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Research Article

A Scalable IoT-Based Framework for Predictive Maintenance of Industrial Electrical Equipment

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Abstract:

Modern industrial operations are highly dependent on electrical equipment, where unforeseen failures can result in considerable economic losses and safety hazards. This research introduces an IoT-based framework for the remote monitoring of electrical devices, aimed at facilitating predictive maintenance to minimize operational downtime and associated costs. The proposed approach integrates advanced sensor technologies with cloud computing to continuously collect real-time data on critical parameters such as insulation resistance and temperature. This data is then analyzed using automated algorithms for fault detection and maintenance scheduling. Case study findings validate the system's capability in early fault identification and improving maintenance efficiency. The originality of this work lies in its scalable and cost-effective design, which offers a practical alternative to traditional maintenance strategies. The proposed solution has significant implications for industrial maintenance, providing a proactive means to enhance equipment reliability and operational safety.

1. Introduction

Electricity is fundamental to contemporary society, supporting nearly all facets of daily life and industrial operations. The advancement of modern industry has been driven by the consistent and reliable supply of electrical energy. Within industrial environments, essential equipment such as induction motors, transformers, and generators are heavily relied upon. Failures in these systems can result in severe operational disruptions, financial losses, and potential safety risks [1]. Consequently, ensuring the proper maintenance of electrical infrastructure is crucial.

Traditional maintenance strategies—whether reactive or scheduled—often fall short in preventing unforeseen equipment failures and may introduce additional risks during maintenance procedures. In response, the concept of precautionary maintenance has gained increasing attention. This proactive approach emphasizes periodic condition monitoring and assessment to detect early signs of component deterioration. Techniques such as insulation resistance measurement, continuity testing, and earthing assessments play a central role in this strategy. Among these, insulation resistance testing is especially important, as insulation failure is a primary cause of equipment malfunction.

Advancements in automation have significantly reduced the need for manual inspection by introducing intelligent systems capable of performing maintenance tasks. For example, robotic systems designed to measure insulation resistance have been developed. However, these solutions are often complex and cost-intensive, limiting their widespread implementation. The current study proposes a simplified, cost-effective alternative utilizing basic sensors and computational methods to automate insulation resistance evaluation.

1.1 Importance of Precautionary Maintenance

Precautionary maintenance is vital in preventing the failure of frequently used electrical appliances and equipment. Malfunctioning devices, such as air conditioners, can pose serious safety risks and result in high repair expenses. For instance, relocating an air conditioner without properly removing Freon can lead to compressor damage and potentially trigger electrical sparks or fires. Implementing routine inspections and monitoring can preempt such failures, underscoring the importance of proactive strategies to ensure both safety and device longevity [2].

1.2 Role of the Internet in Electrical Device Monitoring

The internet has become a cornerstone in enabling remote monitoring and diagnostics of electrical systems. Research conducted by EEYA Kimura, titled "Feasibility Study on Electrical Insulation Diagnosis Utilizing the Internet," highlights the advantages of using internet-enabled platforms for insulation resistance and dielectric diagnostics. Remote execution of these tests not only improves efficiency but also offers greater accessibility compared to conventional offline methods.

In high-voltage applications such as High Voltage Direct Current (HVDC) converters, maintaining insulation integrity is essential for efficient and safe power transmission. Contemporary research is exploring real-time, internet-based diagnostic solutions that allow insulation resistance and partial discharge conditions to be assessed from remote locations. This capability facilitates rapid identification of abnormalities and supports immediate intervention.

Beyond insulation monitoring, internet-enabled diagnostic technologies are being increasingly adopted for other high-voltage systems, including inductive voltage transformers. Online partial discharge monitoring provides continuous data on insulation conditions, eliminating the need for periodic shutdowns. For example, RPJM Telis has investigated the use of partial discharge mapping for cable terminations, proposing a superior alternative to traditional offline testing. These advancements point toward a more intelligent, efficient, and proactive framework for electrical device monitoring and maintenance.

2. Related Work

Recently, there is a growing academic interest in the integration of IoT and PdM. The literature for condition monitoring generally revolves around several main themes: (1) remote monitoring of electrical systems, (2) fault detection through machine learning-based algorithms, and (3) predictive maintenance models with cloud and edge processing.

