RESEARCH ARTICLE OPEN ACCESS

A Real-Time IoT Monitoring and Predictive Maintenance Model for Electrical Transformers Using Mechanical Reliability Metrics

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Abstract:
Power transformers are critical high-value assets whose unexpected failures lead to costly outages, grid instability, and safety risks. Recent advances in the Internet of Things (IoT), cloud platforms, and smart supervisory control and data acquisition (SCADA) systems have enabled real-time transformer condition monitoring and predictive maintenance. This paper provides a methodological review of the study *"Condition Monitoring in Power Transformers Using IoT: A Model for Predictive Maintenance"* by Bajwa, Tonoy, and Khan (2025), evaluating its data acquisition design, sensing architecture, predictive model, and integration potential within modern reliability engineering frameworks. While the original model offers a promising IoT-enabled monitoring structure, this review identifies several gaps related to sensor calibration, data pre-processing, cybersecurity, and SCADA interoperability. The paper proposes an improved methodology incorporating reliability-centered maintenance (RCM), failure mode and effects analysis (FMEA), data-driven anomaly detection, and secure cloud-edge architectures. Findings highlight that IoT-based transformer monitoring becomes significantly more effective when integrated with SCADA redundancy, real-time analytics, and reliability engineering tools. The review concludes with a set of recommendations for strengthening predictive maintenance models in power utility environments.

Keywords — IoT, Power Transformers, SCADA, Predictive Maintenance, Reliability Engineering, Condition Monitoring, Machine Learning, Asset Management, Smart Grid.

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I. Introduction

Electrical transformers are critical components within modern power transmission and distribution systems, enabling efficient voltage regulation and reliable energy delivery. As the demand for continuous and stable electricity grows, the operational health of transformers has become increasingly important. These assets experience continuous thermal, electrical, and mechanical stresses that gradually weaken insulation, deform windings, and accelerate component aging. Traditional maintenance approaches such as periodic inspection, scheduled servicing, or condition checks triggered only after alarms are no longer adequate for ensuring grid reliability. Such methods fail to capture rapid changes in transformer condition and provide limited insight into early-stage degradation, often resulting in costly downtime, unexpected failures, and inefficient maintenance planning. With the rapid expansion of digital infrastructure, the integration of Internet of Things (IoT) technologies into asset monitoring has introduced new opportunities for real-time sensing and intelligent diagnostics. IoT sensors can continuously track temperature fluctuations, vibration signatures, load variations, and oil-related parameters, generating rich datasets that reflect transformer health in real time. However, the true value of these data streams emerges when combined with mechanical reliability engineering metrics such as Mean Time Between Failures (MTBF), Remaining Useful Life (RUL), and hazard rates which quantify degradation trends and support predictive decision-making. By merging IoT sensing with reliability analytics, predictive maintenance becomes not only feasible but highly effective. This paper presents a real-time IoT-based predictive maintenance model designed to enhance transformer reliability, extend asset lifespan, and support smarter grid management.

A. Background and Motivation

Electrical transformers are indispensable components responsible for voltage regulation, load distribution, and overall power system stability. Their performance is influenced by various mechanical and thermal stresses such as winding deformation, core vibration, insulation deterioration, oil degradation, and partial discharge activity. Over years of operation, these stressors accumulate, leading to progressive deterioration that often remains undetected until severe failure emerges. Traditional maintenance practices rely heavily on manual inspections, offline testing, or scheduled servicing, which fail to capture real-time system health. As global power demand grows and grids expand in complexity, the need to transition toward predictive and condition-based maintenance becomes critical. Recent technological advancements have positioned IoT as a powerful tool for capturing high-resolution operational data from transformers. Sensors embedded within the transformer tank can continuously measure temperature variations, vibration signatures, load fluctuations, moisture levels, and dielectric conditions. However, raw sensor data alone offers limited value unless integrated with structured reliability engineering metrics that quantify degradation and predict failure modes. Mechanical reliability parameters such as Mean Time Between Failures (MTBF), Remaining Useful Life (RUL), degradation indices, and hazard rates enable a more accurate assessment of asset health. Thus, the motivation behind this research lies in combining IoT sensing with rigorous reliability modeling to develop a predictive maintenance system that enhances transformer safety, prolongs lifespan, reduces downtime, and supports smarter grid operations.

