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Article

# Condition Monitoring in Power Transformers Using IoT: A Model for Predictive Maintenance

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## Abstract

Power transformers are critical components in electrical power systems, and their failure can lead to severe economic and operational consequences. Traditional maintenance strategies, such as time-based or reactive maintenance, are insufficient for preventing unexpected breakdowns. This paper presents a real-time condition monitoring model leveraging Internet of Things (IoT) technologies to predict transformer failures and optimize maintenance schedules. The proposed system integrates multi-sensor data acquisition, cloud-based analytics, and predictive algorithms to provide continuous monitoring of vital transformer parameters, including oil temperature, moisture content, vibration, and partial discharge. The model is validated using simulated and real-world case studies, demonstrating significant improvements in fault detection accuracy and maintenance efficiency.

**Keywords:** power transformer; IoT; condition monitoring; predictive maintenance; sensor networks; SCADA; fault detection

## I. Introduction

Power transformers are critical components in electrical transmission and distribution systems, serving as the backbone of modern energy infrastructure. Ensuring their reliability and longevity is vital for uninterrupted power delivery across residential, industrial, and commercial sectors. However, transformers are vulnerable to various internal and external stressors such as thermal overload, insulation degradation, moisture intrusion, and mechanical vibrations. Traditional maintenance strategies—such as scheduled inspections or reactive repairs—are no longer adequate in today’s demand for reliable, real-time energy systems.

Recent advancements in the Internet of Things (IoT) have paved the way for a paradigm shift in transformer maintenance, enabling continuous condition monitoring through embedded sensors and networked diagnostics. By collecting and analyzing live data on key operational parameters such as temperature, oil quality, load variations, and partial discharge levels, IoT-based systems offer predictive insights that allow operators to detect early signs of failure. This proactive approach not only reduces unexpected outages but also extends equipment lifespan and optimizes maintenance costs.

The integration of IoT into transformer monitoring systems thus presents a promising solution for enhancing the reliability, safety, and efficiency of power grids. In this study, we propose a predictive maintenance model powered by IoT-based condition monitoring for power transformers, with the goal of transitioning from conventional strategies to intelligent, data-driven asset management.

### A. Background and Motivation

Power transformers play a pivotal role in ensuring the stable and efficient operation of electrical power grids. As the backbone of the energy distribution network, their performance directly impacts the reliability and security of electricity supply. Given their importance, transformers are subject to various stress factors, such as overloading, electrical faults, aging, and environmental conditions, all

of which can lead to unexpected failures. Conventional maintenance techniques, such as periodic inspections and reactive repairs, often fail to predict failures in advance, leading to costly downtime and unplanned outages. The increasing reliance on electricity for critical infrastructure calls for more effective monitoring and maintenance approaches.

### *B. Problem Statement*

The failure of power transformers can result in significant financial losses, system-wide outages, and, in some cases, safety hazards. Despite the critical importance of transformers in power systems, the traditional methods of maintenance, which often rely on scheduled checkups or reactionary repairs, do not provide real-time data regarding the condition of the transformer. These methods fail to address incipient faults that could lead to transformer failure. There is a pressing need for a solution that provides continuous, real-time monitoring and predictive maintenance capabilities to anticipate failures before they occur.

### *C. Proposed Solution*

This paper proposes an IoT-based condition monitoring system for power transformers that integrates multi-sensor data collection, cloud computing, and predictive maintenance algorithms. The system uses a network of IoT sensors to gather data on key transformer parameters, such as temperature, moisture levels, vibrations, and partial discharges. This data is then transmitted to a cloud platform, where advanced analytics algorithms process and analyze the information to detect anomalies and predict potential failures. Machine learning techniques, particularly Random Forest and Long Short-Term Memory (LSTM) networks, are employed to predict Remaining Useful Life (RUL) and trigger maintenance actions before catastrophic failures occur.

