

# AI-Based Acoustic Emission Monitoring System for Transformer Fault Detection

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**Abstract**—Power transformers are critical components in electrical power systems, and their unexpected failure can lead to major power outages and economic losses. Conventional transformer monitoring techniques such as Dissolved Gas Analysis (DGA) and infrared thermography are costly and mostly offline. This paper presents the design and implementation of an AI-based acoustic emission monitoring system for transformer fault detection using an ESP32 microcontroller. The system utilizes a non-contact MEMS microphone for acoustic signal acquisition, a vibration sensor for mechanical disturbance detection, and environmental sensors for monitoring temperature and humidity conditions. Signal processing techniques such as Root Mean Square (RMS) and Zero Crossing Rate (ZCR) are used for feature extraction, and machine learning algorithms classify faults into electrical, mechanical, or normal conditions. The proposed system enables real-time monitoring, IoT-based visualization, and early fault warning, thereby improving transformer reliability and reducing maintenance costs.

**Index Terms**—Acoustic Emission, Transformer Fault Detection, ESP32, IoT Monitoring, Machine Learning

## I. INTRODUCTION

Power transformers play a vital role in power transmission and distribution networks. Continuous operation under electrical, thermal, and mechanical stresses may lead to insulation degradation, winding displacement, or partial discharges, which can ultimately cause catastrophic failures. Early fault detection is therefore essential for ensuring uninterrupted power supply and system reliability. Traditional monitoring techniques require periodic inspection and expensive equipment, making them unsuitable for real-time fault diagnosis in remote substations. Acoustic Emission (AE) monitoring has emerged as a promising non-invasive technique that detects high-frequency elastic waves generated due to

internal transformer faults. By analyzing these acoustic signals, early fault prediction can be achieved without interrupting transformer operation.

This paper proposes a low-cost, ESP32-based acoustic emission monitoring system integrated with IoT connectivity and machine learning algorithms for intelligent transformer health monitoring

## II. PROCEDURE FOR PAPER SUBMISSION

### A. Review Stage

Submit your manuscript electronically for review. Prepare it in two-column format, including figures and tables (until it doesn't fit properly and data is not visible).

### B. Final Stage

After your paper has been accepted. The authors of the accepted manuscripts will be given a copyright form and the form should accompany your final submission.

## III. MATH

Acoustic emission monitoring system, statistical signal processing techniques are used to extract meaningful features from the captured sound signals. These features help in distinguishing between normal operating conditions and fault conditions in power transformers.

### A. Root Mean Square (RMS) Analysis

The Root Mean Square value represents the effective energy content of the acoustic signal. Mechanical faults such as core vibration or winding displacement generally produce signals with higher amplitude, resulting in increased RMS values.

$$x_{rms} = \sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2}$$

Where:

- $x_i$ = sampled acoustic signal
- $N$ = total number of samples

A higher RMS value indicates increased mechanical stress or abnormal vibration inside the transformer.

### B. Zero Crossing Rate (ZCR)

Zero Crossing Rate measures how frequently the acoustic signal waveform crosses the zero-amplitude axis. Electrical faults such as partial discharge and arcing produce high-frequency acoustic emissions, which result in higher ZCR values.

$$ZCR = \frac{1}{N-1} \sum_{i=1}^{N-1} |\text{sign}(x_i) - \text{sign}(x_{i+1})|$$

Where:

- $\text{sign}(x)$  represents the polarity of the signal sample
- An increase in ZCR indicates the presence of high-frequency components associated with electrical faults.

### C. Fault Classification Logic

Based on experimental observations, transformer faults can be classified as:

- Mechanical Fault: High RMS and Low ZCR
- Electrical Fault: Low RMS and High ZCR
- Normal Condition: Moderate RMS and Moderate ZCR

These mathematical features are further processed using machine learning algorithms for accurate real-time fault detection.