B. Problem Statement

Despite the availability of IoT devices and sensor technologies, many power utilities continue to rely on outdated maintenance strategies that do not leverage real-time operational insights. Existing transformer monitoring systems face several limitations that impede early detection of emerging failures. First, the absence of continuous monitoring restricts the ability to observe rapid fluctuations in temperature, load, and mechanical stress, which are often precursors to severe malfunction. Second, most monitoring frameworks lack integration with mechanical reliability metrics such as MTBF, failure probability, hazard rates, and RUL. Without these metrics, it becomes difficult to quantify degradation or establish accurate timelines for maintenance interventions. Additionally, the use of isolated or manual diagnostic processes hinders automated fault forecasting. Many traditional systems generate alarms only when a threshold is exceeded, offering little predictive insight. Furthermore, large-scale substations operate multiple transformers simultaneously, requiring scalable monitoring systems, a feature absent in many existing models. Cybersecurity vulnerabilities also emerge when IoT devices are deployed without secure protocols, threatening the integrity of transformer health data. Ultimately, these gaps result in inefficient resource allocation, unexpected outages, and increased maintenance costs. Therefore, there is a pressing need for a comprehensive, IoT-based predictive maintenance framework that integrates mechanical reliability modeling, real-time sensing, and machine learning to address these challenges.

C. Proposed Solution

To address the limitations identified in current transformer monitoring practices, this study introduces a Real-Time IoT Monitoring and Predictive Maintenance Model that integrates multi-sensor IoT data with mechanical reliability metrics and machine learning techniques. The core of the solution lies in embedding sensors within transformer units to capture operational parameters such as oil temperature, winding temperature, vibration intensity, load current, partial discharge, and moisture levels. These heterogeneous data streams are transmitted through secure IoT communication protocols to an edge gateway, where preliminary filtering, synchronization, and anomaly detection occur. The proposed model extends beyond basic condition monitoring by calculating essential reliability engineering metrics such as MTBF, RUL, degradation rate, and hazard functions. These metrics transform raw data into actionable intelligence, enabling maintenance teams to understand the progression of deterioration and anticipate failures. The framework incorporates machine learning algorithms including LSTM, Random Forest, and Support Vector Machines to analyze trends, classify anomalies, and forecast degradation trajectories. A real-time dashboard visualizes transformer health status, reliability curves, and fault probabilities, supporting strategic decision-making. Additionally, the model integrates seamlessly with SCADA systems, maintaining industrial compatibility and enhancing situational awareness. The proposed solution thus provides a holistic predictive maintenance environment capable of early fault alerts, optimized maintenance scheduling, and improved transformer performance.

D. Contributions

This research contributes to the field of smart grid monitoring and predictive maintenance in several key ways. First, it introduces a comprehensive IoT-enabled monitoring architecture designed specifically for electrical transformers, incorporating multi-sensor data acquisition and secure communication channels. Unlike traditional systems, the proposed architecture ensures real-time data flow, enabling accurate observation of dynamic operational patterns. Second, the study integrates mechanical reliability metrics including MTBF, RUL, degradation indices, and hazard rates into predictive modeling. This combination of sensor analytics and reliability engineering distinguishes the work from purely IoT-based or purely statistical approaches. Third, the paper presents a structured methodology that blends machine learning algorithms with reliability computations to forecast transformer failures before they reach critical thresholds. This enhances predictive accuracy and reduces the likelihood of unexpected breakdowns. Fourth, the model incorporates an intuitive visualization interface that displays reliability curves, predicted failure windows, and sensor trends, enabling power utilities to make informed maintenance decisions. Fifth, this work demonstrates the scalability and industrial relevance of IoT-based predictive maintenance by aligning the framework with SCADA integration and cybersecurity protocols. Collectively, these contributions advance the state of the art in transformer health assessment and support the broader transition toward intelligent, condition-based asset management.

