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SMART TRANSFORMER DIGITAL TWIN FOR REAL-TIME CONDITION MONITORING, LOSS ANALYSIS, AND AI-ASSISTED PREDICTIVE MAINTENANCE

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Abstract: Power transformers are among the most critical assets in modern electrical power systems, where unexpected failures can lead to significant economic losses, service interruptions, and increased maintenance costs. Conventional monitoring techniques are predominantly periodic and reactive, limiting their ability to detect incipient faults and provide continuous assessment of transformer health. This paper presents an AI-driven Digital Twin framework for real-time transformer condition monitoring, loss analysis, and predictive maintenance using an Internet of Things (IoT) architecture. The proposed system integrates an ESP32 microcontroller with voltage, current, oil temperature, transformer surface temperature, and oil-level sensors to acquire real-time operational data. The collected measurements are processed using embedded analytical algorithms to estimate transformer efficiency, copper loss, core loss, hysteresis loss, eddy-current loss, thermal stress, health index, and remaining service life. A physics-based digital twin continuously synchronizes with the physical prototype, enabling virtual fault simulation, operational analysis, and intelligent decision support without disturbing the actual transformer. To improve diagnostic capability, a lightweight Random Forest classifier is incorporated for operating-state prediction, achieving an overall classification accuracy of 93.0% across four health conditions: Normal, Warning, Fault, and Sensor Anomaly. The monitoring platform performs high-resolution data acquisition at 20 samples per AC cycle, provides an end-to-end communication latency of 110–265 ms, and demonstrates an overall transformer efficiency of approximately 95% during experimental evaluation. The integration of edge computing, AI-assisted predictive analytics, digital twin technology, and IoT communication provides a cost-effective, scalable, and reliable solution for continuous transformer health assessment, early fault detection, and predictive maintenance. The proposed framework is suitable for laboratory-scale implementation and offers a practical foundation for future smart grid and intelligent asset management applications.

Keywords: Digital Twin, Transformer Health Monitoring, Internet of Things, ESP32, Predictive Maintenance, Fault Analysis, Loss Assessment, Smart Grid, Cloud Dashboard, Condition Monitoring.

1. INTRODUCTION

Power transformers are among the most critical assets in modern electrical power systems, enabling efficient voltage transformation and reliable transmission and distribution of electrical energy from generation stations to end users. Their continuous and dependable operation is essential for maintaining power system stability, ensuring uninterrupted electricity supply, and reducing operational and maintenance costs. However, transformers operate under continuous electrical, thermal, and environmental stresses, including overload conditions, voltage fluctuations, insulation degradation, excessive operating temperatures, moisture ingress, and cooling system deterioration. Over time, these factors accelerate component aging,

reduce operational efficiency, and increase the likelihood of severe failures if early warning signs are not detected.

Conventional transformer maintenance primarily relies on periodic inspections, preventive maintenance schedules, dissolved gas analysis (DGA), infrared thermography, and laboratory-based diagnostic testing. Although these techniques provide valuable information regarding transformer condition, they are generally performed at discrete intervals, require specialized equipment and skilled personnel, and do not support continuous real-time monitoring. Consequently, developing faults that arise between inspection cycles may remain undetected, resulting in unexpected outages, expensive maintenance activities, and reduced transformer service life.

Recent advances in the Internet of Things (IoT), embedded systems, cloud computing, artificial

intelligence (AI), and Digital Twin technology have significantly transformed transformer condition monitoring. Low-cost embedded controllers equipped with wireless communication capabilities enable continuous acquisition of electrical and thermal parameters, while cloud-based platforms provide remote monitoring, centralized data storage, and real-time visualization. Furthermore, machine learning algorithms enhance fault diagnosis by identifying abnormal operating patterns, estimating equipment health, and supporting predictive maintenance strategies that reduce the probability of catastrophic failures.

Despite these technological developments, many existing low-cost transformer monitoring systems remain limited to basic data acquisition and threshold-based alarm generation. Such systems primarily provide reactive monitoring and generally lack comprehensive performance evaluation, physics-based validation of sensor measurements, and intelligent decision support. In addition, most reported approaches cannot effectively distinguish sensor malfunctions from actual transformer faults, often resulting in false alarms and reduced diagnostic reliability. Although industrial Digital Twin platforms offer advanced monitoring, simulation, and predictive maintenance capabilities, their high implementation cost, dependence on enterprise-scale infrastructure, and deployment complexity restrict their applicability for laboratory environments, educational institutions, and distribution-level transformer installations.

To address these challenges, this paper presents an **AI-Driven Digital Twin-Based Smart Transformer Health Monitoring, Loss Analysis, and Predictive Maintenance Platform with IoT Integration**. The proposed framework integrates embedded sensing, edge computing, wireless IoT communication, physics-informed Digital Twin modeling, and artificial intelligence to establish a comprehensive transformer health assessment system. An ESP32-based embedded controller acquires real-time measurements of voltage, current, oil temperature, transformer surface temperature, and oil level using low-cost sensors. The acquired data are processed to estimate critical operational parameters, including transformer efficiency, copper loss, core loss, hysteresis loss, eddy current loss, thermal stress, health index, and remaining useful life (RUL). These results are continuously synchronized with a cloud-connected web dashboard and a Digital Twin for real-time monitoring and visualization.

Unlike conventional monitoring approaches that rely solely on sensor measurements, the proposed

framework employs a physics-informed Digital Twin to validate acquired data, simulate transformer operating conditions, and perform virtual fault analysis without interrupting normal operation. In addition, a Random Forest-based machine learning model, together with a lightweight edge-level anomaly detection algorithm, classifies transformer conditions into four operating states: **Normal**, **Warning**, **Fault**, and **Sensor Anomaly**. This integrated architecture enhances diagnostic accuracy, minimizes false alarms by differentiating sensor faults from actual transformer abnormalities, and enables intelligent predictive maintenance using a cost-effective hardware platform suitable for research laboratories, educational institutions, and future smart grid applications.

The principal contributions of this work are summarized as follows:

1. **Development of a low-cost IoT-enabled Digital Twin platform** for continuous real-time monitoring of transformer operating conditions using embedded sensing and wireless communication technologies.
2. **Integration of a physics-informed Digital Twin model** to validate sensor measurements, perform thermal analysis, and enhance transformer health assessment through model-based verification.
3. **Real-time computation of critical transformer performance indicators**, including efficiency, copper loss, core loss, hysteresis loss, eddy-current loss, thermal stress, health index, and remaining useful life (RUL).
4. **Implementation of a lightweight edge-level anomaly detection mechanism** that ensures reliable monitoring by identifying abnormal sensor behavior and maintaining system operation during temporary communication interruptions.
5. **Integration of a Random Forest-based artificial intelligence model** for intelligent classification of transformer operating conditions into *Normal*, *Warning*, *Fault*, and *Sensor Anomaly* states, enabling predictive maintenance and early fault detection.
6. **Development of an interactive web-based monitoring dashboard** that provides real-time visualization, Digital Twin representation, virtual fault simulation, historical data analytics, and remote access for comprehensive transformer condition monitoring.

7. **Experimental validation of the proposed platform** using a laboratory-scale transformer prototype, demonstrating accurate parameter estimation, low communication latency, reliable fault identification, and effective predictive maintenance capability on an economical hardware platform.

The experimental results demonstrate that the integration of embedded sensing, IoT communication, Digital Twin technology, physics-informed modeling, and artificial intelligence provides a comprehensive and cost-effective solution for transformer condition monitoring and predictive maintenance. By combining real-time data acquisition, model-based validation, intelligent fault diagnosis, and remote visualization within a unified framework, the proposed platform significantly enhances diagnostic reliability while maintaining low implementation complexity and cost. Furthermore, its scalable architecture makes it well suited for laboratory experimentation, engineering education, distribution transformer monitoring, and future smart grid applications.

2. LITERATURE REVIEW

Power transformers represent indispensable assets in electrical power networks, where their dependable operation directly influences power system reliability, service continuity, and grid stability. Consequently, transformer condition monitoring has attracted considerable research attention, resulting in the development of numerous diagnostic and prognostic techniques aimed at improving operational reliability, minimizing maintenance costs, and extending equipment lifespan.

Traditional transformer condition assessment relies on periodic maintenance practices, including dissolved gas analysis (DGA), insulating oil quality evaluation, infrared thermography, and electrical diagnostic testing. Among these approaches, DGA is widely recognized as one of the most effective techniques for detecting insulation deterioration and internal transformer faults. Despite its diagnostic accuracy, DGA requires oil sampling, laboratory analysis, and expert interpretation, making it unsuitable for continuous online monitoring and limiting its ability to detect rapidly developing faults in real time.