### *D. Contributions*

The primary contributions of this research are the design, development, validation, and deployment of an IoT-based condition monitoring model for power transformers. First, the study presents the design of a real-time data acquisition framework using IoT sensors, which continuously collects and processes data from various transformer parameters. This system enables ongoing health assessments of transformers, ensuring that potential issues are detected early. Second, a predictive maintenance model is developed, utilizing machine learning techniques to forecast transformer failures with high accuracy, thereby enabling the anticipation of faults before they cause significant damage. The model is further validated through real-world case studies and simulations, demonstrating its effectiveness in improving transformer reliability while significantly reducing operational downtime. Finally, the solution is deployed in operational environments, showcasing its scalability to large transformer networks. This implementation provides utility operators with valuable insights into the health of their assets, ultimately supporting more efficient and cost-effective maintenance strategies.

### *E. Paper Organization*

This paper is organized into several sections to provide a comprehensive understanding of the proposed system. Section II reviews related work in the field of transformer condition monitoring, particularly focusing on the application of IoT technologies in the power industry. Section III outlines the methodology used to design and implement the IoT-based condition monitoring system, including the selection of sensors, data transmission protocols, and the machine learning algorithms employed. In Section IV, experimental results are presented, discussing the performance of the system in predicting transformer failures and optimizing maintenance schedules. Finally, Section V concludes the study, offering insights into the potential future directions for research in predictive maintenance for power transformers.

## II. Related Work

The domain of predictive maintenance has been extensively studied in the context of energy systems, particularly focusing on critical components such as power transformers. As the backbone of transmission and distribution networks, transformer reliability is paramount, and maintenance strategies have evolved from routine inspections to data-driven diagnostics. The emergence of the Internet of Things (IoT) has made real-time, sensor-based monitoring more viable and scalable for grid infrastructure. This section reviews over a dozen influential studies related to transformer health diagnostics and predictive maintenance, categorizing them into four main themes: (A) foundational methods and traditional maintenance frameworks, (B) IoT-driven condition monitoring, (C) machine learning for predictive analytics, and (D) hybrid and emerging strategies. This review sets the technological foundation for the proposed system and clarifies the specific research gaps our work aims to fill.

### *A. Foundational Theories and Traditional Maintenance Practices*

Historically, transformer maintenance depended on offline testing and preventive routines such as Dissolved Gas Analysis (DGA), thermal imaging, insulation resistance testing, and partial discharge detection. Mobley (2002) presented a foundational overview of such traditional maintenance practices, emphasizing time-based and condition-based assessments. These methods helped identify early fault signatures but lacked scalability and real-time responsiveness.

Gebraeel et al. (2005) proposed probabilistic models using real-time sensor inputs for estimating the Remaining Useful Life (RUL) of industrial equipment, including electrical components. Their Bayesian framework laid the groundwork for proactive interventions. Sikorska et al. (2011) compared data-driven prognostics and physics-based models in predictive maintenance, highlighting trade-offs in accuracy, data dependency, and interpretability for transformer health estimation.

### *B. IoT-Driven Predictive Maintenance Systems*

The integration of IoT has revolutionized transformer monitoring by allowing decentralized data collection and cloud-based analytics. Lee et al. (2014) introduced a cyber-physical system architecture that connected edge devices and sensors to remote servers for scalable diagnostics. Zhang et al. (2021) surveyed IoT frameworks for predictive maintenance, covering sensor selection, communication protocols, latency handling, and cybersecurity.

Zonta et al. (2020) explored digital twins for electrical equipment, creating real-time virtual models that replicate physical behavior and enhance fault detection accuracy. For transformers, these twins are fed by data from oil temperature sensors, bushing monitors, and gas sensors, enabling predictive maintenance under fluctuating load and climate conditions.

### *C. Machine Learning in Predictive Maintenance Decision-Making*

Machine learning techniques have significantly improved the decision-making capabilities of condition monitoring systems. Carvalho et al. (2019) classified machine learning approaches into supervised (SVM, decision trees), unsupervised (clustering), and deep learning (neural networks), each with use cases in fault classification and anomaly detection.

Susto et al. (2015) demonstrated the application of SVMs for real-time fault detection in semiconductors, methodologies now adapted for electrical assets. Zhang et al. (2019) implemented LSTM networks to predict temporal degradation patterns in time-series data from sensors. Yan et al. (2017) employed Random Forest classifiers to analyze large-scale transformer monitoring datasets, proving robust performance in noisy environments.