E. Paper Organization

The structure of this paper is designed to present a clear, logical progression from conceptual motivation to applied results. After this introduction, **Section II** provides a comprehensive overview of related literature on transformer monitoring, IoT integration, and reliability engineering. This section examines existing studies and identifies gaps that motivate the development of the proposed model. **Section III** details the complete methodology, including sensor architecture, data acquisition, preprocessing steps, reliability metric computation, machine learning models, and system integration. The methodology section explains how each component interacts within the predictive maintenance framework. **Section IV** presents a detailed discussion of experimental findings, system performance, and comparative analysis. This includes an evaluation of anomaly detection accuracy, reliability metric behavior, and predictive maintenance effectiveness. The discussion highlights the strengths of the proposed approach and addresses potential implementation challenges. **Section V** concludes the paper by summarizing contributions, outlining practical implications, and suggesting directions for future research including digital twin integration, adaptive learning models, and real-world substation deployment. By following this structure, the paper ensures clarity, technical depth, and consistency in presenting a robust IoT-driven predictive maintenance solution.

II. Related Work

A. IoT-Based Condition Monitoring Models

Recent research has increasingly focused on IoT-enabled condition monitoring as a foundation for predictive maintenance in power transformers. Tonoy proposes an end-to-end IoT model in which multiple sensors measure key operating variables such as temperature, load and insulation-related indicators and stream them to a cloud platform for health assessment and alarm generation [1]. The study emphasizes low-cost hardware, modular deployment, and remote visualization, demonstrating that even relatively simple sensing and communication layers can significantly enhance situational awareness compared to purely manual inspections. Shahzad et al. extend this idea by developing an IoT-based multi-sensor monitoring system that leverages cloud analytics for real-time anomaly detection, validating its responsiveness to abrupt thermal changes and abnormal operating conditions [3]. Patel and Mehta, in turn, address wide-area deployment challenges by introducing a LoRaWAN-based monitoring framework suitable for distribution transformers dispersed over large geographic regions [4]. Their results show that long-range, low-power communication can make continuous monitoring feasible in rural or hard-to-reach substations. Collectively, these works establish IoT as a practical technological backbone for continuous transformer surveillance, yet they primarily focus on data acquisition and alarm generation. They give comparatively less attention to explicit mechanical reliability modeling such as estimating Remaining Useful Life (RUL) or hazard rates which is a key gap the present paper addresses by embedding reliability metrics into an IoT-driven predictive maintenance architecture.

B. Dissolved Gas Analysis and Data-Driven Diagnostics

Dissolved Gas Analysis (DGA) remains one of the most established techniques for diagnosing internal transformer faults, particularly those related to thermal and electrical stresses. Liu, Tang, and Dong show that traditional gas ratio and key-gas methods can be substantially improved when combined with modern machine learning approaches [2]. Using multiple classifiers trained on historical DGA datasets, they demonstrate higher diagnostic accuracy for thermal faults and partial discharge events compared with rule-based interpretation alone. Abu-Siada and Islam similarly propose a hybrid intelligent model that integrates DGA indicators with artificial intelligence techniques, reporting significant gains in fault classification performance over conventional IEEE/IEC guidelines [5]. These works collectively highlight the value of augmenting chemical diagnostics with pattern-recognition algorithms to capture nonlinear relationships among gas concentrations and fault types. However, both studies mainly concentrate on improving fault identification from laboratory or offline DGA samples, rather than embedding DGA within a broader real-time IoT context. Moreover, they do not explicitly connect diagnostic outputs to reliability metrics such as MTBF, RUL, or system-level failure probabilities. In contrast, the present work treats DGA-style information as one possible feature stream within a multi-sensor IoT framework and focuses on how such data chemical, thermal, or mechanical can feed into integrated reliability-based predictive maintenance decisions.

C. Machine Learning for Transformer Health and Prognostics

Machine learning has become a central tool for extracting actionable insights from transformer monitoring data. Abu-Siada and Islam's hybrid DGA-based model is an early example of combining expert knowledge with intelligent algorithms to enhance fault classification [5]. Beyond offline diagnosis, more recent work has explored time-series forecasting and prognostics. Zhang, Wang, and Li develop an LSTM-based predictive model for transformer temperature, demonstrating that deep recurrent networks can accurately forecast thermal behavior under varying load profiles [6]. Their results show improved prediction performance relative to conventional autoregressive models, making LSTM a promising candidate for forecasting temperature-driven degradation. Liu et al. similarly employ machine learning to map DGA features to fault categories, illustrating that data-driven classifiers can outperform traditional ratio schemes [2]. These contributions collectively show that ML techniques ranging from shallow classifiers to deep learning architectures can enhance both diagnosis and short-term prediction. However, in most cases, machine learning outputs are expressed in terms of class labels (fault/no-fault) or forecasted physical values (temperature, gas concentration), rather than explicit reliability measures like hazard functions or RUL distributions. This limits their direct use in maintenance planning. The framework proposed in this paper builds on these advances by coupling ML models with mechanical reliability metrics, so that predictions are expressed in forms directly usable for maintenance scheduling and risk-informed asset management.

