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IOT-ENABLED CONDITION MONITORING IN POWER TRANSFORMERS: A PROPOSED MODEL

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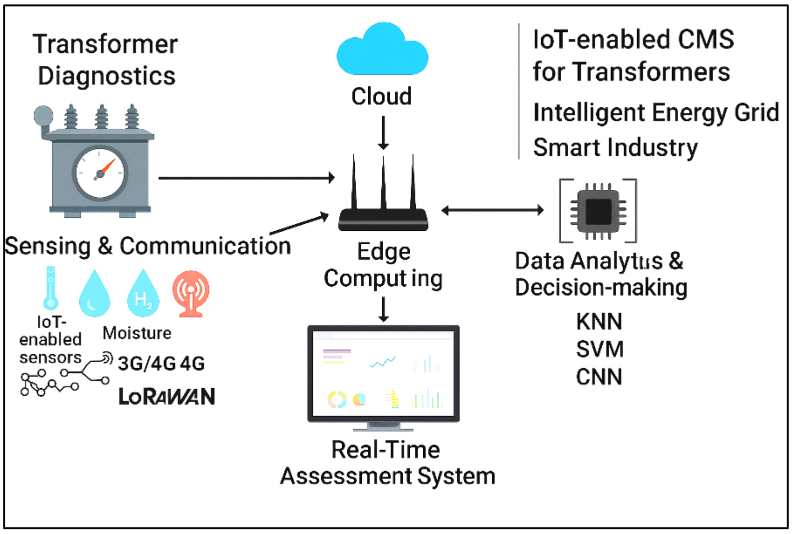
Abstract
The growing complexity and operational demands of modern electrical power systems have necessitated the adoption of intelligent, real-time monitoring solutions for critical grid assets such as power transformers. As these components age and loads increase, the integration of Internet of Things (IoT) technologies into condition monitoring systems has emerged as a pivotal strategy to enhance asset reliability, enable predictive maintenance, and minimize unplanned outages. This systematic review explores the current landscape of IoT-enabled condition monitoring in power transformers, synthesizing technological advances across sensor deployment, edge and cloud computing architectures, communication protocols, machine learning diagnostics, and cybersecurity frameworks. A total of 84 peer-reviewed articles, published between 2010 and 2024, were analyzed in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. Key findings indicate a strong emphasis on thermal and gas-based sensors, with fiber-optic temperature sensors and dissolved gas analysis remaining the most dominant diagnostic tools. Edge computing and lightweight AI models are increasingly used to filter and process data in real time, while LoRaWAN and NB-IoT have emerged as the communication protocols of choice in remote substations. Furthermore, machine learning—particularly support vector machines, decision trees, CNNs, and LSTMs—has advanced from exploratory modeling to deployment-ready applications for fault classification and health indexing. Despite these advancements, significant gaps persist in the integration of cybersecurity protocols and adherence to regulatory standards, highlighting a critical need for secure and compliant system architectures. This review contributes a comprehensive and structured analysis of the state-of-the-art approaches in the field, providing insights for researchers, utility operators, and policymakers aiming to modernize power transformer management within the broader context of smart grid infrastructure.

Keywords
IoT, Power Transformers, Condition Monitoring, Edge Computing, Dissolved Gas Analysis (DGA)

INTRODUCTION

The evolution of the Internet of Things (IoT) has revolutionized numerous industrial sectors, including the power transmission and distribution domain. At its core, IoT refers to a network of interconnected physical devices—embedded with sensors, communication modules, and intelligent software—that collect, process, and transmit real-time data (Munirathinam, 2020). Within the energy sector, IoT enables the transformation of conventional grid infrastructures into intelligent systems capable of autonomous monitoring and decision-making. Power transformers—integral components in the electrical grid—require stringent maintenance and monitoring to ensure grid stability and longevity. Condition monitoring (CM) of power transformers refers to a proactive diagnostic approach aimed at evaluating the operational health and performance of transformers in real-time, thereby enabling predictive maintenance and reducing unplanned outages (Khanna & Kaur, 2020). The convergence of IoT and CM in transformer systems empowers utilities to capture multidimensional parameters such as oil temperature, dissolved gas content, moisture, partial discharge, and vibration signals via wireless sensor networks and edge computing devices. This integration not only minimizes human intervention but also enhances the granularity of diagnostic precision. The international significance of this technological fusion is underscored by its growing adoption in energy systems across North America, Europe, and rapidly industrializing nations in Asia, where power grid reliability is a critical concern. According to the International Energy Agency (IEA), the global demand for predictive maintenance technologies in the power sector is expected to remain robust due to aging infrastructure and increasing pressure for operational resilience (Bedi et al., 2018). Thus, IoT-enabled transformer monitoring not only supports grid modernization but also aligns with sustainable development goals by preventing energy losses and enhancing fault detection capabilities.

