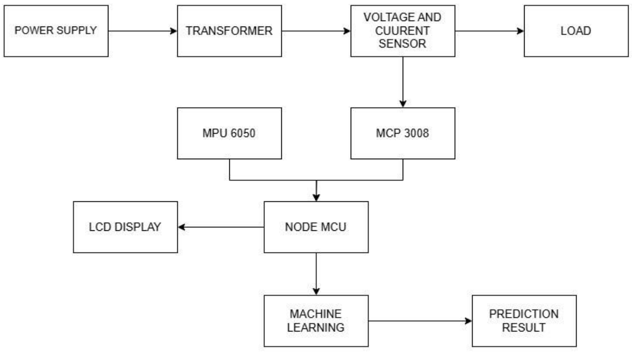

Figure 1: Block Diagram

BLOCK DIAGRAM DESCRIPTION

The block diagram illustrates the architecture of a transformer fault detection system that integrates vibration analysis with machine learning. The system begins with a power supply unit, which provides the necessary energy to the transformer. The transformer, the core component, is monitored for vibrations using an MPU6050 gyroscope sensor. Simultaneously, voltage and current sensors (MCP3008) measure the electrical parameters of the transformer. These sensor readings are then transmitted to a NodeMCU microcontroller, which acts as the central processing unit of the system. The NodeMCU processes the data and communicates with an LCD display, providing real-time information about the transformer's condition. Additionally, the NodeMCU transmits the data to a computer for further analysis. The computer utilizes machine learning algorithms to analyze the collected data, identify patterns associated with different fault types (e.g., short circuits, overloads, overheating), and generate predictions about the transformer's health. The results of the machine learning analysis are then displayed, providing insights into the transformer's condition and potential risks.

HARDWARE SETUP

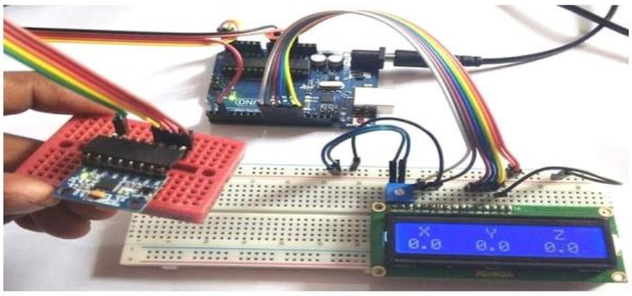

Figure 2. HARDWARE SETUP

HARDWARE DESCRIPTION

The hardware architecture of this transformer fault detection system revolves around a sensor module integrated with a gyroscope, tasked with continuously monitoring vibrations emanating from the transformer. These vibration signals are crucial inputs for the fault detection module, which leverages the power of machine learning, specifically the K-Nearest Neighbors (KNN) algorithm. This algorithm is designed to autonomously identify and categorize various fault conditions, including short circuits, overloads, and mechanical issues. At the heart of the system lies the NodeMCU microcontroller, acting as the central processing unit. It interfaces with the gyroscope sensor, collects the vibration data, and manages the integration of fault detection results. Facilitating real-time data exchange, the IoT module enables seamless communication between the NodeMCU and a dedicated computer. This computer serves as the platform for in- depth data analysis, employing the KNN algorithm within a Python environment to scrutinize the vibration data, identify anomalies, and predict potential faults. The system also incorporates an on-site LCD display, controlled by the NodeMCU, to provide real-time feedback on the transformer's condition, enabling prompt responses to any detected issues. This integrated approach, combining vibration sensing, machine learning, and real-time communication, enables proactive and efficient fault detection, ultimately enhancing the reliability and lifespan of the transformer

3. MACHINE LEARNING OVERVIEW

Machine learning algorithms play a pivotal role in the fault detection system by analyzing vibration, current, and voltage data from transformers. The dataset consists of 300 samples collected from a 2V 5A transformer operating under various conditions, including resistive and inductive loads. The K-Nearest Neighbors (KNN) algorithm is employed for its simplicity and effectiveness in classifying faults based on proximity, making it well-suited for smaller datasets. To enhance accuracy and manage data complexity, the Random Forest algorithm is also utilized, leveraging its ensemble of decision trees for robust fault classification.

These models are trained to detect fault patterns such as short circuits, overvoltage, undervoltage, and excessive vibrations, enabling the system to provide real-time fault detection with high precision. By integrating these algorithms, the system ensures reliable monitoring, early fault identification, and timely preventive measures to maintain transformer health and operational efficiency.

A. DATA ACQUISITION MONITORING AND MAINTENANCE WORKFLOW

The transformer fault detection system integrates sensor technology, edge computing, and machine learning to ensure reliable operation and proactive maintenance. The stages of the workflow, as illustrated in the flowchart, are explained in detail below.