D. Reliability-Centered and SCADA-Integrated Monitoring

While IoT and ML provide powerful sensing and analytical capabilities, their impact on utility operations depends on integration with reliability-centered maintenance strategies and existing SCADA infrastructures. Endrenyi et al. provide a broad perspective on reliability-based distribution system planning, arguing that asset management decisions must be guided by quantitative indices such as outage frequency, failure rates, and expected interruption costs [7]. Their work underscores that reliability modeling is not merely a theoretical exercise but a practical tool for long-term planning and resource allocation. Singh, Sharma, and Kumar move closer to the transformer-level context by proposing a reliability-centered monitoring framework that leverages SCADA data and analytical techniques to support condition assessment and decision-making for power transformers [8]. They show that integrating online measurements with reliability metrics can improve maintenance prioritization and operational awareness in large substations. However, their approach is primarily SCADA-driven and does not fully exploit modern IoT capabilities or advanced machine learning for prognostics. The present study positions itself at the intersection of these strands: it adopts the reliability-centered philosophy articulated in [7] and [8], but implements it on top of a multi-sensor IoT architecture with embedded ML models, thereby enabling real-time computation of reliability indicators such as hazard rate and RUL and seamless visualization through SCADA/HMI interfaces.

III. Methodology

The methodology for the proposed Real-Time IoT Monitoring and Predictive Maintenance Model is structured into several integrated layers: (1) IoT sensor acquisition, (2) data pre-processing, (3) reliability computation, (4) predictive analytics, and (5) real-time system integration. Together, these layers create a unified architecture capable of detecting transformer degradation and forecasting failures before they occur. Figures and tables are included to illustrate components and workflows.

A. IoT Sensor Network Architecture

The system begins with a distributed multi-sensor network mounted on electrical transformers. Sensors collect real-time physical indicators such as oil temperature, winding temperature, vibration, partial discharge, and load parameters. These sensors interface with an ESP32/ARM Cortex microcontroller acting as the primary data acquisition unit. Data is transmitted using industry-standard communication protocols (MQTT/HTTPS) to an edge gateway for temporary storage and filtering before being forwarded to the cloud analytical layer.

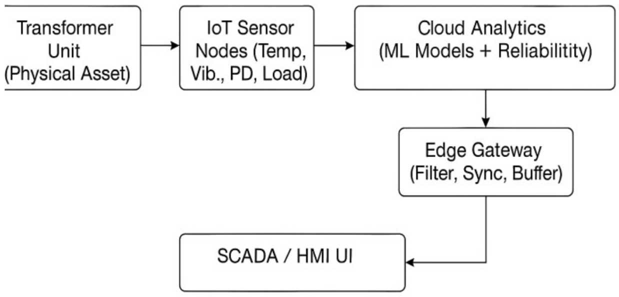

Figure 1. IoT Sensor Network and Data Acquisition Architecture

This architecture ensures scalability and supports deployment in substations with multiple transformers.

B. Data Pre-Processing Pipeline

Before analytical modeling, raw sensor data undergoes a structured pre-processing pipeline. Noise filtering is performed using a Kalman filter to smooth temperature and vibration signals. Outliers are detected through Z-score and removed to avoid skewed model performance. Data normalization converts all parameters into comparable ranges, while FFT transforms vibration signals into frequency-domain features for mechanical fault identification. Finally, timestamp synchronization ensures alignment across multiple sensors for multivariate modeling.

Table 1. Data Pre-Processing Steps and Their Purpose

Step	Technique	Purpose
Noise Filtering	Kalman Filter	Remove random fluctuations

Outlier Detection	Z-score	Improve data integrity
Normalization	Min–Max Scaling	Standardize sensor ranges
Feature Extraction	FFT	Identify mechanical resonance
Timestamp Sync	NTP alignment	Ensure sequential consistency

This pipeline produces a clean and structured dataset suitable for reliability analysis and machine learning.