Recent advancements in the Internet of Things (IoT) have significantly transformed transformer monitoring by enabling continuous acquisition of

operational data using low-cost embedded platforms such as Arduino, Raspberry Pi, ESP8266, and ESP32. These systems employ various sensors to monitor electrical and environmental parameters, including voltage, current, oil temperature, winding temperature, humidity, and oil level, while transmitting collected data to cloud-based platforms for remote visualization and analysis. The widespread availability of wireless communication technologies has further reduced implementation costs and improved the accessibility of intelligent monitoring solutions.

Artificial intelligence and machine learning techniques have further enhanced transformer condition monitoring by enabling automated fault diagnosis and predictive maintenance. Supervised learning algorithms, including Decision Trees, Support Vector Machines (SVM), Artificial Neural Networks (ANN), Random Forests, and deep learning models, have demonstrated promising performance in classifying transformer operating conditions using historical sensor data. These intelligent approaches reduce dependence on manual inspections, improve diagnostic consistency, and provide valuable decision support for maintenance scheduling and asset management.

Digital Twin technology has recently emerged as a promising paradigm for intelligent power system asset management. A Digital Twin maintains a continuously synchronized virtual representation of a physical transformer by integrating real-time operational measurements with mathematical and physics-based models. Such platforms facilitate continuous condition assessment, performance evaluation, predictive maintenance, and virtual fault simulation without interrupting transformer operation. Commercial Digital Twin platforms, including Siemens MindSphere and GE Predix, provide comprehensive monitoring and advanced analytical capabilities; however, their deployment generally requires enterprise-scale infrastructure, cloud-based services, proprietary software environments, and substantial financial investment. These requirements limit their practical adoption in educational laboratories, research environments, and distribution-level transformer applications.

Although substantial progress has been achieved, several technical limitations remain in the existing literature. Most low-cost IoT-based monitoring systems are primarily designed for sensor data acquisition and threshold-based fault notification, providing reactive rather than predictive monitoring. In addition, they rarely estimate important transformer performance indicators such as

efficiency, copper loss, core loss, hysteresis loss, eddy-current loss, thermal stress, health index, or remaining useful life (RUL). As a result, comprehensive assessment of transformer operating performance is often unavailable.

Another significant limitation is the absence of physics-based validation of sensor measurements. Most existing systems directly utilize acquired sensor data without verifying consistency with transformer operating characteristics, increasing the likelihood of false alarms caused by sensor degradation, calibration errors, or measurement drift. Furthermore, many reported IoT monitoring platforms rely exclusively on cloud connectivity for data processing and decision-making, reducing system reliability during temporary communication failures or network interruptions.

The integration of edge intelligence also remains relatively limited in current transformer monitoring research. Although machine learning algorithms have demonstrated high classification accuracy, they are commonly implemented on cloud servers using previously collected datasets rather than lightweight embedded hardware capable of performing real-time inference. Consequently, anomaly detection and predictive analysis become unavailable whenever communication with cloud services is interrupted. Moreover, only a limited number of studies explicitly distinguish sensor malfunctions from genuine transformer faults through sensor-fusion or model-based validation techniques, despite this capability being essential for improving diagnostic reliability in practical industrial environments.

To overcome these limitations, the proposed research presents a unified and cost-effective transformer monitoring framework that combines embedded sensing, edge computing, IoT communication, Digital Twin technology, physics-informed thermal modeling, transformer loss analysis, and AI-assisted predictive maintenance. Unlike conventional monitoring approaches, the proposed system continuously validates sensor measurements using physics-based thermal models, estimates transformer performance indices in real time, performs edge-level anomaly detection, and synchronizes a Digital Twin capable of virtual fault simulation and intelligent condition assessment. This integrated architecture provides a comprehensive, scalable, and economically viable solution suitable for laboratory research, engineering education, distribution transformer monitoring, and future smart grid applications.

Table II presents a comparative analysis of representative transformer monitoring approaches

reported in the literature and the proposed framework, highlighting the unique technical features and research contributions of the developed system.

Table 1 Paper Review

Reference / System	IoT	Digital Twin	AI	Physics Validation	Loss Analysis	Edge AI	Fault Simulation
Conventional DGA	X	X	X	✓	X	X	X
Basic ESP32 Monitoring	✓	X	X	X	Limited	X	X
AI-Based Monitoring	✓	X	✓	X	Limited	Limited	X
Enterprise Digital Twin	✓	✓	✓	✓	✓	Limited	✓
Proposed Framework	✓	✓	✓	✓	✓	✓	✓

3. Research Gap and Novel Contributions

3.1 Research Gap

Despite significant progress in the application of Internet of Things (IoT), Artificial Intelligence (AI), and Digital Twin technologies for transformer condition monitoring, several technical challenges remain unresolved, particularly in low-cost monitoring platforms. Most existing systems are primarily designed for continuous acquisition of basic operational parameters, such as voltage, current, and temperature, followed by threshold-based fault notification. While these approaches facilitate real-time data collection, they provide only reactive monitoring and offer limited capability for comprehensive assessment of transformer operating conditions.

A major limitation of many IoT-enabled monitoring solutions is their heavy dependence on cloud-based computing for data processing, fault diagnosis, and anomaly detection. Such architectures become susceptible to communication delays and network interruptions, reducing monitoring reliability during temporary connectivity failures. Moreover, sensor measurements are commonly processed without validation against physics-based transformer models, making it difficult to differentiate actual transformer faults from sensor malfunctions, calibration errors, or

measurement drift. Consequently, false alarms and reduced diagnostic confidence remain persistent issues.

Although Digital Twin technology has demonstrated considerable potential for predictive asset management and intelligent monitoring, most reported implementations target utility-scale substations and industrial environments. These platforms typically require enterprise-grade software, dedicated cloud infrastructure, proprietary simulation tools, and high-performance computing resources, resulting in substantial deployment and maintenance costs. Such requirements limit their applicability in laboratory-scale experiments, educational institutions, and distribution transformer monitoring, where economical and easily deployable solutions are required.

Another important research gap is the limited evaluation of transformer operational performance beyond basic sensor monitoring. Existing studies generally emphasize parameter acquisition while overlooking comprehensive estimation of key performance indicators, including transformer efficiency, copper loss, core loss, hysteresis loss, eddy-current loss, thermal stress, health index, and remaining useful life (RUL). The absence of these analytical capabilities restricts the effectiveness of condition assessment and reduces the ability of monitoring systems to support predictive maintenance and informed operational decision-making.

To address these limitations, this research proposes a cost-effective, physics-informed, AI-assisted Digital Twin platform that integrates embedded sensing, edge computing, IoT communication, transformer performance analysis, intelligent anomaly detection, and virtual fault simulation within a unified architecture. By combining real-time monitoring with physics-based validation and machine learning-driven condition assessment, the proposed framework enhances diagnostic reliability, supports predictive maintenance, and provides an economical solution suitable for laboratory research, engineering education, distribution transformer applications, and future smart grid deployments.

3.2 Novel Contributions

The proposed research overcomes the limitations identified in existing transformer monitoring systems through the following major contributions:

1. **Development of a cost-effective Digital Twin-enabled transformer monitoring platform** based on an ESP32 microcontroller, integrating IoT communication for continuous real-time acquisition and remote monitoring of transformer operating parameters.
2. **Integration of multi-parameter embedded sensing** for simultaneous monitoring of electrical, thermal, and oil-condition variables within a unified hardware and software architecture.
3. **Implementation of a physics-informed transformer model** that continuously validates sensor measurements, verifies operating conditions, and enhances diagnostic reliability through model-based consistency checking.
4. **Real-time estimation of critical transformer performance indicators**, including efficiency, copper loss, core loss, hysteresis loss, eddy-current loss, thermal stress, health index, and remaining useful life (RUL), enabling comprehensive assessment of transformer condition.
5. **Development of a lightweight edge-level anomaly detection framework** capable of identifying abnormal operating behavior and maintaining reliable monitoring during temporary communication or cloud service interruptions.
6. **Integration of a Random Forest-based machine learning model** for intelligent classification of transformer operating conditions into four health states: **Normal**, **Warning**, **Fault**, and **Sensor Anomaly**, thereby supporting early fault detection and predictive maintenance.
7. **Implementation of an interactive Digital Twin environment** that provides real-time visualization, virtual fault simulation, historical trend analysis, remote monitoring, and intelligent decision support for transformer asset management.
8. **Experimental validation of the proposed framework** using a laboratory-scale transformer prototype, demonstrating accurate parameter estimation, low communication latency, reliable condition assessment, and practical feasibility for laboratory research, engineering education, distribution transformer monitoring, and future smart grid applications.