This workflow ensures efficient, reliable, and proactive transformer monitoring and maintenance. By integrating sensor technology, edge computing, and machine learning, the system achieves real-time fault detection, classification, and prediction. The use of tools like Seaborn and confusion matrices enhances data visualization and model evaluation, providing engineers with actionable insights. This comprehensive approach reduces downtime, improves grid reliability, and sets a new standard for intelligent maintenance systems.

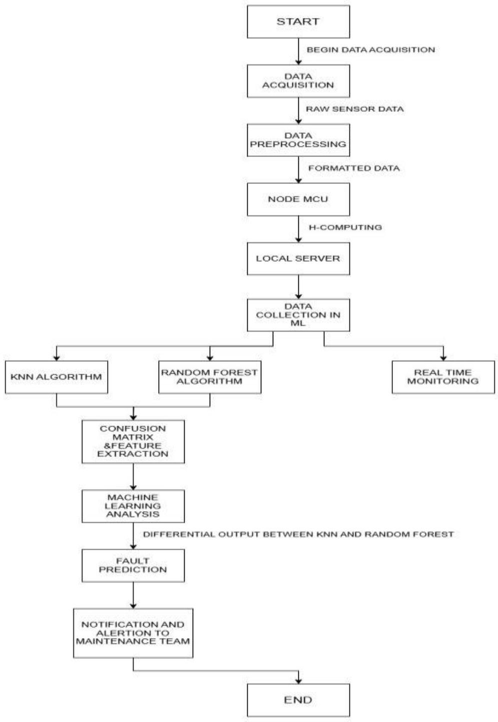

Figure 3. ML MODEL WORKFLOW

THE DETAILED WORKFLOW OF THE MACHINE LEARNING MODEL GOES AS FOLLOWS:

1. Data Acquisition

The process begins with collecting real-time data from sensors deployed on transformers.

The primary sensors used are:

MPU6050 Gyroscope: Monitors vibration levels to detect mechanical abnormalities.

MCP3008 Sensors: Measure electrical parameters like voltage and current to assess transformer health.

These sensors provide raw, real-time data, including vibration signals and electrical metrics, which serve as the foundation for fault detection.

2. Data Preprocessing

Raw sensor data is often noisy and inconsistent, necessitating preprocessing to enhance its quality and usability:

Noise Filtering: Removes irrelevant data artifacts.

Scaling: Ensures uniformity in measurements across different sensors.

Formatting: Structures the data for seamless transmission and machine learning processing.

For instance, vibration data is normalized to detect deviations effectively, and electrical signals are formatted to eliminate baseline shifts.

3. NodeMCU and Edge Computing

The processed data is transmitted to the NodeMCU microcontroller, which performs edge computing tasks. These tasks include aggregating the data and executing preliminary computations before forwarding it to the local server. This step minimizes server workload and enables efficient real-time data handling.

4. Data Storage on Local Server

The NodeMCU sends the preprocessed data to a local server. The server acts as a central repository for all collected data, facilitating the following:

Long-term data analysis.

Real-time monitoring integration.

Smooth data flow to machine learning algorithms.

This storage system bridges the acquisition process and machine learning stages, creating a cohesive monitoring pipeline

5. Machine Learning Workflow

The machine learning component leverages historical and real-time data to classify and predict faults. The following steps detail this process:

Feature Extraction:

Using Seaborn visualizations, key features like voltage variations, current spikes, and vibration anomalies are identified. These features enhance the model's ability to differentiate between fault types.

Algorithms:

Two machine learning models, K-Nearest Neighbors (KNN) and Random Forest, are employed:

KNN helps classify faults based on similarity to known patterns.

Random Forest increases robustness and provides ensemble-based predictions.

Evaluation:

A Confusion Matrix is used to evaluate each algorithm’s performance. Metrics like precision, recall, and accuracy are analyzed to compare model effectiveness.

6. Real-Time Monitoring

The trained models are deployed for live transformer monitoring. Detected faults are classified in real time, with results displayed on an LCD screen connected to the NodeMCU. The local server logs fault data continuously for future analysis.

7. Fault Prediction and Maintenance

When a fault is detected, the system triggers a fault prediction module, providing detailed classification. Notifications and alerts are sent to the maintenance team through integrated messaging systems. This ensures timely action to mitigate transformer risks.

8. Comparative Analysis and Continuous Improvement

The output from both KNN and Random Forest models is compared to improve fault detection accuracy. Differences in their predictions guide refinements in the models. Seaborn is used to visualize trends, identify anomalies, and adjust features as required.