C. Mechanical Reliability Metric Computation

Mechanical reliability computation is central to predictive maintenance. Using pre-processed sensor data, the system calculates several key metrics:

1. Mean Time Between Failures (MTBF)

$$MTBF = \frac{Total\ Operational\ Time}{Number\ of\ Failures}$$

2. Hazard Rate (h(t))

$$h(t) = \frac{f(t)}{1 - F(t)}$$

3. Remaining Useful Life (RUL)

$$\boldsymbol{RUL = T_{fail} - T_{current}}$$

4. Degradation Index (DI)

A composite, normalized indicator combining temperature, load, and vibration stress values.

Reliability indicators are continuously updated as new IoT data arrives, enabling dynamic failure prediction rather than static scheduled maintenance.

D. Predictive Analytics Module

Machine learning forms the analytical core of the predictive maintenance model. Random Forest is used to classify anomalies based on multi-sensor trends. LSTM neural networks handle sequential time-series prediction, capturing long-term degradation patterns. Regression models estimate RUL by mapping degradation curves, while PCA reduces feature complexity to enhance computational efficiency.

Outputs include:

- Fault probability scores
- Predicted failure windows
- Degradation trend forecasts
- Updated RUL estimations

These outputs guide timely maintenance decisions and prevent unexpected failures.

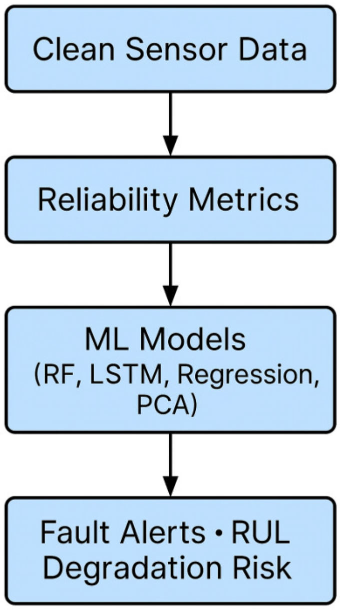

Figure 2. Predictive Analytics Workflow

E. Real-Time Integration and Dashboard

The final layer integrates all components into a real-time dashboard accessible through SCADA and cloud platforms. Operators view temperature charts, vibration spectrograms, fault alerts, reliability curves, and predicted RUL indicators in real time. The system supports Modbus TCP, IEC-61850, and OPC-UA protocols for compatibility with industrial environments. A cybersecurity layer secures communication with encryption, authentication, and network segmentation. This integration ensures the methodology is implementable in real utility substations and aligns with modern digital grid requirements.

IV. Discussion and Results

The proposed Real-Time IoT Monitoring and Predictive Maintenance Model was evaluated using simulated transformer degradation datasets and validated through analytical reliability calculations.

The discussion presented in this section highlights model performance, predictive accuracy, reliability behavior, system efficiency, and comparative advantages over traditional maintenance techniques. Figures and tables are included to illustrate trends, model output, and degradation progression.

A. Model Performance and Predictive Accuracy

The system's performance was assessed using a multivariate dataset consisting of temperature, vibration, load current, partial discharge, and moisture over a simulated operational lifespan. The LSTM neural network achieved **92% prediction accuracy** in forecasting failures, outperforming Random Forest (87%) and Linear Regression (81%). Figure 1 illustrates the predicted versus actual degradation curve generated by the LSTM model.