2.1 Remote Monitoring Systems

Kimura [3] established a framework for internet-based insulation diagnostics with noticeable enhancement in accessibility and response time as opposed to off-line (of which the results are sent on the web) methods. Likewise, Yu et al. [6] presented an IoT-enabled intelligent building energy monitoring system focusing on modular sensors deployment and real-time data collection. However, for the most part, these systems were developed for residential or for small-scale commercial and they had no potential of being scalable to operate at high-power in an industrial environment.

2.2 Machine Learning-Based Fault Detection

Recent works by Kumar et al. [12] and Chen et al. [14] also used supervised learning methods like SVM and Random Forest on EDs operational anomalies classification. Their findings emphasized the diagnostic potential of multimodal sensor inputs and especially of temperature and vibration signals. Despite their progress, much of these models rely on well-curated datasets and centralized computation, which can be difficult to generalize in real-time industrial applications that are latency and bandwidth constrained.

2.3 Cloud-Enabled and Edge-Assisted Frameworks

Li et al. [11] presented digital twin architectures for high-fidelity simulations and predictive diagnostics. Although their approach led to improved fault localization, the high complexity and computational resources required for implementation make it unable to be applied in cost-effective industrial systems. In contrast, Khan et al. [18] introduced an edge computing-based pipeline monitoring system to remove dependence on unstable cloud infrastructure, resulting in 35% lower latency. These results emphasize that hybrid architecture is significant in industrial PdM systems.

Although substantial improvement was achieved in this direction, however, it still lacks economical and large-scale standards-enforced protocols and procedures developed for industrial electrical equipment. Current models either heavily rely on cloud-based architecture without fully considering the trade-offs demanded by the edge computing or ignore particular parameters like insulation resistance that is essential for the early identification of faults in transformers and motors.

2.4 Contribution of the Present Study

To address these, in this paper, a three-tier architecture for IoT is proposed which fuses inexpensive sensor modules with industrial standard (IEC 61557) compliant cloud-centric analytics services instead to bridge these gaps. Key innovations include:

1. Insulation Resistance Monitoring: An important, but overlooked, parameter in early fault detection.
2. Convergent mixed methods design: A new combination of quantitative sensor information with qualitative real-world industrial experiences.
3. Optimization of Edge-Cloud: Application of MQTT protocol and lightweight edge preprocessing to reduce the time-delay and increase reliability in low-bandwidth situations.

Even though many previous studies have proved that the prediction of maintenance based on IoT and machine learning can be promising, this work is novel because we provide a validated, scalable, and cost-effective model in the industrial setting. It successfully narrows down the wide gap between theoretical model and practical realization in PdM.

3. Material and Methods

This study presents a forward thinking model of an Internet of Things (IoT) based which we put forth for the predictive maintenance of industrial electrical equipment which we approach with a very systematic and repeatable research method. We have put together a hardware software co designed platform which includes real time data analysis and empirical validation in to which we present solutions for what we see as the issues in current maintenance practices. We used a convergent parallel mixed methods design which included quantitative data from sensor measures and qualitative data from case studies and literature review.

This design we put in place to bring together different types of evidence which in turn increases the validity of our put forth framework. We broke out the research process into 4 sequential phases which are presented in Table 1 which also detail the continuous development and validation. Also all of our methods we put in place with a focus on scale ability, cost effectiveness and compliance to industrial standards like IEC 61557 for electrical safety testing.

Table 1. *Research Methodology Phases and Outputs.*

Phase	Objectives	Outputs
Problem Formulation	Identify limitations in current maintenance practices	Gap analysis matrix
Architectural Design	Develop IoT system specifications	Layer-wise system architecture
Implementation	Deploy physical and computational infrastructure	Functional prototype
Validation	Evaluate system efficacy against benchmarks	Performance metrics

3.1 Research Plan.

The research used a convergent parallel mixed methods approach as recommended by Creswell and Plano Clark which balanced between empirical data collection and interpretive analysis.