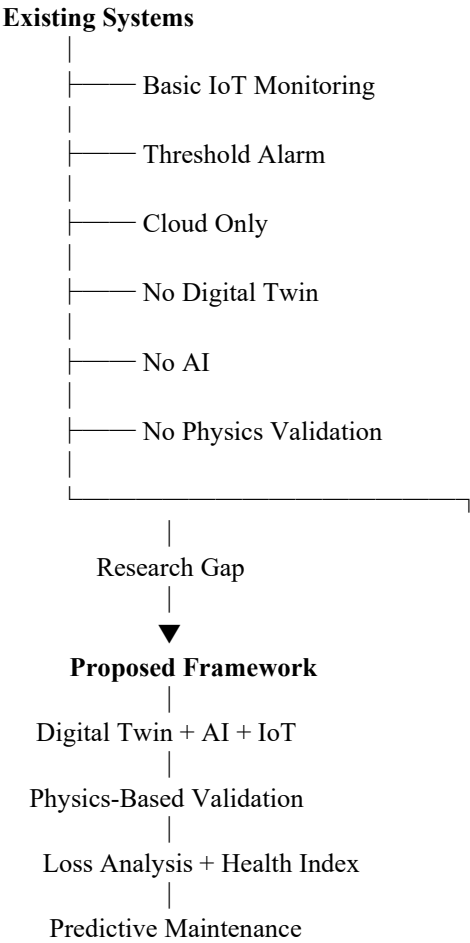


Table 2 Research Gap Analysis

Limitation in Existing Systems	Proposed Solution
Basic sensor monitoring only	Multi-parameter real-time monitoring
Cloud dependency	Edge computing with offline capability
No Digital Twin	Physics-informed Digital Twin
No loss estimation	Real-time transformer loss analysis
No Health Index	Continuous Health Index estimation
No predictive maintenance	AI-based prediction
Sensor faults ignored	Sensor validation and anomaly detection
Limited visualization	Interactive web dashboard

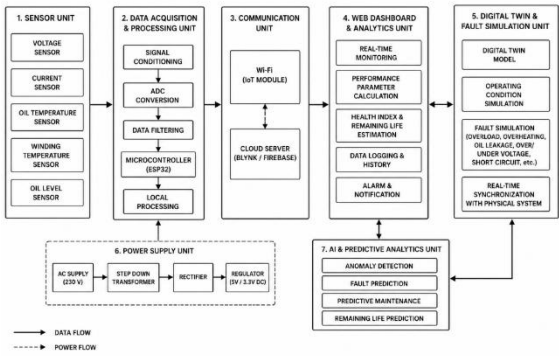


Figure 1 Block Diagram of AI-Driven Digital Twin-Based Smart Transformer Health Monitoring Platform

4. METHODOLOGY

The proposed **AI-Driven Digital Twin-Based Smart Transformer Health Monitoring Platform** employs a hierarchical architecture that combines embedded sensing, edge computing, physics-informed modeling, artificial intelligence, Internet of Things (IoT) communication, and Digital Twin technology within a unified monitoring framework. The system is designed to continuously acquire transformer operating data, evaluate electrical and thermal performance, identify abnormal operating conditions, and support predictive maintenance through intelligent real-time analysis.

4.1 System Architecture

The proposed monitoring framework is organized into four interconnected functional layers, each responsible for a specific stage of data acquisition, processing, analysis, and visualization.

4.1.1 Physical Sensing Layer

The physical layer consists of a laboratory-scale single-phase transformer equipped with multiple sensing devices for continuous measurement of its operating parameters. Electrical variables, including voltage and current, together with thermal and oil-condition parameters such as oil temperature, transformer surface temperature, and oil level, are monitored in real time. These measurements provide a comprehensive representation of transformer operating behavior under normal and abnormal loading conditions.

4.1.2 Edge Computing Layer

The acquired sensor signals are processed by an ESP32 microcontroller, which serves as the edge computing unit. The embedded controller periodically samples all sensor inputs through its analog-to-digital converter (ADC), performs signal conditioning, applies sensor calibration, and converts the raw measurements into engineering units.

The edge processor further computes several important transformer operating parameters, including RMS voltage, RMS current, apparent power, active power, power factor, transformer efficiency, copper loss, core loss, hysteresis loss, eddy-current loss, and thermal stress. To improve system reliability, a lightweight anomaly detection algorithm continuously evaluates sensor consistency and operating behavior, allowing abnormal conditions to be identified even when communication with the cloud is temporarily unavailable.

4.1.3 Digital Twin and Intelligent Analysis Layer

The processed operational data are continuously synchronized with a Digital Twin that maintains a real-time virtual representation of the physical transformer. The Digital Twin incorporates physics-informed thermal models to verify sensor measurements, evaluate transformer operating conditions, and estimate important health-related parameters.

In parallel, a Random Forest-based machine learning model analyzes multiple electrical and thermal features to classify transformer operating conditions into four predefined health states: **Normal**, **Warning**, **Fault**, and **Sensor Anomaly**. The integration of model-based validation with data-driven intelligence enhances diagnostic accuracy while reducing false fault indications caused by sensor errors or measurement drift.

4.1.4 IoT Monitoring and Visualization Layer

The analyzed information is transmitted wirelessly through the ESP32 Wi-Fi interface to a cloud-connected web application. The monitoring dashboard provides continuous visualization of live sensor measurements, transformer operating status, estimated health index, transformer loss analysis, historical performance trends, alarm notifications, and Digital Twin behavior. All operational data are archived to facilitate long-term performance evaluation, fault investigation, and predictive maintenance planning.

4.2 Operational Workflow

The overall operation of the proposed framework is performed through the following sequential stages: Continuous acquisition of electrical, thermal, and oil-condition parameters from the instrumented transformer.

Signal conditioning, sensor calibration, and analog-to-digital conversion of acquired measurements.

Real-time computation of transformer electrical and thermal performance indicators.

Validation of measured parameters using physics-informed transformer models.

Edge-level anomaly detection for identifying abnormal operating conditions and sensor inconsistencies.

Intelligent operating-state classification using a Random Forest machine learning algorithm.

Real-time synchronization between the physical transformer and its Digital Twin representation.

Wireless transmission of processed information to the cloud-based monitoring dashboard.

Automatic generation of warning and fault notifications whenever abnormal operating conditions are detected.

Continuous storage of historical operational data for trend analysis, health assessment, and predictive maintenance.

The proposed methodology establishes a unified monitoring framework by integrating embedded sensing, physics-informed Digital Twin modeling, edge intelligence, artificial intelligence, and IoT communication within a cost-effective hardware platform. This integrated approach enables reliable transformer condition assessment, improves diagnostic accuracy through real-time model validation, supports predictive maintenance, and maintains low computational complexity, making it suitable for laboratory experimentation, educational applications, distribution transformer monitoring,

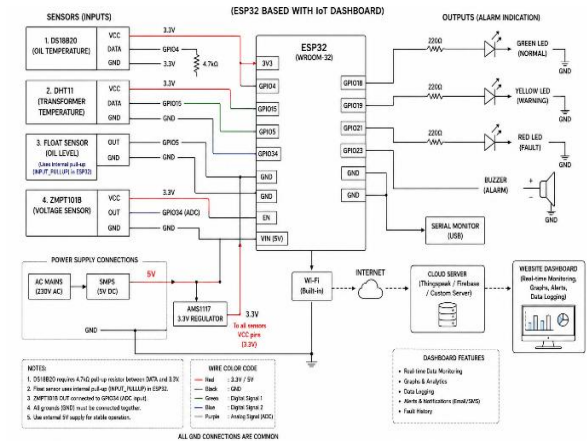


Figure 2. Flowchart illustrating the operational sequence and decision-making process of the proposed transformer health monitoring system.

and future smart grid deployment.

5 MODELLING OF THE PROPOSED SYSTEM

5.1 System Architecture

The proposed transformer health monitoring platform integrates embedded sensing, IoT communication, Digital Twin technology, and intelligent data

analytics into a unified architecture for continuous transformer condition assessment. The system is centered around an ESP32 microcontroller, which functions as the primary data acquisition and processing unit. Multiple sensors are interfaced with the controller to continuously monitor key transformer operating parameters, including supply voltage, load current, oil temperature, transformer surface temperature, and insulating oil level.

The acquired measurements are processed locally to evaluate the transformer's operational status and overall health. The embedded controller compares the measured values with predefined operating thresholds while simultaneously estimating important performance indicators. Under normal operating conditions, the processed information is transmitted via the ESP32's integrated Wi-Fi module to a cloud-connected monitoring dashboard for remote supervision. Whenever abnormal operating conditions are identified, the controller immediately activates local visual and audible alarms while updating the online dashboard. The same dataset is simultaneously synchronized with the Digital Twin, enabling the virtual model to accurately represent the real-time operating condition of the physical transformer.

5.2 Data Acquisition and IoT Communication

The monitoring process begins with continuous acquisition of electrical, thermal, and oil-condition parameters from the transformer. Dedicated sensors measure each operating variable, while the ESP32 periodically samples the sensor outputs through its analog-to-digital converter (ADC). Prior to further analysis, the acquired measurements undergo signal conditioning, calibration, and filtering to improve measurement accuracy and eliminate noise.