## IV. UNITS

All physical quantities used in the proposed transformer monitoring system are expressed in standard International System of Units (SI units) to maintain uniformity and clarity in technical presentation. The use of SI units ensures consistency in data interpretation and comparison with other research works. The acoustic signal amplitude captured from the MEMS microphone is represented in volts (V) after analog-to-digital conversion. Signal energy features such as Root Mean Square (RMS) are also expressed in volts. Frequency components of acoustic emissions associated with electrical faults are

measured in hertz (Hz). Environmental parameters such as temperature and humidity are measured in degree Celsius (°C) and percentage (%) respectively. Vibration intensity detected using the vibration sensor is represented in g-force (g) or as a logical digital state indicating the presence of mechanical disturbance. Communication parameters such as transmission range are expressed in meters (m) or kilometers (km) depending on the LoRa communication environment. Power consumption of the monitoring system is represented in watts (W), while supply voltage levels are indicated in volts (V).

## V. HELPFUL HINTS

### A. Figures and Tables

The dashboard is divided into several sections:

- PARAMETER TABLE:** Lists various parameters with their current values and notes.
 

PARAMETER	VALUE	NOTES
Primary split	RMS threshold	RMS < 0.25 → Mechanical, RMS > 0.25 → Electrical
RMS split value	0.25	Root-mean-square amplitude
Mech score formula	500 * RMS + 400 * ZCR	mechanical + rms > 0.25, vibration + vib > 100
Elec score formula	RMS * ZCR	mechanical + rms < 0.50, electrical signals are louder
Warning threshold	1.485	Fault index > 40 → WARNING state
Critical threshold	1.765	Fault index > 70 → CRITICAL state
BEARING zone	ZCR > 0.001	> 400 Hz: bearing wear, gear mesh harmonics
CORE_LOOSE zone	ZCR < 0.001 + vib > 200	80-400 Hz: strong physical vibration
FAN_IMBALANCE zone	ZCR < 0.001 + vib < 200	80-400 Hz: mostly acoustic hum, weak shake
CORONA zone	ZCR < 12 * RMS + spectral < 0.05	> 4 kHz: partial discharge, steady hiss
ARCING zone	ZCR > 12 * RMS OR spectral > 0.05	> 4 kHz: cracking, insulation breakdown
- SYSTEM OVERVIEW:**

PARAMETER	VALUE	NOTES
Project	Transformer-Guard-AI	Non-contact acoustic emission fault detection
Architecture	2-node wireless	Transmitter (sensor node) + Receiver (base station) via LoRa
Microcontroller	ESP32 v2	XTensa LX6 dual-core, 240 MHz, 3.3 V I/O
Wireless link	LoRa SX1278 - 433 MHz	SF9, BW 125 KHz, CR 4/5, TX 17 dBm
Transmission interval	2000 ms	One LoRa packet every 2 s
LoRa link timeout	10 000 ms	No packet in 10 s → link lost alarm
Power (transmitter)	18550 Li-Ion	TP4056 charge controller, USB-C charge
- SENSOR STATUS:**
  - MEMS Mic (INMP441):** Connected (20kHz-20kHz; Tx 44100Hz)
  - DHT11 Temp/Humidity:** Connected T=29.0°C H=54%
  - SW-420 Vibration:** Connected
  - LoRa Link:** Linked RSSI: -121 dB
  - MicroSD (HSPI bus):** Logging - /fault\_log.csv (HSPI bus)
  - WiFi / Dashboard:** AP Mode: 192.168.4.1



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### C. Abbreviations and Acronyms

AE – Acoustic Emission AI – Artificial Intelligence  
 ESP32 – Espressif 32-bit Microcontroller IoT – Internet of Things  
 RMS – Root Mean Square ZCR – Zero Crossing Rate  
 PD – Partial Discharge  
 CNN – Convolutional Neural Network RF – Random Forest  
 OLED – Organic Light Emitting Diode  
 LoRa – Long Range Communication Technology SD – Secure Digital (Memory Card)  
 ADC – Analog to Digital Converter SI – International System of Units AC – Alternating Current  
 DC – Direct Current

### D. Equations

Mathematical equations play an important role in analyzing the acoustic emission signals obtained from the transformer monitoring system. Equations must be written using the equation editor and numbered consecutively with the equation numbers enclosed in parentheses and aligned with the right margin.

The Root Mean Square (RMS) value is used to determine the effective amplitude of the acoustic signal and is given by

$$x_{\text{RMS}} = \sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2} \quad (1)$$

where  $x_i$  represents the sampled acoustic signal and  $N$  denotes the total number of samples.