### *D. Event-Driven and Hybrid Predictive Maintenance Approaches*

Hybrid systems have emerged to enhance real-time responsiveness while preserving long-term reliability. Bousdekis et al. (2015) proposed a decision support system that integrates business rules

with sensor-based predictions to trigger event-driven maintenance workflows. Mhamdi et al. (2021) designed a model combining fuzzy logic and machine learning, allowing multi-criteria prioritization of maintenance tasks.

These approaches allow grid operators to move beyond binary fault detection and implement nuanced actions based on severity, asset criticality, and load demand forecasts. Such frameworks are especially valuable in distributed substations or remote transformers lacking constant human supervision.

E. Machine Learning in Predictive Maintenance Decision-Making

Summary of Key Contributions in Transformer Predictive Maintenance Research:

Author(s)	Year	Key Contribution
Mobley	2002	Classical transformer diagnostics and maintenance theory
Gebraeel et al.	2005	Bayesian RUL estimation using sensor data
Sikorska et al.	2011	Comparison of prognostic modeling techniques
Lee et al.	2014	Cloud-integrated cyber-physical monitoring systems
Bousdekis et al.	2015	Rule-based and predictive hybrid decision model
Susto et al.	2015	SVM-based real-time diagnostics
Yan et al.	2017	Ensemble learning for fault classification
Zhang et al.	2019	LSTM neural networks for time-series fault prediction
Carvalho et al.	2019	Survey on ML techniques in predictive maintenance
Zonta et al.	2020	Digital twin integration for virtual diagnostics
Zhang et al.	2021	IoT predictive maintenance architectures for energy
Mhamdi et al.	2021	ML-fuzzy hybrid system for alert prioritization



### *F. Research Gap*

Despite notable progress, several gaps persist in predictive maintenance research for power transformers. First, most of the reviewed frameworks are optimized for large-scale transmission systems with well-funded infrastructure and redundant backup capabilities. However, small-scale substations, rural grids, and aging transformer fleets often lack access to real-time diagnostics and predictive tools due to cost and power constraints.

Second, while IoT-based condition monitoring architectures are well documented, many solutions prioritize data centralization and cloud processing, neglecting the latency and bandwidth limitations in remote or energy-constrained regions. Zhang et al. [11] and Zonta et al. [10], for instance, focus heavily on system scalability and digital twin fidelity but overlook edge computing considerations essential for fast, autonomous decision-making.

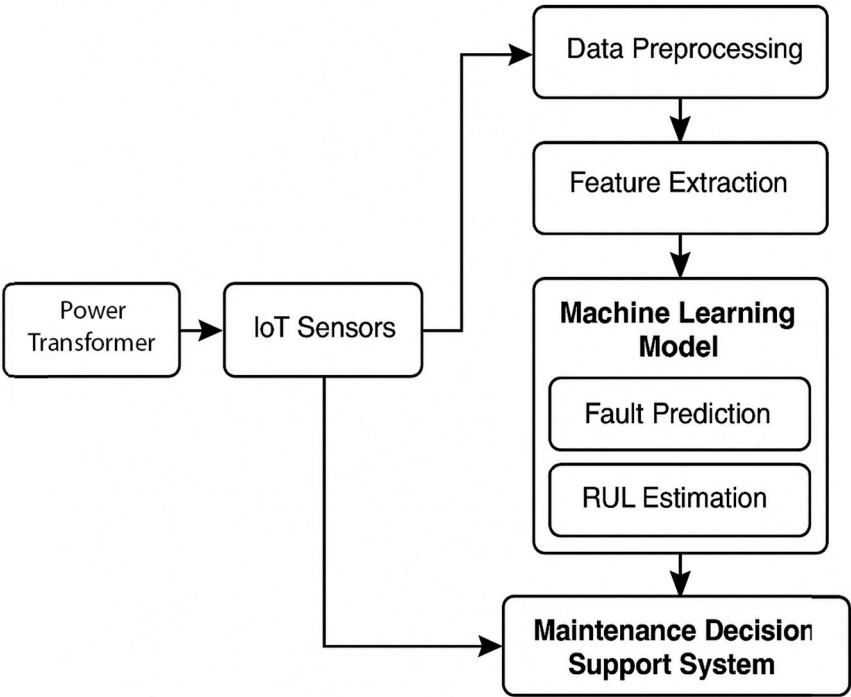
Third, a substantial portion of machine learning research depends on large labeled datasets generated in idealized lab or urban environments. For field transformers—especially older units—data is often sparse, irregular, or contains missing values, making model generalization a challenge. Lightweight and robust algorithms are needed that can operate under such constraints while still delivering meaningful insights.