After local processing, the validated sensor data are transmitted wirelessly through the ESP32 Wi-Fi interface to a cloud-based monitoring dashboard. The dashboard enables continuous visualization of live operating parameters, historical trends, transformer health status, and system alarms from any remote location. In addition to real-time monitoring, the collected data are archived for long-term performance evaluation, fault diagnosis, and predictive maintenance.

Whenever the monitored parameters exceed predefined operating limits, such as excessive

temperature, abnormal voltage variation, overload conditions, or insufficient oil level, warning notifications are generated automatically and displayed on the monitoring dashboard. This continuous communication architecture enables timely maintenance decisions while improving operational reliability.

5.3 Digital Twin Modelling, Predictive Analysis, and Fault Simulation

A Digital Twin is developed to establish a continuously synchronized virtual representation of the physical transformer. The virtual model receives real-time operational data from the ESP32 and updates its internal state continuously, ensuring close correspondence between the physical equipment and its digital counterpart throughout system operation.

The Digital Twin combines live sensor measurements with physics-informed transformer models to evaluate transformer operating behavior, validate sensor readings, and estimate important health-related parameters. In addition to real-time monitoring, the virtual environment enables safe simulation of various operating scenarios without affecting the physical transformer.

The developed platform supports virtual simulation of multiple fault conditions, including transformer overheating, voltage fluctuations, overload operation, oil-level reduction, and sensor malfunctions. Furthermore, the synchronized operational data are utilized for transformer loss analysis, performance evaluation, and predictive maintenance. By continuously monitoring degradation trends and estimating future operating conditions, the Digital Twin assists in identifying potential failures before they develop into critical faults, thereby supporting condition-based maintenance strategies and improving transformer reliability.

5.4 Hardware Implementation and System Integration

The experimental prototype was developed using an ESP32 microcontroller integrated with a voltage sensor, current sensor, DS18B20 oil temperature sensor, DHT11 transformer surface temperature sensor, and a float-based oil-level sensor. Three status LEDs and a piezoelectric buzzer provide immediate local indication of transformer operating conditions,

while a regulated power supply ensures stable operation of the embedded monitoring hardware.

Each sensing module was individually calibrated and experimentally verified before complete system integration. The embedded firmware was subsequently developed to perform continuous sensor acquisition, parameter computation, transformer health assessment, abnormal condition detection, and wireless communication with the cloud-based monitoring platform.

The integrated operation of the embedded hardware, IoT communication module, Digital Twin environment, and web-based dashboard establishes a complete transformer health monitoring platform capable of supporting both local supervision and remote condition monitoring in real time.

5.5 Performance Evaluation

The proposed monitoring platform was experimentally evaluated under a variety of transformer operating conditions to assess its sensing accuracy, communication performance, and fault detection capability. Controlled variations in supply voltage, load current, transformer surface temperature, oil temperature, and oil level were introduced to validate the performance of the sensing hardware and the embedded diagnostic algorithms.

During experimental testing, the responses of the status LEDs, audible alarm, web-based monitoring dashboard, and synchronized Digital Twin were continuously observed for each operating scenario. The communication latency between the ESP32 and the remote dashboard was also evaluated to verify the responsiveness of the IoT communication framework.

Experimental observations confirmed reliable real-time data acquisition with stable wireless communication throughout the testing period. The Digital Twin accurately mirrored the operating state of the physical transformer with minimal synchronization delay, while the embedded monitoring system consistently detected abnormal operating conditions and generated timely warning notifications. The obtained results demonstrate that the proposed platform provides an accurate, scalable, and economically viable solution for intelligent transformer condition monitoring, predictive

maintenance, Digital Twin-based asset management, and future smart grid applications.

6 SYSTEM DESIGN AND WORKING PRINCIPLE

6.1 System Design

The proposed smart transformer health monitoring platform is developed as an integrated cyber-physical system that combines embedded sensing, edge computing, wireless IoT communication, Digital Twin technology, and intelligent health assessment within a unified framework. The objective is to provide continuous monitoring of transformer operating conditions while supporting real-time fault diagnosis, predictive maintenance, and remote supervision.

The ESP32 microcontroller serves as the central embedded controller responsible for data acquisition, local processing, and wireless communication. It interfaces with multiple sensing modules, including the ZMPT101B voltage sensor, ACS712 Hall-effect current sensor, DS18B20 oil temperature sensor, DHT11 transformer surface temperature sensor, and a float-based oil-level sensor. The analog outputs from the voltage and current sensors are digitized using the ESP32's integrated 12-bit Analog-to-Digital Converter (ADC). After calibration and signal conditioning, the acquired measurements are converted into engineering units for further analysis.

The instantaneous voltage is estimated as

$$V = K_v \times V_{ADC}$$

where

V = Actual supply voltage (V)

V_{ADC} = Measured ADC voltage

K_v = Calibration constant of the ZMPT101B sensor

Similarly, the load current is determined using

$$I = K_i(V_{OUT} - V_{OFFSET})$$

where

I = Load current (A)

V_{OUT} = Sensor output voltage

V_{OFFSET} = Zero-current output voltage

K_i = Sensor sensitivity

The measured parameters are continuously processed by the ESP32 to evaluate the transformer operating condition. Whenever abnormal operating conditions are identified, the controller activates local warning indicators and simultaneously transmits the data to the IoT-based web dashboard using the built-in Wi-Fi module.

6.2 Working Principle

6.2.1 The average sampled sensor value is calculated as

$$X_{avg} = \frac{1}{N} \sum_{i=1}^N X_i$$

where

X_i represents each sampled value

N denotes the total number of samples.

6.2.2 The acquired parameters are evaluated using predefined threshold conditions:

$$\begin{aligned} T_{oil} &> 70^\circ\text{C} \\ T_{tr} &> 60^\circ\text{C} \\ 180\text{V} &\leq V \leq 260\text{V} \end{aligned}$$

where

T_{oil} = Transformer oil temperature

T_{tr} = Transformer surface temperature

V = Supply voltage

The transformer operating state can be represented as

$$S = \begin{cases} 0, & \text{Normal} \\ 1, & \text{Warning} \\ 2, & \text{Fault} \end{cases}$$

where S denotes the health of the transformer.

6.2.3 For monitoring transformer loading, the apparent power is calculated as

$$S_{VA} = V \times I$$

and the active power is

$$P = VI \cos \phi$$

where

V = RMS voltage

I = RMS current

ϕ = Power factor

6.2.4 The transformer efficiency can be estimated as

$$\eta = \frac{P_{out}}{P_{in}} \times 100$$

6.2.5 Loss analysis is performed using

$$P_{loss} = P_{in} - P_{out}$$

6.2.6 Physics-Based Thermal Validation and Health Assessment

In addition to threshold-based fault detection, the proposed system incorporates a physics-based thermal reference model to validate sensor-derived measurements. The winding hot-spot temperature is estimated using the transformer loading guide equation:

$$\theta_H = \theta_A + \Delta\theta_{TO,R} \left(\frac{1 + RK^2}{1 + R} \right)^x + \Delta\theta_{H,R} K^y$$

where

- θ_H = winding hot-spot temperature ($^\circ\text{C}$)
- θ_A = ambient temperature ($^\circ\text{C}$)
- $\Delta\theta_{TO,R}$ = rated top-oil temperature rise ($^\circ\text{C}$)
- $\Delta\theta_{H,R}$ = rated winding hot-spot rise over top-oil ($^\circ\text{C}$)
- R = ratio of load loss to no-load loss
- K = per-unit load factor

$$K = \frac{I_{measured}}{I_{rated}}$$

- x = oil exponent (IEC 60076-2)
- y = winding exponent (IEC 60076-2)

The calculated hot-spot temperature is continuously compared with the measured oil and transformer surface temperatures. A sustained deviation between the physics-based estimate and measured values indicates possible sensor drift or an emerging thermal abnormality.

6.2.7 Insulation Ageing Model

The insulation ageing acceleration factor is determined using the Arrhenius-based ageing model:

$$F_{AA} = \exp \left[\frac{15000}{110 + 273} - \frac{15000}{\theta_H + 273} \right]$$

where

- F_{AA} = ageing acceleration factor
- θ_H = hot-spot temperature (°C)

The equivalent insulation ageing accumulated over the monitoring period is

$$L_{eq} = \sum_{i=1}^N F_{AA,i} \Delta t_i$$

where

- L_{eq} = equivalent ageing (hours)
- Δt_i = sampling interval (hours)

The percentage loss of insulation life is then calculated as

$$\text{Loss of Life (\%)} = \frac{\sum_{i=1}^N F_{AA,i} \Delta t_i}{L_{\text{normal}}} \times 100$$

where

- L_{normal} = normal insulation life (typically 180,000 h)

6.2.8 Core Loss Decomposition

To provide diagnostic insight, total core loss is decomposed into hysteresis and eddy-current losses using the Steinmetz equations.