4. SIMULATION

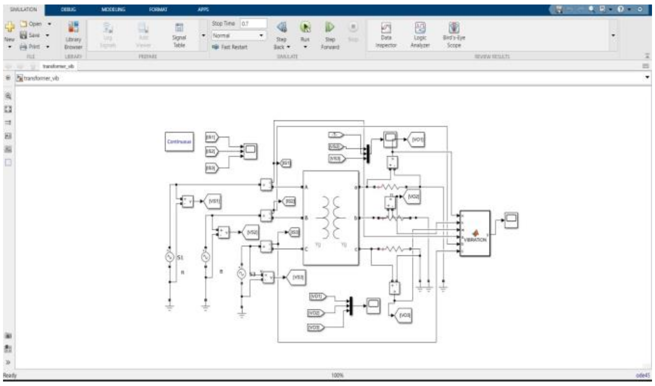

Figure 3. SIMULATION

A. SIMULATION DESCRIPTION

This MATLAB simulation model provides a virtual representation of the transformer fault detection system. The model incorporates key components and functionalities of the real-world system, allowing for testing and analysis of the system's behaviour under various conditions.

KEY COMPONENTS AND FUNCTIONALITIES:

Transformer Model:

The core of the simulation is the transformer model, which simulates the electrical and mechanical behavior of a real transformer. This model likely incorporates parameters such as winding resistances, inductances, and core losses to accurately represent the transformer's characteristics.

Vibration Source: To simulate the vibrations generated by the transformer, a vibration source block is likely included. This block could generate synthetic vibration signals based on predefined patterns or models, or it could be configured to read vibration data from external sources, such as recorded measurements from a real transformer.

Sensor Model: The simulation includes a sensor model to emulate the behavior of the gyroscope sensor used in the real system. This model simulates the sensor's response to the vibrations generated by the transformer, producing output signals that represent the measured vibration data.

Data Acquisition and Processing: The simulation incorporates blocks to simulate the data acquisition and processing steps performed by the NodeMCU microcontroller. These blocks would likely include signal conditioning, filtering, and data conversion to prepare the vibration data for further analysis.

Fault Detection and Classification: The simulation includes logic and decision-making blocks to interpret the predictions from the machine learning model and classify the detected faults. These blocks would generate alerts or trigger specific actions based on the identified fault conditions.

Visualization and Analysis: The simulation includes blocks for visualizing the simulation results, such as plots of vibration signals, fault classifications, and system performance metrics. These visualization tools enable the user to analyze the simulation results, assess the accuracy of the fault detection system, and identify areas for improvement

5. RESULTS AND CONCLUSION

Overall, the project presents a promising approach to transformer fault detection using vibration analysis and machine learning (ML). The integration of vibration sensors, data acquisition, and ML techniques offers a potential solution for early fault detection and prevention of catastrophic failures in transformers.

Key Strengths of the Project:

Comprehensive Approach: The project considers multiple aspects of fault detection, including data collection, feature engineering, algorithm selection, and real-time implementation.

Integration of ML: The use of ML algorithms like K-Nearest Neighbors (KNN) and Random Forest allows for automated and accurate fault classification.

Focus on Vibration Analysis: Vibration analysis provides valuable insights into the mechanical condition of the transformer, which can complement other diagnostic methods.

Simulation and Validation: The MATLAB simulation model provides a valuable tool for testing and validating the proposed system before deployment.

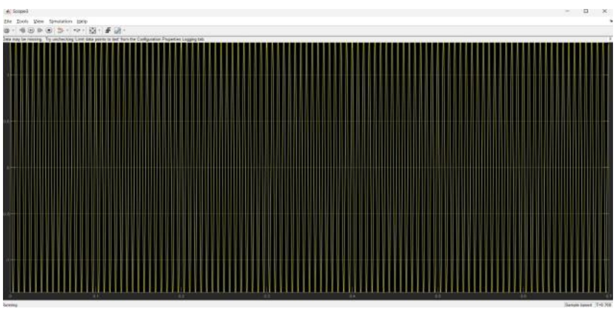

Figure 4. UNDER NORMAL CONDITION

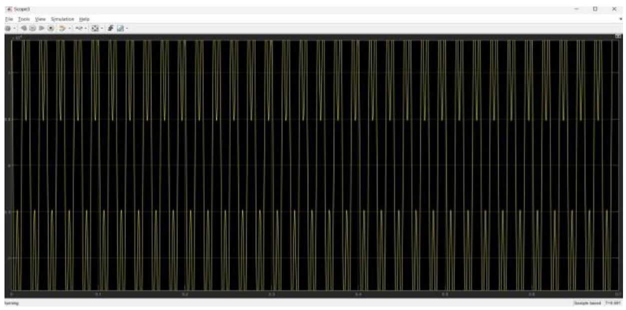

Figure 5. UNDER FAULT CONDITION

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