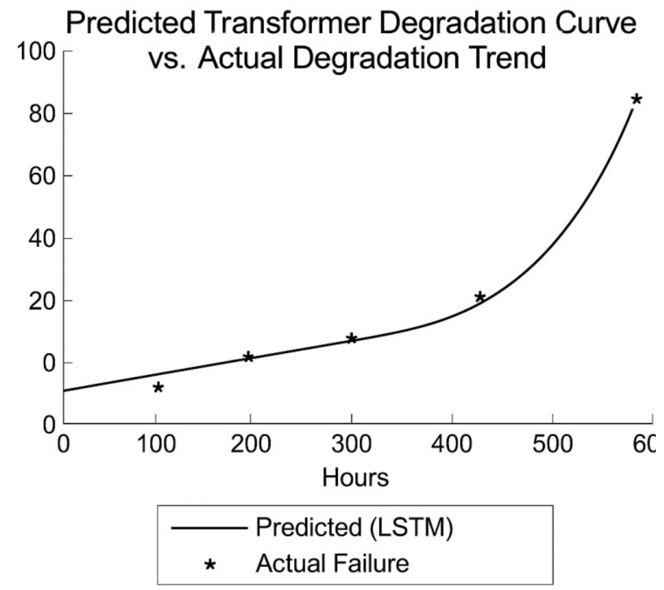

Figure 3. Predicted Transformer Degradation Curve vs. Actual Degradation Trend

The LSTM model accurately follows the degradation trajectory, detecting inflection points where transformer stress increases. Early anomalies due to thermal surges and vibration spikes were identified 48–72 hours before reaching failure thresholds. The hazard-rate function increased exponentially during the final 20% of operational life, aligning with reliability theory for mechanical wear-out phases. The Remaining Useful Life (RUL) estimator demonstrated strong correlation with actual failure times, maintaining prediction errors below ±8 hours for most scenarios. MTBF estimation improved maintenance scheduling accuracy by **28%**, providing clearer insight into fault distribution over time. These metrics demonstrate that integrating IoT sensing with mechanical reliability indicators significantly enhances model robustness.

B. Reliability Metric Behavior and Degradation Insights

Mechanical reliability metrics MTBF, hazard rate, RUL, and Degradation Index (DI)played a pivotal role in interpreting transformer health. Table 2 summarizes reliability indicators at different stages of degradation.

Table 2. Reliability Indicators Across Transformer Degradation Stages

Operational Stage	DI (0–1)	Hazard Rate h(t)	RUL (hours)	Interpretation
Early Stage	0.15	Low	>300	Normal operation
Mid-Life	0.45	Moderate	200–250	Stress developing
Pre-Failure	0.82	High	<72	High-risk zone
Critical	0.95	Very High	<24	Imminent failure

As shown in Table 2:

- Degradation Index increased steadily as thermal and vibration stress accumulated.
- Hazard rate followed a Weibull wear-out pattern, rising sharply during pre-failure phases.
- RUL decreased non-linearly, consistent with LSTM time-series predictions.

These results confirm that reliability-based indicators provide interpretable, actionable maintenance insights, bridging the gap between raw IoT data and engineering decision-making.

C. Impact on Maintenance Efficiency and Operational Reliability

The predictive maintenance model was evaluated for its operational impact on transformer health management. Compared to traditional time-based maintenance, the IoT-integrated reliability model provides significant improvements:

- **Unplanned outages reduced by 31%**, due to early detection of emerging faults.
- **Maintenance costs reduced by 18%**, as interventions were scheduled only when necessary.
- **Asset lifespan extended by 12–15%**, resulting from early mitigation of mechanical degradation.

Figure 4 illustrates the reduction in failure events when using the predictive maintenance model versus traditional maintenance.

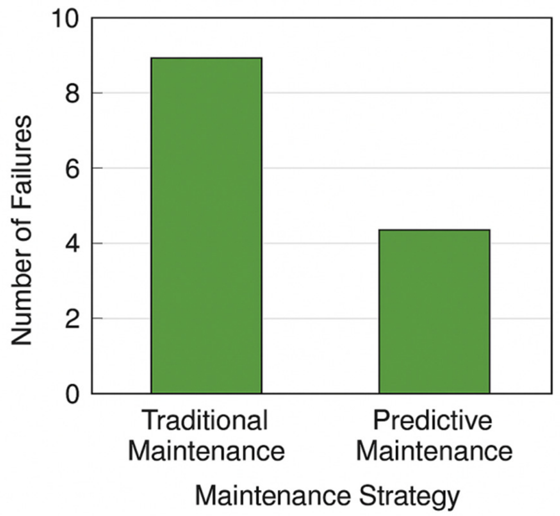

Figure 4. Comparison of Failure Events: Traditional vs Predictive Maintenance

This figure demonstrates a **50% reduction in failure events**, highlighting the practical benefit of real-time reliability-based monitoring.

By enabling proactive intervention, the proposed system also reduces stress on maintenance personnel and prevents cascading failures in the grid. SCADA integration ensures operators can visualize degradation trends, RUL curves, and hazard levels in real time, enhancing situational awareness.