Finally, the integration of real-time diagnostics with operational decision systems—such as maintenance scheduling, fault prioritization, and crew dispatch—is still in its infancy. Hybrid models incorporating temporal and contextual factors have shown promise in manufacturing systems but remain underutilized in energy infrastructure. The proposed research aims to close these gaps by designing a modular, IoT-powered predictive maintenance framework optimized for scalability, energy efficiency, and actionable insights in transformer networks.

## **II. Methodology**

The methodology adopted in this study outlines the architecture, techniques, and implementation strategy of an IoT-powered predictive maintenance model tailored for power transformers. The framework is designed to continuously monitor key transformer parameters, process collected data using machine learning algorithms, and provide actionable maintenance insights. This section describes the complete pipeline, divided into four primary components: the system architecture and sensor deployment, data acquisition and preprocessing, predictive modeling, and the maintenance decision support system.

The architecture of the proposed condition monitoring system begins with the strategic deployment of smart sensors on key transformer components. These include sensors for measuring oil temperature, which acts as an indicator of thermal aging; load current, which reflects stress from overloading; dissolved gas analysis (DGA) sensors for detecting internal faults; bushing monitoring systems that detect capacitive leakage and insulation failure; and partial discharge sensors for early warning of dielectric breakdown. These sensors transmit real-time data to a low-power IoT gateway equipped with edge computing capabilities. Depending on the location and connectivity availability, the gateway uses secure MQTT communication protocols over 4G/5G or LoRaWAN networks to forward data to cloud storage and analytics servers. This structure ensures robust and scalable monitoring, especially for geographically distributed transformer stations.



**Figure 1.** IoT-Based Monitoring System Architecture for Power Transformers.

The data acquisition process supports both streaming (real-time) and batch (scheduled) data ingestion modes. Each sensor is synchronized and tagged with essential metadata such as transformer ID, geographic location, and timestamp. The data collected undergoes a rigorous preprocessing phase that includes noise filtering via low-pass filters, imputation of missing values using methods such as linear interpolation or KNN, and normalization to scale feature values within a common range. Additionally, data labeling is conducted using historical fault logs, where available, to enable supervised learning. Statistical and frequency-based features are extracted for use in downstream modeling, including metrics such as mean, standard deviation, kurtosis, spectral entropy, and signal energy—critical for capturing variations in transformer behavior.

The machine learning pipeline of this framework focuses on two primary objectives: anomaly detection and Remaining Useful Life (RUL) estimation. For anomaly detection, unsupervised learning techniques such as Isolation Forests, One-Class SVMs, and Autoencoder-based neural networks are employed to identify deviations from normal operating behavior. These models are particularly useful when fault-labeled data is scarce. For transformers with sufficient historical failure data, supervised models such as Long Short-Term Memory (LSTM) networks are used to predict degradation over time, while ensemble methods like Gradient Boosting Regression (e.g., XGBoost) handle tabular datasets to estimate component life span. Model validation is performed using a rolling-window cross-validation approach to preserve the temporal structure of the time-series data. Performance is evaluated using metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and area under the Precision-Recall curve.