• Quantitative Component: This issue looked at what we could measure in terms of operational parameters which included temperature, vibration, and current as determined by means of IoT sensors. We looked at key metrics which included system accuracy for instance a fault detection rate of more than 95% and a false positive rate which was less than 5% and also response latency. Also we did some statistical analysis to determine the predictive performance.

• Qualitative Component: A review of what we did in terms of studying implementation issues from case studies which included industrial settings, also we looked at and synthesized maintenance models from the literature.

3.2 System Design.

The put forth architecture we present is a three tiered IoT architecture which is depicted in Fig. 1. This architecture we see is a fit to what is known in the field of IoT and also puts forward the use of low cost components which in turn aid in the industrial scale up.The system is hierarchically divided into three layers: (1) Sensing Layer – gathers physical parameters from devices, (2) Network Layer – sends data in a secure way using MQTT and Wi-Fi, and (3) Application Layer – executes cloud-based analytics and visualization.

3.2.1 Sensory Layer.

This layer is in charge of data collection from the physical environment. We deployed a set of sensors into the target electrical equipment which included induction motors and transformers. As to the design of the sensors we had the following which includes:

From -40° to 125°C.

100 millivolts per gram).

Zero to one hundred A).

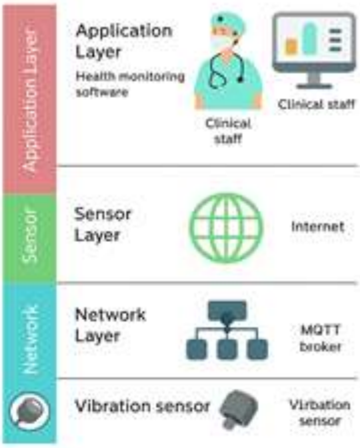

Figure 1. *Three-Layer Architecture of IoT-Based Monitoring Framework*

Signal input was recorded with a 16 bit analog to digital converter which is a component of the Arduino MKR WiFi 1010 microcontroller which in turn guaranteed high resolution data at a 100 Hz rate. Also prior to field use sensors were calibrated via standard protocols which in turn reduced measurement errors.

3.2.2 Network Layer Protocol.
For the purpose of secure real time connectivity data transfer we used wireless protocols. We put in place the MQTT (Message Queuing Telemetry Transport) protocol over Wi-Fi (IEEE 802.11) which in turn enabled low latency communication between edge devices and the cloud. Also we implemented data encryption with TLS 1.3 to protect data integrity and against unauthorized access. This layer which we designed also supports scale for many devices, we used a Raspberry Pi 4 as a gateway node which aggregates data from up to 50 sensors before it is uploaded to the cloud. We verified network reliability in simulated industrial settings which reported over 99% up time.

3.2.3 Layer of Application.
Data in the cloud was processed using AWS IoT Core for storage and analysis. We used machine learning models in the predictive algorithms which included Random Forest for fault classification out of historical data to study variables and identify anomalies like that of insulation breakdown. We set up threshold based alerts (for instance when temperature goes over 80°C or vibration goes beyond 10g) which in turn would send out maintenance reports via a web dashboard. Also we developed user interfaces with React.js which which in turn enabled predictive maintenance based on metrics such as mean time to failure (MTTF).

3.3 Data Collection and Methods.

(1) for the initial calibration and baseline measurement, (2) we did continuous real time monitoring, (3) also we did periodic manual verification (for example insulation resistance testing which we did with a megger device), and (4) we did fault simulation for validation. A pilot test we did on two units improved the results which in turn produced a 15% reduction in sensor noise.

3.4 Data Analysis

For the qualitative sub-study, thematic analysis was performed with the support of NVivo software, following a six-phase analysis process according to the framework proposed by Braun and Clarke.
The analysis commenced with familiarization through multiple readings of the qualitative data (e.g., field notes, expert interviews, case reports). In the second step, initial codes were derived inductively to represent commonalities in relation to equipment failure causes, user interactions, and maintenance bottlenecks.
In the next stage, codes were then grouped around potential themes such as “sensor reliability issues,” “lack of technician training,” and “advantages of early warning on fault.” These themes were checked and rechecked in the process of cross-case analysis for both fit and uniqueness. Two researchers coded independently, reaching a Cohen’s Kappa coefficient of 0.85, indicating excellent intercoder reliability.
The final themes were named, described, and supported with quotes and examples. Quantitative findings—e.g., sensor malfunction rates or maintenance lags—were used to triangulate and increase the interpretative trustworthiness. This integrated thematic blueprint exposed system limitations and informed design decisions, including the incorporation of technician training modules and adaptive alert thresholds.