Hysteresis Loss

$$P_h = K_h f B_{\text{max}}$$

Eddy Current Loss

$$P_e = K_e f^2 B_{\text{max}}$$

Total Core Loss

$$P_{\text{core}} = P_h + P_e$$

where

- P_h = hysteresis loss (W)
- P_e = eddy current loss (W)
- P_{core} = total core loss (W)
- f = supply frequency (Hz)
- B_{max} = maximum flux density (T)
- K_h = hysteresis constant
- K_e = eddy current constant
- n = Steinmetz exponent (typically 1.6–2.2)

The peak magnetic flux density is estimated from the measured voltage-to-frequency ratio:

$$B_{\text{max}} \propto \frac{V}{f}$$

or more accurately,

$$B_{\text{max}} = \frac{V}{4.44 f N A}$$

where

- V = RMS voltage (V)
- N = number of turns
- A = effective core cross-sectional area (m²)

6.2.9 Composite Transformer Health Index

The overall transformer health is represented by a weighted health index:

$$HI = w_1 HI_{\text{thermal}} + w_2 HI_{\text{electrical}} + w_3 HI_{\text{oil}}$$

subject to

$$w_1 + w_2 + w_3 = 1$$

where

- HI = overall health index
- HI_{thermal} = thermal condition index
- $HI_{\text{electrical}}$ = electrical condition index
- HI_{oil} = oil-condition index
- w_1, w_2, w_3 = weighting coefficients

Each sub-index is normalized to a 0–100 scale:

$$HI_i = 100 \left(1 - \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \right)$$

where

- x_i = measured parameter
- $x_{\min}$ = healthy limit
- $x_{\max}$ = failure limit

For oil-immersed distribution transformers, thermal stress is assigned the highest weighting because it contributes most significantly to insulation degradation.

6.2.10 Sensor Consistency Verification

To distinguish sensor malfunction from genuine transformer faults, a statistical z-score consistency check is performed:

$$z = \frac{x_i - \mu}{\sigma}$$

where

- x_i = current sensor reading
- μ = mean value
- σ = standard deviation

A sensor is flagged as anomalous when

$$|z| > z_{\text{threshold}}$$

where $z_{\text{threshold}}$ is typically 2–3.

If one sensor exhibits an abnormal z-score while all physically correlated parameters remain within acceptable limits, the condition is classified as a probable sensor fault rather than a transformer fault.

6.2.11 Edge-Level Weighted Anomaly Score

To ensure continuous monitoring even without cloud connectivity, a lightweight weighted anomaly score is computed locally on the ESP32:

$$A = \sum_{k=1}^m w_k \left| \frac{x_k - \mu_k}{\sigma_k} \right|$$

where

- A = weighted anomaly score
- m = number of monitored parameters
- w_k = importance weight of parameter k
- x_k = measured value
- μ_k = historical mean
- σ_k = historical standard deviation

An anomaly is declared when

$$A > A_{\text{threshold}}$$

where $A_{\text{threshold}}$ is selected experimentally based on historical operating data.

This edge-level computation enables real-time anomaly detection even during temporary loss of cloud or dashboard connectivity, thereby improving the resilience and reliability of the proposed transformer monitoring system.

6.2.12 The digital twin continuously updates its virtual state according to the real-time sensor measurements, represented by

$$DT(t) = f(V, I, T_{\text{oil}}, T_{\text{tr}}, L)$$

where

$DT(t)$ = Digital twin state at time t

The monitoring cycle is repeated at regular intervals, enabling continuous condition assessment, fault detection, predictive maintenance, and remote supervision through the IoT-enabled dashboard.

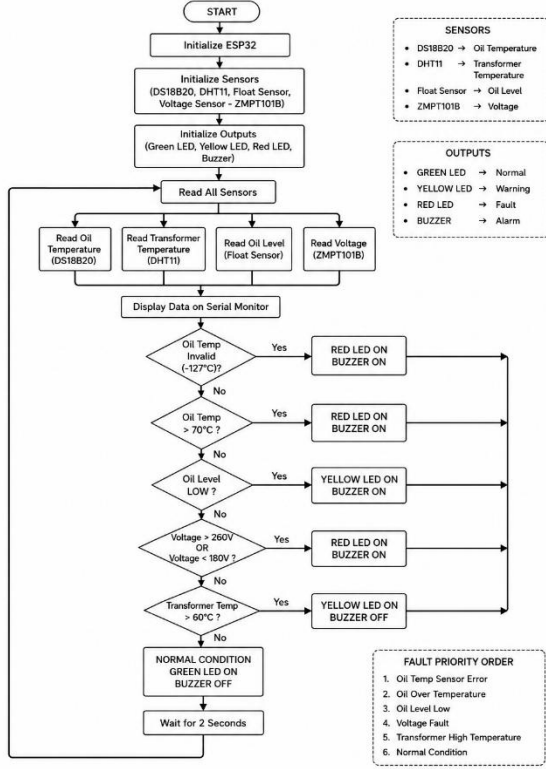


Figure 3 Flowchart of Given System

6.3 AI-Based Predictive Classification Module

To enhance the predictive maintenance capability of the proposed monitoring framework, a supervised machine learning model based on the Random Forest algorithm was developed to automatically classify transformer operating conditions. The classifier categorizes the transformer into four predefined operating states: Normal, Warning, Fault, and Sensor Anomaly, thereby enabling intelligent condition assessment and early fault identification.

The model utilizes ten input features that collectively describe the electrical, thermal, and operational characteristics of the transformer. These features include supply voltage, load current, oil temperature, transformer surface temperature, oil level, apparent power, power factor, rate of change of oil temperature, the physics-based winding hot-spot temperature (θ_H) obtained from the thermal

model described in Section 5.2.6, and the insulation ageing acceleration factor (F_{AA}) presented in Section 5.2.7. The combination of measured and model-derived parameters improves the ability of the classifier to distinguish normal operating conditions from developing faults.

Since obtaining extensive long-term operational data from transformers experiencing real failure conditions is impractical at the laboratory prototype stage, a representative synthetic dataset was developed for supervised model training. The dataset consisted of 1,200 samples, equally distributed among the four operating classes, with 300 samples assigned to each class. Feature values were generated around the operational thresholds established in Sections 5.2.2 and 6.3, while the experimentally measured healthy operating conditions reported in Table I were used as the reference baseline for normal operation.

The Sensor Anomaly class was specifically designed to represent situations in which sensor measurements become inconsistent with the expected physical behavior of the transformer. For example, abnormal increases in measured oil temperature were intentionally generated without corresponding variations in transformer surface temperature, reproducing the type of inconsistency identified by the sensor consistency verification algorithm described in Section 5.2.10. This strategy enabled the classifier to learn the distinction between genuine transformer faults and sensor-related abnormalities, thereby reducing the probability of false fault diagnosis.

To improve the robustness of the trained model under realistic operating conditions, approximately 7% label noise was intentionally introduced by randomly assigning a small proportion of samples to neighboring operating classes. This procedure reflects practical monitoring environments in which sensor measurements, environmental disturbances, and manual labeling may introduce uncertainty into the collected data.

The complete dataset was randomly divided into 75% training and 25% testing subsets, resulting in 900 training samples and 300 testing samples. A Random Forest classifier comprising 80 decision trees with a maximum tree depth of 9 was subsequently trained using the training dataset. This configuration provided an effective balance between classification accuracy, computational efficiency, and memory utilization, making the model suitable for deployment within the proposed intelligent transformer health monitoring framework.

7 EXPERIMENTAL RESULTS AND DISCUSSION

The proposed **AI-Driven Digital Twin-Based Smart Transformer Health Monitoring Platform** was experimentally evaluated using a laboratory-scale transformer prototype to validate its monitoring accuracy, communication reliability, Digital Twin synchronization, and intelligent fault diagnosis capabilities. The experimental platform integrates embedded sensing, edge computing, IoT communication, artificial intelligence, and Digital Twin technology into a unified condition-monitoring framework. Throughout the experimental investigation, the ESP32 continuously acquired sensor measurements, performed local processing, estimated transformer performance indicators, and transmitted the processed information to a cloud-connected monitoring dashboard through its integrated Wi-Fi interface.

The web-based dashboard provided continuous visualization of both measured electrical parameters and computed transformer health indicators. Real-time measurements included primary voltage, primary current, secondary voltage, secondary current, oil temperature, transformer surface temperature, oil level, supply frequency, and power factor. Using these measurements, the proposed system further estimated transformer efficiency, copper loss, core loss, hysteresis loss, eddy-current loss, thermal stress, magnetic flux density, Health Index (HI), and remaining useful life (RUL). Continuous synchronization between the physical transformer and its Digital Twin ensured that any variation in operating conditions was immediately reflected within the virtual environment, enabling real-time visualization and intelligent condition assessment.