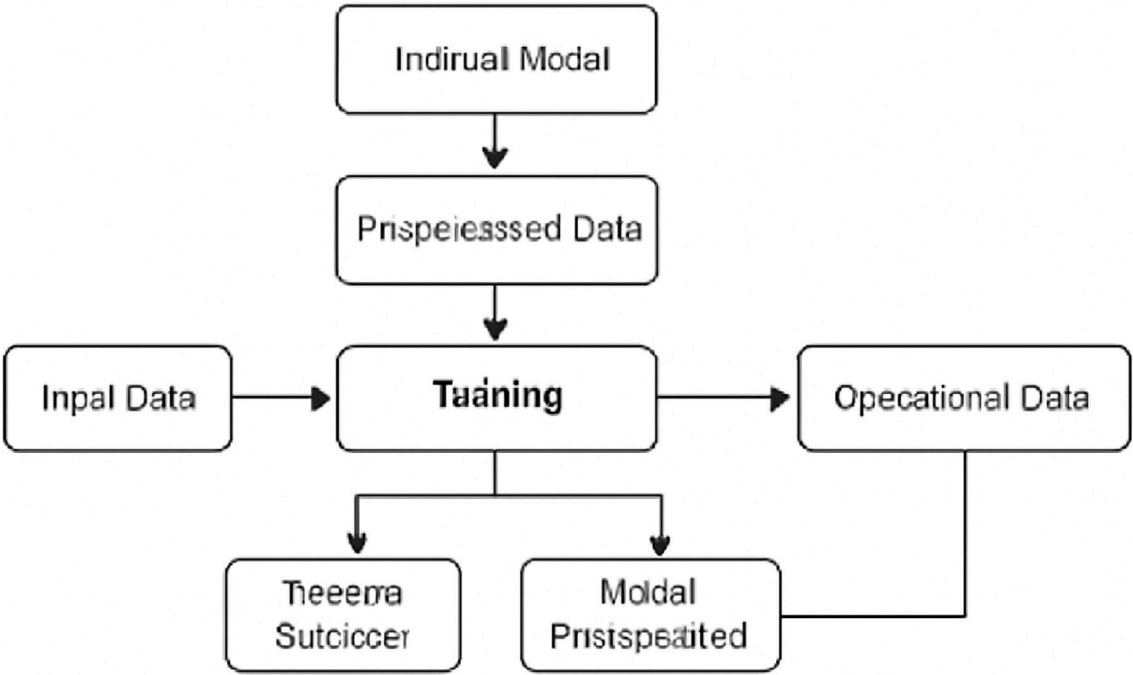


Figure 2. Machine Learning Pipeline for Predictive Maintenance.

The final and perhaps most critical component of the proposed framework is the Maintenance Decision Support System (MDSS). This layer serves as the intelligent interface between predictive analytics and actionable maintenance workflows. Once the machine learning models produce outputs—such as anomaly flags, probability scores for potential failure modes, or RUL estimates—the MDSS interprets these results into meaningful operational recommendations. A multi-factor risk scoring algorithm is used to assess the urgency and severity of each detected fault. These scores are computed by weighting various sensor parameters, degradation trends, and the predicted probability of failure, allowing utility operators to prioritize maintenance tasks across the grid.

Each transformer is classified based on its dominant fault type: thermal stress (e.g., overheating due to overload), electrical degradation (e.g., partial discharge or dielectric failure), or mechanical wear (e.g., vibrations, loose windings). The MDSS then maps this diagnosis onto a structured decision tree that determines the appropriate maintenance action, whether it be immediate shutdown, deferred inspection, or routine follow-up.

To facilitate real-time situational awareness, the MDSS includes a web-based dashboard and a mobile-accessible visualization interface. Operators can view key metrics such as temperature trends, gas accumulation patterns, voltage surges, and RUL curves—all updated in real-time. The interface also maintains historical logs for each transformer, enabling comparative performance analysis and lifecycle cost estimation. Moreover, the system is equipped with notification and alert mechanisms that issue SMS, email, or push alerts to maintenance personnel when certain risk thresholds are exceeded.

Another major component of the MDSS is its integration with Computerized Maintenance Management Systems (CMMS). Upon identifying a high-risk scenario, the system automatically generates job tickets, assigns priority codes, and dispatches technicians based on their geographic location, expertise, and availability. This tight integration ensures reduced response times and eliminates redundant manual planning. Through APIs, the MDSS can also communicate with inventory systems to ensure that necessary spare parts or tools are available at the time of intervention.