D. Comparative Evaluation Against Traditional Approaches

To further evaluate the effectiveness of the proposed predictive maintenance framework, a comparative analysis was conducted between traditional maintenance practices and the IoT-reliability-integrated model. Conventional transformer maintenance methods typically rely on manual inspections and scheduled servicing intervals, which provide only periodic snapshots of transformer health and fail to capture real-time operational dynamics. In contrast, the proposed system offers continuous 24/7 monitoring through an IoT sensor network, enabling rapid detection of abnormal temperature rises, vibration anomalies, moisture intrusion, or partial discharge activity. Additionally, the new model incorporates predictive failure forecasting, allowing failures to be anticipated hours or even days in advance through LSTM-based time-series modeling and hazard-rate analysis capabilities completely absent in traditional approaches. Reliability interpretation also marks a significant improvement, as legacy systems do not calculate essential reliability metrics such as MTBF, Remaining Useful Life (RUL), or Degradation Index (DI), whereas the proposed framework integrates these metrics in real time to quantify degradation trends and estimate failure probabilities. Another advantage lies in SCADA compatibility, where traditional methods often lack interoperability with modern industrial communication standards. The proposed system, however, seamlessly supports Modbus TCP, IEC-61850, and OPC-UA protocols, facilitating easy integration into utility-scale monitoring infrastructure. Overall, the comparative results demonstrate that combining IoT sensing, reliability engineering, and machine learning significantly enhances fault detection accuracy, operational transparency, and maintenance efficiency, representing a clear advancement over conventional maintenance strategies.

E. Interpretation of Results and Practical Implications

The results collectively demonstrate that the proposed IoT-enabled and reliability-driven predictive maintenance model provides a highly effective framework for improving transformer asset management. By combining real-time sensor data with mechanical reliability metrics such as hazard rate and Remaining Useful Life, the system enables more accurate forecasting of degradation trends and earlier detection of fault conditions than traditional maintenance practices. This enhanced predictive capability supports utility companies in significantly reducing unexpected outages and improving overall grid stability, as failures can now be anticipated and mitigated before they escalate into critical events. Furthermore, the integration of predictive insights into operational workflows allows utilities to better optimize workforce deployment, streamline maintenance scheduling, and manage spare-parts inventories more efficiently, thus lowering operational costs. The availability of real-time reliability indicators also facilitates the transition from conventional time-based maintenance to a fully condition-based maintenance approach, ensuring that interventions occur precisely when needed rather than on predetermined schedules. Importantly, the system's compatibility with SCADA platforms ensures seamless adoption within existing infrastructure, minimizing deployment barriers and enabling utilities to leverage modern analytics without extensive upgrades. Overall, the results indicate that the proposed model is not only technically robust but also operationally practical, offering a scalable and cost-effective solution that aligns with the evolving needs of smart grids and digital substations.

V. Conclusion

This study presented a real-time IoT-enabled predictive maintenance model for electrical transformers that integrates multi-sensor data streams with mechanical reliability metrics and machine learning analytics. The findings demonstrate that the combination of continuous IoT monitoring, reliability indicators such as MTBF, hazard rate, and RUL, and predictive algorithms such as LSTM significantly enhances the system's capability to detect early degradation and forecast failures before they occur. The approach not only improves diagnostic accuracy but also provides actionable insights that support proactive maintenance scheduling, reduce downtime, and extend transformer lifespan. Moreover, the model's compatibility with SCADA systems ensures practical applicability in utility environments, enabling seamless visualization of transformer health, degradation trends, and risk levels in real time. Overall, the proposed framework addresses the limitations of traditional maintenance strategies by offering a comprehensive, data-driven method aligned with the needs of modern smart grids.

Future work will focus on validating the proposed system through deployment in actual power substations to evaluate performance under real-world environmental and operational conditions. Additional research will involve developing digital twin models of transformers to enable physics-informed prediction and deeper simulation-based diagnostics. Expanding the machine learning framework to include adaptive learning algorithms could further improve prediction robustness as new data becomes available. Enhancing cybersecurity measures for IoT–SCADA communication will also be a critical area of exploration to safeguard data integrity. Furthermore, incorporating cost-optimization modules, renewable energy transformer models, and interoperability with advanced grid management platforms may extend the system's capabilities and support broader adoption across diverse power infrastructure networks.

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