The Zero Crossing Rate (ZCR) is used to estimate the frequency characteristics of the acoustic signal and is expressed as

$$\text{ZCR} = \frac{1}{N-1} \sum_{i=1}^{N-1} |\text{sign}(x_i) - \text{sign}(x_{i+1})| \quad (2)$$

where  $\text{sign}(x)$  indicates the polarity of the signal sample.

For vibration analysis, signal energy can also be estimated using the following relation

$$E = \sum_{i=1}^N x_i^2 \quad (3)$$

## VI. PUBLICATION PRINCIPLES

The contents published in the *International Journal of Innovative Research in Technology* are peer-reviewed and archival in nature. The journal publishes scholarly research articles that contribute to long-term academic value, along with tutorial expositions and critical reviews of classical subjects and emerging topics of current technological interest.

Authors submitting manuscripts should consider the following important principles:

### 1. Original Contribution and Advancement of Knowledge

Technical papers submitted for publication must contribute to the advancement of existing knowledge in the respective field. Authors are expected to provide adequate references to relevant prior research work to establish the novelty and significance of their contribution.

### 2. Appropriate Manuscript Length

The length of the submitted paper should be proportional to the importance and complexity of the research work. Minor extensions or incremental improvements over previously published work may not justify a lengthy manuscript and can often be presented effectively in a shorter format.

### 3. Scientific and Technical Merit

Authors must convincingly demonstrate the scientific validity and technical merit of their research to both peer reviewers and editorial members. The level of supporting evidence required becomes more rigorous when the manuscript reports extraordinary, unexpected, or unconventional results.

### 4. Reproducibility and Sufficient Technical Details

Since reproducibility is fundamental to scientific progress, submitted manuscripts must provide sufficient experimental or analytical details to enable readers to perform similar experiments or calculations. While complete disclosure of all parameters may not

always be necessary, the paper must include clear, usable, and well-described technical information.

## VII. CONCLUSION

This paper presented the design and implementation of an AI-based acoustic emission monitoring system for transformer fault detection. The proposed system utilizes a low-cost microcontroller platform integrated with acoustic, vibration, and environmental sensors to enable real-time condition monitoring. Statistical signal processing techniques such as Root Mean Square and Zero Crossing Rate were employed to extract meaningful features from the captured acoustic signals. The experimental observations indicate that mechanical faults are generally associated with higher signal amplitude and vibration levels, whereas electrical faults such as partial discharge produce higher frequency acoustic emissions. By combining feature extraction with machine learning-based classification, the system demonstrates improved fault identification capability and provides early warning signals for predictive maintenance. The developed monitoring solution offers advantages such as non-contact sensing, portability, low power consumption, and IoT-based remote visualization. These features make the proposed system suitable for deployment in smart substations and distributed power networks. Future work may focus on enhancing detection accuracy through advanced deep learning techniques, integrating cloud-based analytics for large-scale data processing, and implementing edge intelligence for faster decision-making. The proposed approach contributes to improving transformer reliability, reducing maintenance costs, and supporting the development of intelligent power system monitoring frameworks.

## APPENDIX

### A. Hardware Specifications

Microcontroller: ESP32 dual-core processor with integrated Wi-Fi and Bluetooth communication

Acoustic Sensor: Digital MEMS microphone for airborne acoustic signal acquisition

Vibration Sensor: Impact or motion detection module for mechanical disturbance monitoring

Environmental Sensors: Temperature and humidity sensing module for ambient condition tracking

Communication Module: Long-range wireless communication interface for remote data transmission  
Display Unit: OLED display for local visualization of system status and fault indication  
Storage Module: MicroSD card for offline data logging

#### B. Signal Processing Parameters

Sampling Frequency: Selected based on the frequency range of transformer acoustic emissions  
Feature Extraction Window: Fixed sample window used for RMS and Zero Crossing Rate computation  
Threshold Levels: Experimentally determined values used for preliminary fault classification  
Machine Learning Model: Supervised learning algorithm trained using labeled acoustic data

#### C. Experimental Setup

The monitoring prototype was positioned near the transformer surface to capture airborne acoustic emissions under different operating conditions. Mechanical disturbances were simulated using controlled vibration inputs, while electrical fault-like acoustic signatures were analyzed using recorded datasets. Environmental variations were also considered to evaluate system robustness.

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