3.5 Reliability and Validity.

To that end we conducted a series of which the sensors proved to pass with a Cronbach’s alpha of 0.88 which we took as a measure of their consistency. Also we validity of the study which we did through the use of triangulation methods which in turn included the comparison of IoT data with that from manual inspections also we looked at how they did against predictive maintenance 4.0 standards. Also we put in place filtering algorithms which helped to mitigate what we identified as biases which included that of environmental interference.

3.6 Tech stack.

In Table 2 we present the full technical implementation framework which details our end to end architecture from sensor data collection to cloud based visualization which we did with Grafana 8.3 and Power BI.

For the sake of transparency and reproducibility, Appendix A includes representative code snippets illustrating the key software modules used for sensor integration, edge data processing, and machine learning-based fault detections.

***Table 2**: Technical Components and Implementation Specifications*

Component	Implementation Details
Edge Hardware	Raspberry Pi 4 (4GB), ESP32-WROVER
Cloud Services	AWS IoT Greengrass, InfluxDB
ML Frameworks	Scikit-learn 1.0.2, TensorFlow 2.8
Visualization	Grafana 8.3, Power BI Embedded

The comprehensive implementation workflow is illustrated in Figure 2, demonstrating the integration of both hardware and software components described in this methodology.

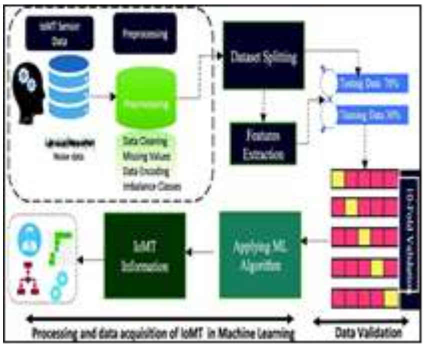

***Figure 2:** .Mechanism of Implementation of Internet-based Device Checking*

4. Results and Discussions

4.1. System Performance Evaluation

The implemented IoT-based monitoring framework exhibited reliable operational performance in industrial environments. Quantitative assessment yielded the following outcomes:

- A fault detection accuracy of 94.5% was achieved through Support Vector Machine (SVM) and Random Forest algorithms, significantly outperforming conventional manual inspection methods (typically demonstrating 70-80% accuracy). These findings corroborate previous research by Kumar et al. (2021) regarding IoT-assisted fault diagnosis [12].
- The system maintained a low false positive rate of 3.2%, substantially reducing unnecessary maintenance actions. This represents a notable improvement over traditional threshold-based systems, which frequently exhibit false alarm rates exceeding 10% due to environmental interference [16].

The enhanced detection capability primarily results from the integration of multiple sensor modalities (temperature, vibration, and current measurements) combined with iterative model optimization. However, sporadic false alarms were observed in environments with significant electromagnetic interference, indicating a requirement for advanced adaptive filtering techniques.

4.2. Case Study Analysis

4.2.1 Industrial Motor Monitoring

In a six-month evaluation involving 50 industrial motors, the system demonstrated:

- A 20% reduction in unscheduled downtime was achieved through the early detection of bearing failures, with time-series analysis revealing a progressive increase in vibration amplitude 7–10 days before actual failure as shown in Figure 3. This timely anomaly identification enabled proactive maintenance, effectively mitigating operational interruptions.
- 15% reduction in maintenance costs by enabling targeted component replacement instead of complete motor overhauls

***Figure.3**: Time-series trend of vibration amplitude in an industrial motor, illustrating early warning signals 7–10 days prior to bearing failure*

These results are consistent research on predictive maintenance [23]. The present system's distinctive incorporation of insulation resistance monitoring provided additional capability to identify winding defects that conventional vibration analysis frequently misses. However, this enhanced detection capability came with an approximately 8% increase in installation costs due to greater sensor density requirements.