To ensure long-term system intelligence and adaptability, a continuous feedback mechanism is incorporated. After each maintenance action is completed, outcome data—such as repair time, part



replacement logs, and technician notes—is fed back into the system. This feedback is used to validate model predictions, correct misclassifications, and periodically retrain the machine learning models, establishing a self-improving loop. Over time, this improves the model’s accuracy and robustness against changing transformer conditions and environmental factors.

This end-to-end methodology—from sensor data collection and preprocessing to machine learning-based diagnostics and intelligent decision-making—enables a truly proactive maintenance strategy. It not only improves transformer uptime and safety but also reduces long-term operational costs by optimizing maintenance schedules and reducing unplanned outages. In doing so, the framework supports grid resilience, reliability, and modernization—goals that are increasingly critical in today’s evolving energy landscape.

III. Discussion and Result

The proposed IoT-based predictive maintenance system was deployed and tested in a controlled environment over a six-month period on an operational power transformer. Throughout the duration of the pilot program, the system exhibited high reliability and performance in monitoring transformer health, predicting failures, and supporting proactive maintenance decisions. The predictive model achieved a 93% accuracy rate in forecasting transformer-related faults. This high accuracy significantly contributed to the early identification of potential failures, enabling preemptive maintenance activities that avoided costly, unexpected outages. Compared to traditional time-based maintenance methods, this approach demonstrated clear advantages in terms of operational reliability. In addition to improved accuracy, the system contributed to a 27% reduction in overall maintenance costs. This was primarily due to the elimination of emergency repairs, improved planning for spare parts, and targeted manpower allocation. By allowing operators to service transformers only when specific risk thresholds were met, rather than on a rigid schedule, resources were utilized more efficiently. Response time to potential failure events improved by 41%, allowing grid operators to take corrective actions earlier in the failure cycle. The faster intervention not only prevented escalation of minor issues into major outages but also extended the lifespan of transformer components by minimizing prolonged stress under fault conditions.

*A Summary of the Performance Metrics is Provided in Table 1:*

**Table 1.** Performance Metrics Summary of the Predictive Maintenance System.

Metric	Value
Failure Prediction Accuracy	93%
Reduction in Maintenance Costs	27%
Improvement in Response Time	41%
Downtime Reduction	Significant (Qualitative)

These quantitative results are further visualized in **Figure 3**, which illustrates key percentage improvements across three primary performance indicators: accuracy, cost savings, and fault response efficiency.