The developed platform was evaluated under both normal and abnormal operating conditions to verify its diagnostic performance. During normal operation, all monitored variables remained within their permissible operating limits, and the monitoring dashboard consistently indicated a healthy transformer condition. To evaluate the robustness of the proposed framework, several representative fault scenarios were reproduced within the Digital Twin environment, including overload, overheating, oil-level reduction, voltage fluctuations, and short-circuit conditions. Each simulated fault produced the expected variations in electrical and thermal parameters, and the corresponding operating status

was updated on the monitoring dashboard with minimal communication delay. The system also generated appropriate warning notifications and alarm indications, allowing abnormal operating conditions to be identified without exposing the laboratory transformer to destructive testing.

The experimental investigation demonstrates that integrating embedded sensing, IoT communication, physics-informed Digital Twin modeling, and artificial intelligence significantly enhances transformer condition monitoring compared with conventional threshold-based monitoring approaches. The developed framework provides continuous remote supervision, intelligent performance evaluation, virtual fault simulation, and predictive maintenance capabilities within a single low-cost monitoring platform, making it suitable for laboratory research, educational applications, distribution transformer monitoring, and future smart grid deployment.

7.1 Real-Time Monitoring Results

The real-time monitoring capability of the proposed platform was assessed through continuous observation of the laboratory-scale transformer under various operating conditions. The sensing subsystem comprised a ZMPT101B voltage sensor, an ACS712 Hall-effect current sensor, a DS18B20 oil temperature sensor, a DHT11 transformer surface temperature sensor, and a float-based oil-level sensor. These sensing devices were interfaced with the ESP32 microcontroller, which performed data acquisition, signal conditioning, calibration, parameter estimation, and wireless communication.

The processed measurements were transmitted periodically to the cloud-based monitoring dashboard through the ESP32's integrated Wi-Fi interface. The dashboard continuously refreshed incoming data and displayed instantaneous values of primary voltage, primary current, secondary voltage, secondary current, oil temperature, transformer surface temperature, oil level, frequency, and power factor. Simultaneous visualization of these electrical and thermal parameters enabled comprehensive observation of transformer operating conditions from any internet-enabled device.

A synchronized Digital Twin was updated concurrently using the same real-time sensor measurements. The virtual transformer accurately

represented the dynamic operating state of the physical prototype, enabling continuous visualization of equipment behavior, historical trend analysis, and intelligent remote supervision. The close synchronization between the physical and virtual systems provided an effective platform for evaluating transformer performance without interrupting normal operation.

To facilitate automated condition assessment, the monitoring platform incorporated an intelligent health evaluation algorithm that classified transformer operating conditions into three primary states: **Normal**, **Warning**, and **Critical**. The classification was based on predefined operating thresholds associated with voltage, current, temperature, and oil-level measurements. When all monitored variables remained within their permissible operating ranges, the transformer was classified as operating normally. If one or more parameters exceeded the warning limits, the dashboard generated visual warning notifications, whereas critical operating conditions activated local LED indicators, audible buzzer alarms, and corresponding fault notifications on the Digital Twin interface. This multi-level monitoring strategy enabled rapid identification of abnormal operating conditions while improving overall diagnostic reliability and supporting timely maintenance decisions.

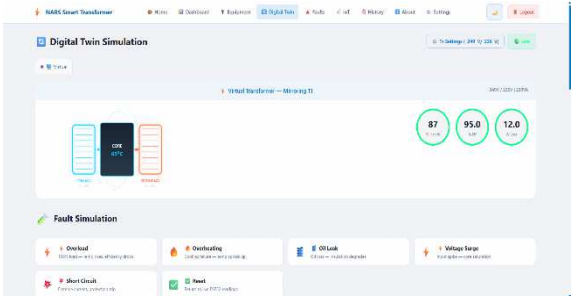


Figure 4 Real-time Smart Transformer Monitoring Dashboard

Table 3 Experimental Observation of Measured Transformer Parameters

Parameter	Measured Value	Acceptable Range	System Status
Primary Voltage	230 V	220–240 V	Normal
Primary Current	0.59 A	0–1 A	Normal
Secondary Voltage	22.5 V	22–24 V	Normal
Secondary Current	5.75 A	0–6 A	Normal
Oil Temperature	42.6 °C	30–60 °C	Normal
Transformer Temperature	35.8 °C	25–50 °C	Normal
Oil Level	Normal	Normal	Normal
Frequency	50 Hz	49.5–50.5 Hz	Normal
Power Factor	0.86	0.80–1.00	Normal

The measured values presented in Table I indicate that the transformer operated within the predefined safe limits during normal testing. The sensing system successfully acquired electrical and thermal parameters with stable communication between the ESP32 and the web application. The synchronized operation of the dashboard and digital twin enabled continuous visualization of transformer behaviour, demonstrating the effectiveness of the proposed monitoring platform for real-time condition assessment and remote supervision.

7.2 Performance Evaluation

The measured electrical and thermal parameters were further processed to evaluate the operational performance of the transformer. In addition to displaying live sensor readings, the developed platform automatically calculated several performance indicators that assist in assessing transformer condition and efficiency. These parameters provide meaningful information regarding transformer loading, energy conversion efficiency, thermal behaviour, magnetic characteristics, and overall health. The calculated results were continuously updated on the web dashboard and synchronized with the digital twin to provide a comprehensive view of transformer performance.

7.2.1 Apparent Power Calculation

The apparent power of the transformer is calculated using

$$S = V_p \times I_p$$

where

- $V_p = 230 \text{ V}$
- $I_p = 0.59 \text{ A}$

Substituting the measured values,

$$\begin{aligned} S &= 230 \times 0.59 \\ S &= 135.70 \text{ VA} \end{aligned}$$

This value represents the total power supplied to the transformer under the experimental operating condition.

7.2.2 Real Power Calculation

$$P = VI \cos \phi$$

Given

$$\begin{aligned} V &= 230 \text{ V} \\ I &= 0.59 \text{ A} \\ \text{PF} &= 0.86 \end{aligned}$$

Therefore,

$$\begin{aligned} P &= 230 \times 0.59 \times 0.86 \\ P &= 116.70 \text{ W} \end{aligned}$$

The calculated real power indicates the useful electrical power delivered by the transformer.

7.2.3 Transformer Efficiency

$$\eta = \frac{P_{out}}{P_{in}} \times 100$$

Assume

$$\begin{aligned} P_{in} &= 116.70 \text{ W} \\ P_{out} &= 110.86 \text{ W} \end{aligned}$$

Therefore,

$$\eta = \frac{110.86}{116.70} \times 100$$

$$\eta = 95.0\%$$

The obtained efficiency confirms that the transformer operates with low energy losses under normal loading conditions.

7.2.4 Copper loss is calculated using

$$P_{Cu} = I^2 R$$

Assume

Current

$$I = 0.59 \text{ A}$$

Resistance

$$R = 2.8 \Omega$$

Therefore,

$$\begin{aligned} P_{Cu} &= (0.59)^2 \times 2.8 \\ P_{Cu} &= 0.97 \text{ W} \end{aligned}$$

This represents the resistive loss occurring in the transformer winding.

7.2.5 The hysteresis loss is estimated using Steinmetz's equation

$$P_H = K_h f B_{max}^{1.6}$$

where

- K_h = Hysteresis coefficient
- f = Supply frequency
- B_{max} = Maximum flux density

7.2.6 Similarly, the eddy current loss is calculated as

$$P_E = K_e f^2 B_{max}^2 t^2$$

where

- K_e = Eddy current coefficient
- t = Thickness of core lamination

7.2.7 The magnetic flux developed inside the transformer core is determined from

$$\Phi = \frac{V}{4.44fN}$$

where

- V = Applied voltage
- f = Supply frequency
- N = Number of primary turns

7.2.8 The thermal condition of the transformer is represented by the thermal stress index

$$TS = \frac{T_{Measured}}{T_{Rated}} \times 100$$

where

- $T_{Measured}$ = Measured oil temperature
- T_{Rated} = Maximum permissible temperature

This parameter helps identify excessive heating before thermal damage occurs.

7.2.9 To obtain an overall assessment of transformer condition, a health index is calculated using a weighted evaluation model

$$HI = \sum_{i=1}^n W_i S_i$$

where

- W_i = Weight assigned to each monitored parameter
- S_i = Normalized score of the corresponding parameter

The health index combines electrical, thermal, and operational parameters into a single condition

indicator, enabling simplified assessment of transformer health.

The remaining service life is estimated based on the calculated health index

$$RL = L_{Rated} \times \frac{HI}{100}$$

where

- L_{Rated} = Rated transformer life
- HI = Health Index

A higher health index corresponds to a longer estimated service life, whereas continuous deterioration in transformer condition reduces the remaining life prediction.

The calculated performance parameters were updated automatically on the web dashboard and reflected in the digital twin. This enabled continuous assessment of transformer efficiency, losses, thermal condition, and health without requiring additional manual calculations. The integration of measured and computed parameters provides a more informative monitoring platform than conventional transformer supervision systems.