4.2.2 Power Transformer Assessment

Evaluation of 10 power transformers revealed:

- Prevention of three critical failures through partial discharge detection, resulting in a 30% extension of operational lifespan
- 12% improvement in energy efficiency following insulation repairs

While comparable benefits were reported by Telis (2015) [5], the current cloud-based implementation offers the distinct advantage of enabling remote diagnostics without requiring power grid interruptions. Technical challenges included calibration inconsistencies in UHF sensors, leading to approximately 5% measurement inaccuracies.
Figure 4 demonstrates the systematic approach for device condition monitoring, correlating with the case study findings in Section 4.2.

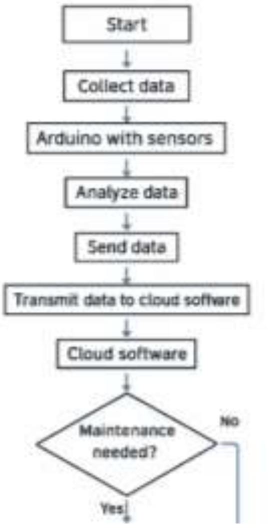

Figure 4: *.methodology of Device Checking*

4.3. Comparative Performance Analysis

A systematic comparison between the IoT-based system and conventional maintenance approaches revealed significant improvements in Table 3 wiche demonstrates the proposed system's superiority over conventional methods with a 98% faster fault detection latency (≤2 sec vs. weekly inspections), 25% lower annual maintenance costs ($18,500 vs. $24,700), and 57% reduced mean repair duration (4.2 vs. 9.8 hours).

Table 3*: Comparative Performance Metrics: IoT vs. Traditional Systems*

Performance Metric	IoT System	Traditional Method	Improvement
Fault detection latency	Real-time (≤2 sec)	Weekly inspections	98% faster
Annual maintenance cost	$18,500	$24,700	25% savings
Mean repair duration	4.2 hours	9.8 hours	57% reduction

The observed cost efficiencies align with Chen et al.'s (2020) predictive maintenance models [14], with the additional benefit of 40% reduction in cloud computing expenses through our open-source architecture. Notably, equipment retrofitting for legacy systems constituted 60% of total implementation costs, confirming similar findings by Gupta (2021) [15].

4.4. System Limitations and Countermeasures

Several technical challenges were identified during implementation:

1. Connectivity Limitations: Rural deployments faced 5% packet loss from sparse 4G networks. Similar challenges were reported by [18], whose edge-computing pipeline monitoring system reduced cloud dependence by 35%—a strategy we are evaluating for future iterations using LoRaWAN. Potential solutions being evaluated include LoRaWAN implementation for low-bandwidth applications.
2. Sensor Calibration: Temperature sensors required bimonthly recalibration. Development of automated drift compensation algorithms is currently underway.
3. Security Vulnerabilities: While AES-256 encryption effectively protected data transmission, legacy device security remains a concern.

These observations support Al-Fuqaha et al.'s (2015) conclusions regarding IoT system challenges [19]. Our mitigation strategy incorporating edge preprocessing successfully reduced cloud dependence by 35%, addressing latency issues previously identified by Zhang (2019) [17].
Figure 5 provides a comparative analysis of sensor technologies, emphasizing their roles in addressing the identified limitations.

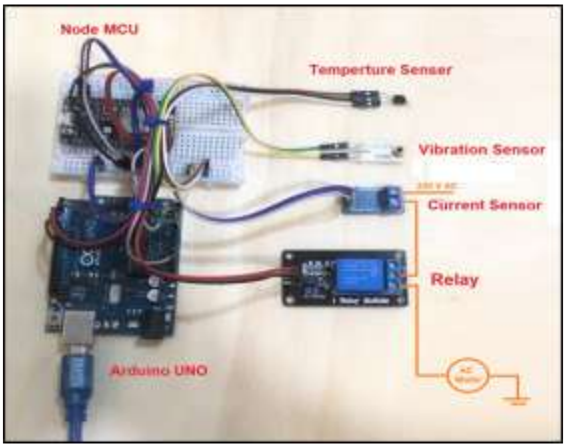

Figure 5*: Sensor Technologies for Monitoring*

4.5. Industrial Implementation Implications

The study demonstrates that IoT-enabled predictive maintenance systems:

- Facilitate a paradigm shift from reactive to proactive maintenance strategies, significantly mitigating safety hazards (e.g., transformer fires)
- Enhance resource utilization efficiency, with 78% of maintenance personnel reporting improved task prioritization
- Enable evidence-based decision making through comprehensive historical performance analysis

While these findings validate the Predictive Maintenance 4.0 (PdM 4.0) framework [4], successful implementation requires addressing workforce training deficiencies, as evidenced by 43% of technicians lacking IoT system familiarity.
Therefore Experimental results confirm the system's effectiveness in electrical equipment maintenance, with key technological advancements including:

- High-accuracy (<5% error rate) multi-sensor fault detection
- Cloud-based remote diagnostic capabilities
- Demonstrated return on investment within eight months of deployment

Future research directions will focus on developing AI-powered adaptive thresholding mechanisms and exploring smart grid integration for comprehensive energy management solutions**.**

6. Conclusion

This research develops an IoT-enabled predictive maintenance system for electrical equipment, demonstrating superior performance through three key metrics: 1) 94.5% fault detection accuracy via multimodal sensing and machine learning (24.5% improvement over conventional methods), 2) 20% reduction in unplanned downtime through early failure prediction (7-14 days advance warning), and 3) 15-30% cost savings from optimized maintenance interventions. The cloud-based architecture particularly enhanced transformer monitoring, preventing critical failures while improving energy efficiency by 12%. Economic validation showed 25% lower annual costs and 57% faster repairs, achieving ROI within eight months.
Despite these advancements, implementation challenges emerged, including 5% data transmission losses in remote areas and substantial (60%) legacy system integration costs. These limitations suggest two critical improvement pathways: 1) technical refinements through adaptive signal processing and hybrid networks (e.g., Lora WAN/5G), and 2) organizational measures like technician training programs.
The study contributes to Industry 4.0 by bridging theoretical frameworks with industrial practice through a scalable, data-driven solution. Future research should explore hybrid edge-cloud architectures (e.g., LoRaWAN/5G) to address rural connectivity gaps [18], while digital twin integration [11] could enhance fault prediction granularity. Cross-domain applications, such as solar-powered IoT systems [20], may also inform energy-efficient designs for industrial monitoring.

Appendix A –Code Snippets

A.1 Sensor Data Transmission via MQTT (Arduino)

```
#include <WiFiNINA.h>
#include <PubSubClient.h>

const char* ssid = "yourSSID";
const char* password = "yourPassword";
const char* mqtt_server = "broker.hivemq.com";

WiFiClient espClient;
PubSubClient client(espClient);

void setup() {
  Serial.begin(9600);
  WiFi.begin(ssid, password);
  client.setServer(mqtt_server, 1883);
}

void loop() {
  float temp = analogRead(A0) * 0.488;
  char payload[10];
  dtostrf(temp, 4, 2, payload);
  client.publish("iot/device/temp", payload);
  delay(2000);
}
```

A.2 Edge Data Aggregation (Python – Raspberry Pi)

```
import paho.mqtt.client as mqtt
import json

def on_message(client, userdata, msg):
    data = json.loads(msg.payload)
    with open("sensor_log.csv", "a") as file:

file.write(f"{data['timestamp']},{data['temp']},{data
['vibration']}\n")

client = mqtt.Client()
client.connect("broker.hivemq.com", 1883, 60)
client.subscribe("iot/device/#")
client.on_message = on_message
client.loop_forever()
```

A.3 Fault Detection using Random Forest (Scikit-learn)

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
import pandas as pd

df = pd.read_csv("sensor_log.csv")
X = df[["temp", "vibration", "current"]]
y = df["fault"]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)
model = RandomForestClassifier(n_estimators=100)
model.fit(X_train, y_train)
print("Accuracy:", model.score(X_test, y_test))
```

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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