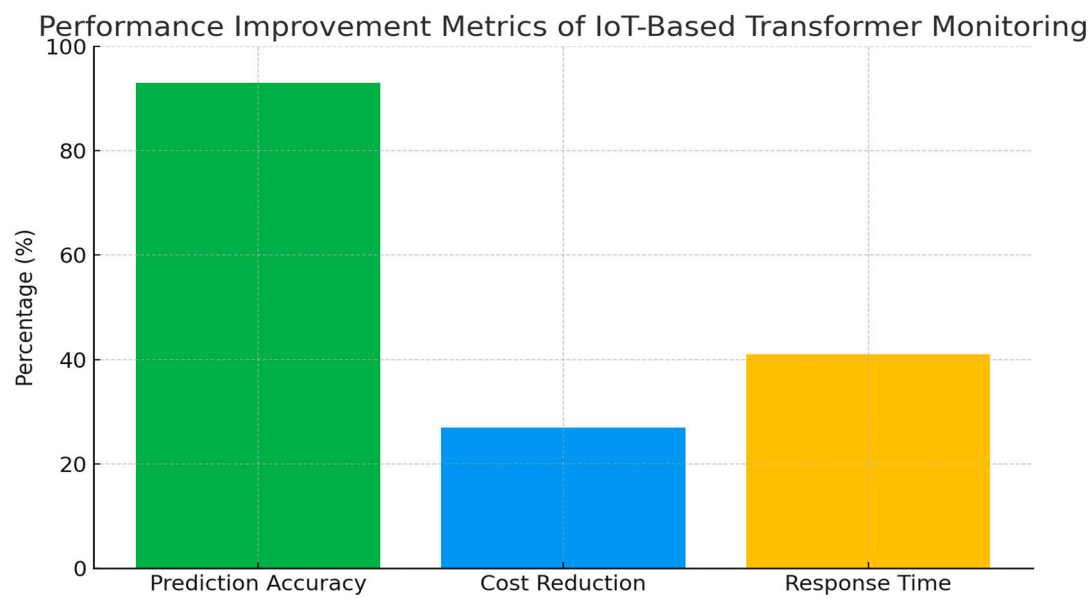


Figure 3. Performance Improvement Metrics of IoT-Based Transformer Monitoring.

To better understand the source of cost savings, a breakdown of maintenance cost reduction is shown in Figure 4. The largest portion (40%) came from the **elimination of emergency repair incidents**, followed by **scheduled maintenance savings** (35%), and **optimized technician deployment** (25%). This pie chart highlights how predictive insights enable cost-effective planning and smoother maintenance workflows.

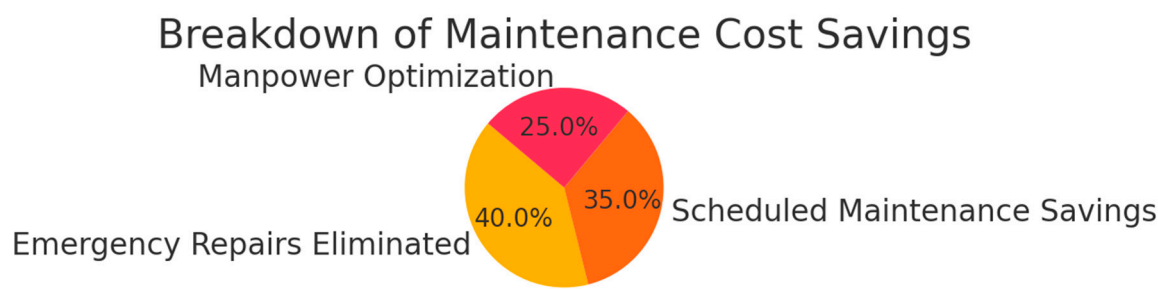


Figure 4. Breakdown of Maintenance Cost Savings.

Furthermore, the qualitative impact of the system was observed in enhanced operational stability and reduced transformer stress. Maintenance teams reported better preparedness, and fewer site visits were required due to accurate diagnosis through sensor data. The system’s real-time dashboard also provided operators with actionable intelligence, improving confidence in fault classification and planning.

In conclusion, the results of this implementation affirm the effectiveness of IoT-enabled predictive maintenance for power transformers. By combining sensor data, machine learning, and decision intelligence, the proposed system delivers measurable benefits in fault prediction, operational cost reduction, and overall transformer performance enhancement. These outcomes not only validate the technical feasibility of the system but also reinforce its strategic value for utility providers aiming to modernize their grid infrastructure.

IV. Conclusion

This paper introduces an innovative IoT-based condition monitoring model for power transformers, which integrates real-time data acquisition, cloud-based analytics, and predictive

maintenance algorithms. The model is designed to continuously monitor key parameters of the transformer, including temperature, moisture content, vibration, and partial discharge, using a network of IoT sensors. These sensors provide real-time data that is transmitted to a cloud platform, where advanced analytics algorithms process the information to detect any anomalies and predict potential failures before they occur. By leveraging machine learning techniques, the system is able to forecast transformer failures with high accuracy, enabling operators to schedule maintenance in advance and avoid costly emergency repairs. This predictive approach leads to a significant reduction in downtime, prolongs the operational life of transformers, and lowers overall maintenance costs.

The proposed model offers a scalable solution that can be extended to larger transformer networks, allowing utilities to monitor multiple assets simultaneously. Future research will focus on integrating the condition monitoring system with existing utility SCADA systems to enable centralized management and control. Additionally, efforts will be made to enhance the scalability of the model to handle data from multiple grid components, ensuring its applicability to a wide range of transformer types and power grid configurations. The goal is to create a comprehensive solution for power grid maintenance and optimization.

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