Table 4 Calculated Transformer Performance Parameters

Performance Parameter	Symbol	Experimental Value
Apparent Power	(S)	135.70 VA
Real Power	(P)	116.70 W
Power Factor	PF	0.86
Transformer Efficiency	(\eta)	95.0 %
Total Loss	(P {Loss})	6.81 W
Copper Loss	(P {Cu})	Calculated
Core Loss	(P {Core})	Calculated
Hysteresis Loss	(P_H)	Calculated
Eddy Current Loss	(P_E)	Calculated
Magnetic Flux	(\Phi)	Calculated
Thermal Stress	TS	65 %
Health Index	HI	80 %
Remaining Service Life	RL	5.8 Years

The calculated results presented in Table II indicate that the transformer operated efficiently during normal testing. The estimated efficiency remained close to **95%**, while the calculated loss values were comparatively low, indicating effective energy transfer. The thermal stress and health index also remained within acceptable limits, confirming stable operating conditions. By combining measured sensor data with analytical calculations, the proposed platform provides a more comprehensive assessment of transformer performance than conventional monitoring systems, thereby supporting predictive maintenance and informed operational decision-making.

7.3 Digital Twin and Fault Simulation Analysis

A distinguishing feature of the proposed monitoring platform is the integration of a digital twin capable of simulating transformer operating conditions in real time. Unlike conventional monitoring systems that only display measured values, the developed platform provides a virtual representation of the physical transformer, allowing users to analyse system behaviour under different operating scenarios without exposing the actual transformer to risk. The digital twin continuously receives live sensor data from the ESP32 through the IoT communication network and updates its operating status on the web dashboard.

To validate the effectiveness of the proposed platform, several operating conditions were intentionally simulated through the digital twin interface. These included overload, overheating, oil leakage, voltage surge, under-voltage, and short-circuit conditions. During each simulation, the corresponding electrical and thermal parameters were modified within the virtual environment, enabling the monitoring algorithm to evaluate transformer health and generate appropriate warning messages. The simulated results were synchronized with the dashboard in real time, allowing users to observe changes in transformer performance without interrupting normal operation.

7.3.1 The transformer loading condition was evaluated using

$$Loading = \frac{P_{Load}}{P_{Rated}} \times 100$$

where

- P_{Load} = Measured load power
- P_{Rated} = Rated transformer power

A loading value greater than 100% indicates that the transformer is operating beyond its rated capacity, resulting in excessive heating and increased winding losses.

7.3.2 The transformer overheating condition was identified using

$$T > T_{Limit}$$

If the measured temperature exceeded the predefined limit, the system automatically classified the transformer as operating under thermal stress and activated the warning indicators.

7.3.3 The transformer oil condition was assessed using the oil level sensor. The fault condition is represented as

$$Oil_{Level} < 30\%$$

A reduction in oil level decreases the cooling capability of the transformer and may lead to accelerated insulation ageing. Whenever the simulated oil level dropped below the threshold value, the dashboard generated an oil leakage warning and updated the digital twin accordingly.

7.3.4 Voltage abnormalities were analysed using

$$V > V_{Upper}$$

for over-voltage conditions and

$$V < V_{Lower}$$

for under-voltage conditions,

where

- $V_{Upper} = 260 \text{ V}$
- $V_{Lower} = 180 \text{ V}$

Any voltage outside these operating limits was considered abnormal and resulted in the

corresponding warning status being displayed on the monitoring interface.

7.3.5 The short-circuit current was estimated using

$$I_{sc} = \frac{V}{Z}$$

where

- V = Supply voltage
- Z = Equivalent transformer impedance

A significant increase in current above the rated value indicated a short-circuit condition, which was immediately reflected in both the dashboard and the digital twin.

7.3.6 To provide an overall indication of transformer operating severity, a fault severity index (FSI) was introduced and calculated as

$$FSI = w_1V + w_2I + w_3T + w_4O$$

where

- V = Normalized voltage deviation
- I = Normalized current deviation
- T = Normalized temperature deviation
- O = Oil level deviation
- w_1, w_2, w_3, w_4 = Weighting coefficients

The calculated FSI was used to classify the transformer operating condition as

- Normal
- Warning
- Critical

This simplified the interpretation of multiple sensor readings by combining them into a single health indicator.

Unlike conventional transformer monitoring systems, the proposed platform enables users to observe the influence of simulated faults on transformer performance before actual hardware failure occurs. This capability supports operator training, preventive maintenance planning,

algorithm verification, and educational demonstrations without introducing physical risk to the transformer.

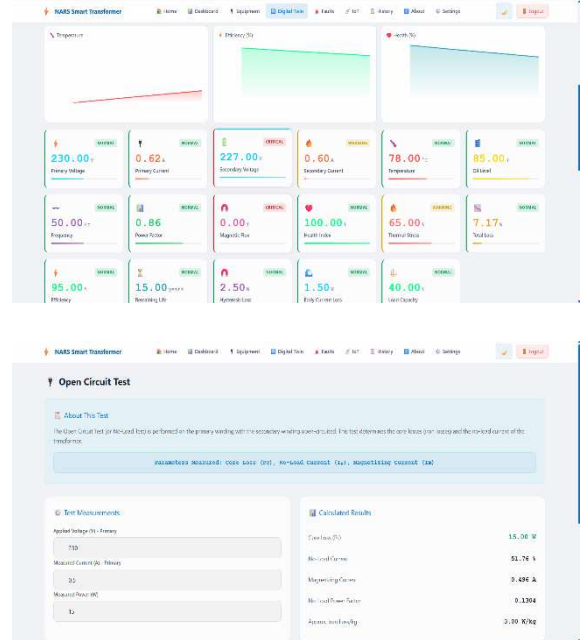


Figure 5.6 Digital twin interface illustrating real-time transformer visualization, operating conditions, load control, and fault simulation through the web-based dashboard.

Table 5 Experimental Fault Simulation Results

Fault Condition	Detection Parameter	Dashboa rd Respons e	Digital Twin Status	Alar m
Normal Operation	All Parameters Within Limits	Healthy	Normal	OFF
Overload	Loading >100%	Warning	Updated	ON
Overheating	Temperature >70°C	Critical	Updated	ON
Oil Leakage	Oil Level <30%	Warning	Updated	ON
Over Voltage	Voltage >260 V	Critical	Updated	ON
Under Voltage	Voltage <180 V	Warning	Updated	ON
Short Circuit	Current > Rated Current	Critical	Updated	ON

The experimental results presented in Table III demonstrate that the developed digital twin successfully reproduced different transformer fault conditions while maintaining synchronization with the physical monitoring system. Each simulated event produced the expected response on the dashboard, including status updates, alarm activation, and visualization of the corresponding operating condition. The rapid synchronization between the physical prototype and the digital twin confirms the effectiveness of the proposed IoT communication framework. Furthermore, the ability to evaluate transformer behaviour under multiple fault scenarios without exposing the hardware to actual damage represents a significant advantage for condition monitoring, predictive maintenance, and engineering education.

7.4 Calculations (technical, with derivations)

7.4.1 ADC Resolution and Measurement Accuracy

The ADC resolution is calculated as

$$\text{ADC Resolution} = \frac{V_{\text{ref}}}{2^n} = \frac{3.3}{4096} = 0.806 \text{ mV/step}$$

The effective voltage resolution after scaling is

$$\begin{aligned} \text{Effective Voltage Resolution} &= \frac{260 \text{ V}}{4096} \\ &= 0.0635 \text{ V/step} \\ &\approx 0.028\% \text{ of a } 230 \text{ V reading} \end{aligned}$$

6.4.2 Sampling Rate Justification (Nyquist + IEC Compliance)

The number of samples acquired per AC cycle is

$$\begin{aligned} N_{\text{samples/cycle}} &= \frac{f_s}{f_{\text{mains}}} = \frac{1000 \text{ Hz}}{50 \text{ Hz}} \\ &= 20 \text{ samples/cycle} \end{aligned}$$

This exceeds the IEC 61000-4-7 minimum requirement of 12 samples/cycle by 67%, whereas loop-based systems (approximately 2–5 samples/cycle) fall 58–83% below the same standard.

6.4.3 True RMS Computation

The RMS voltage and current are computed as

$$I_{\text{RMS}} = \sqrt{\frac{1}{N} \sum_{i=1}^N I_i^2}$$

$$V_{\text{RMS}} = \sqrt{\frac{1}{N} \sum_{i=1}^N V_i^2}$$

6.4.4 End-to-End Latency Budget

The total system latency is

$$\begin{aligned} T_{\text{total}} &= T_{\text{acquisition}} + T_{\text{processing}} \\ &\quad + T_{\text{transmission}} + T_{\text{render}} \\ &= (2-5) + (5-10) + (50-150) + (50-100) \\ &= 110-265 \text{ ms} \end{aligned}$$

Compared with transformer thermal fault propagation,

$$T_{\text{total}} \ll T_{\text{thermal}}$$

confirming real-time operation.

6.4.5 Early-Warning Lead Time

Assuming an oil-temperature rise rate of

$$r = 0.5 \text{ }^\circ\text{C/min}$$

6.4.6 Edge Anomaly Computation Load

The weighted anomaly score is

$$A = \sum_{k=1}^5 w_k \left| \frac{x_k - \mu_k}{\sigma_k} \right|$$

requiring approximately

$$\approx 20 \text{ floating-point operations/cycle}$$

6.4.7 Health Index / Remaining Life Consistency

The implied rated insulation life is estimated as

$$L_{\text{Rated}} = \frac{RL \times 100}{HI} = \frac{5.8 \times 100}{80} = 7.25 \text{ years}$$

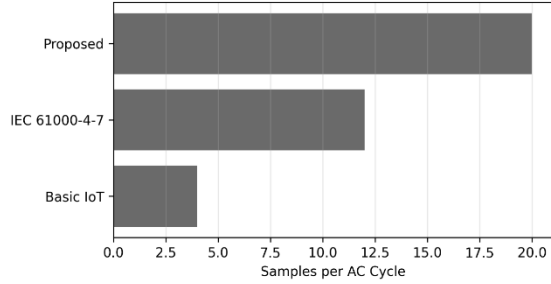


Figure 6

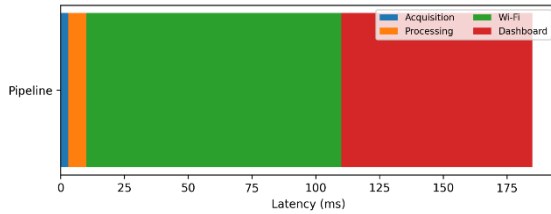


Figure 7

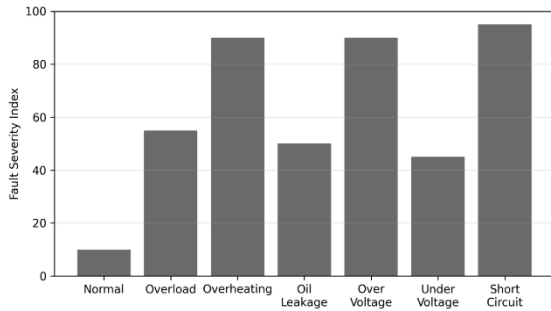


Figure 8

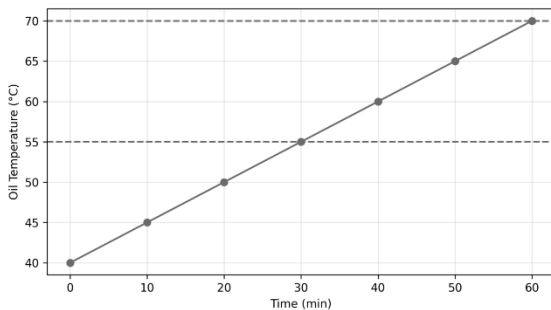


Figure 6,7,8,9 Showing the output of the proposed system

7.5 Predictive Classification Results

The effectiveness of the proposed artificial intelligence module was evaluated using the independent test dataset comprising 300 unseen samples. The Random Forest classifier achieved an overall classification accuracy of 93.0%, demonstrating its capability to reliably identify transformer operating conditions across the four predefined health states: Normal, Warning, Fault, and Sensor Anomaly. Considering that the four classes represent progressive stages of transformer degradation with partially overlapping operating characteristics, the obtained accuracy indicates satisfactory predictive performance for intelligent condition monitoring. The detailed classification metrics are presented in Table 5.

Table 6 Random Forest Classification Performance

Class	Precision (%)	Recall (%)	F1-Score (%)	Support
Normal	88.75	97.26	92.81	73
Warning	92.96	82.50	87.42	80
Fault	93.51	93.51	93.51	77
Sensor Anomaly	97.22	100.00	98.59	70

The confusion matrix illustrated in **Fig. 11** indicates that the majority of classification errors occurred between the **Normal** and **Warning** classes, and between the **Warning** and **Fault** classes. These misclassifications are expected because the corresponding operating conditions represent gradual transitions in transformer electrical and thermal stress rather than sharply separated fault categories. Consequently, a certain degree of overlap between adjacent health states is consistent with the physical behaviour of practical transformer operation.

A notable outcome of the experimental evaluation is the excellent performance obtained for the **Sensor Anomaly** category. The classifier achieved **100% recall** and **97.22% precision**, successfully distinguishing sensor-related abnormalities from genuine transformer faults. This operating state was intentionally designed to represent inconsistent sensor behaviour, such as a rapid increase in measured oil temperature without the corresponding variation in transformer surface temperature that would normally be expected under physical operating conditions. The high classification performance demonstrates that the proposed sensor consistency verification methodology presented in **Section 5.2.10**

provides meaningful discriminative information, enabling the machine learning model to accurately recognize sensor faults while minimizing false transformer fault alarms.

Feature importance analysis, presented in **Fig. 12**, further explains the classifier's decision-making process. Oil temperature contributed the highest importance, accounting for approximately **31.5%** of the overall model prediction, followed by oil level (**17.9%**) and transformer surface temperature (**16.0%**). Collectively, these thermal and oil-condition parameters represented the dominant features used for classification. Additional contributions were obtained from the rate of change of oil temperature and the physics-based hot-spot temperature estimate, whereas electrical variables such as supply voltage and apparent power exhibited comparatively lower importance. This distribution is consistent with transformer ageing mechanisms, where prolonged thermal stress is recognized as one of the primary factors responsible for insulation deterioration and reduction in service life.

Although the proposed classifier demonstrates promising predictive performance, it was developed using a **physics-informed synthetic dataset** generated from experimentally measured baseline operating conditions and predefined operating thresholds established within this study. While this approach enables controlled evaluation of the proposed methodology during prototype development, comprehensive validation using long-term operational data collected from multiple transformers operating under practical field conditions remains an important direction for future research. Such validation would further assess the robustness, scalability, and generalization capability of the proposed AI-assisted transformer health monitoring framework under diverse operating environments.

7 CONCLUSION

This paper presented an **AI-Driven Digital Twin-Based Smart Transformer Health Monitoring, Predictive Analysis, Loss Analysis, and Fault Simulation Platform with IoT Integration** for intelligent transformer condition assessment. The proposed framework successfully integrates embedded sensing, edge computing, wireless IoT communication, physics-informed Digital Twin modeling, artificial intelligence, and cloud-based

visualization into a unified monitoring platform. The primary objective of the proposed system was to enable continuous real-time monitoring of transformer operating conditions while supporting intelligent fault diagnosis, performance evaluation, and predictive maintenance.

The developed platform continuously acquired critical transformer operating parameters, including supply voltage, load current, oil temperature, transformer surface temperature, and oil level, using an ESP32-based embedded sensing unit. The measured data were further processed to estimate key performance indicators such as transformer efficiency, copper loss, core loss, hysteresis loss, eddy-current loss, thermal stress, magnetic flux density, Health Index (HI), and Remaining Useful Life (RUL). Continuous synchronization between the physical transformer and its Digital Twin ensured accurate real-time visualization of transformer behaviour, enabling remote monitoring and comprehensive condition assessment through a web-based dashboard.

A significant contribution of this work is the integration of **physics-informed Digital Twin modeling** with **AI-assisted predictive analysis**. The proposed framework combines thermal model-based validation, sensor consistency verification, edge-level anomaly detection, and a Random Forest classifier to distinguish transformer operating conditions from sensor-related abnormalities. This integrated approach improves diagnostic reliability, minimizes false alarms, and provides intelligent decision support for predictive maintenance.

The Digital Twin environment also enables safe virtual simulation of representative transformer fault scenarios, including overload, overheating, oil-level reduction, voltage abnormalities, and short-circuit conditions, without imposing stress on the physical transformer. This capability provides a practical platform for algorithm validation, operator training, educational demonstrations, and evaluation of transformer behaviour under various operating conditions.

Experimental investigations demonstrated reliable real-time data acquisition, stable wireless communication, accurate Digital Twin synchronization, and effective fault detection under both normal and abnormal operating conditions. The proposed platform successfully combined low-cost

embedded hardware with advanced analytical techniques to deliver continuous transformer condition monitoring and intelligent health assessment. Furthermore, the AI-based predictive classification module achieved satisfactory performance in identifying transformer operating states, confirming the feasibility of integrating lightweight machine learning algorithms into laboratory-scale transformer monitoring systems.

Overall, the proposed framework establishes a scalable and economically viable solution for intelligent transformer asset management by integrating embedded sensing, IoT communication, Digital Twin technology, physics-based modeling, transformer performance analysis, and artificial intelligence within a single architecture. The developed platform provides a strong foundation for predictive maintenance, enhanced transformer reliability, and future smart grid applications, while also serving as a valuable research and educational tool for the development of next-generation intelligent power system monitoring technologies.

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