Figure 1: IoT-Based Transformer Monitoring Architecture



Transformers serve as the backbone of electrical power systems by enabling voltage regulation during transmission and distribution. Their uninterrupted functioning is crucial for maintaining load balance, reducing transmission losses, and ensuring end-user power quality (Hu et al., 2024). Any operational failure within transformers can lead to cascading failures across the grid, resulting in large-scale blackouts and economic losses. The traditional schedule-based maintenance of transformers often falls short in detecting early signs of degradation, making real-time condition monitoring indispensable. Critical parameters such as winding temperature, Buchholz gas evolution, dielectric strength, and core vibration patterns serve as vital indicators of impending failures. IoT-based sensor frameworks now provide continuous visibility into these internal parameters, with micro-sensor networks enabling spatial data acquisition and cloud platforms facilitating centralized diagnostics. The integration of machine learning models with IoT-generated datasets further allows for pattern recognition and anomaly detection (Yalli et al., 2024). Such systems play an essential role in grid modernization initiatives, particularly in smart cities and utility-scale solar or wind farms where distributed energy resources (DERs) amplify the complexity of transformer operations. Moreover, international regulations such as IEEE Std C57.104-2019 and IEC 60076-18:2012 now advocate for advanced diagnostics in power transformers, thereby reinforcing the role of IoT-driven CM frameworks. These standards have catalyzed global research and pilot programs aimed at demonstrating the feasibility of such systems in diverse geographical and climatic environments. Therefore, understanding the transformative impact of IoT on transformer monitoring systems necessitates a systematic synthesis of existing literature spanning engineering, data analytics, and industrial automation domains (Serpanos & Wolf, 2018).

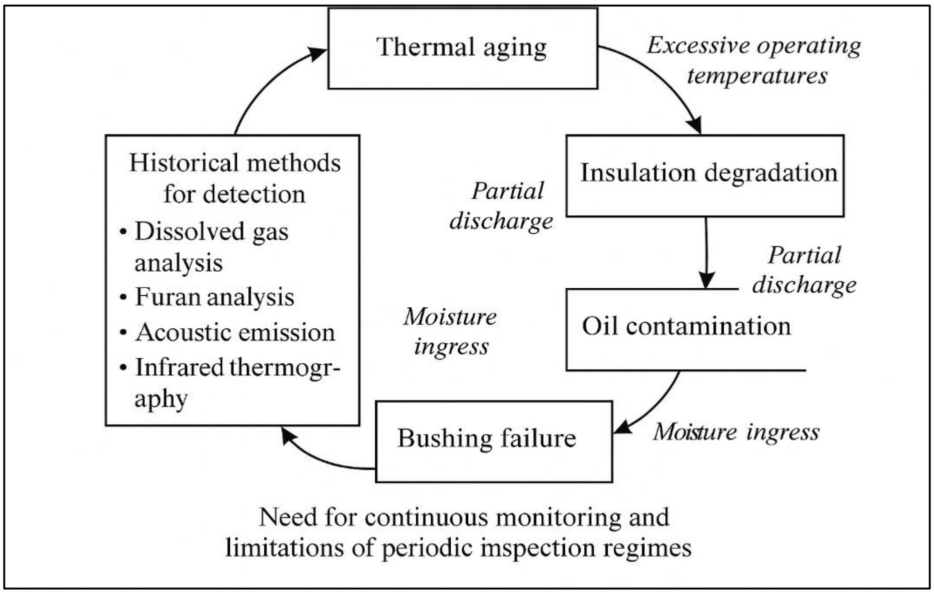
LITERATURE REVIEW

The literature surrounding the implementation of IoT-based condition monitoring in power transformers has grown extensively over the past decade, reflecting the increased urgency to modernize critical infrastructure in response to rising energy demands, aging grid components, and environmental constraints. This body of research is multidisciplinary, encompassing electrical engineering, computer science, data analytics, wireless sensor networks, and industrial asset management. As IoT technologies enable high-frequency, low-latency data collection from diverse sensing sources, researchers have shifted their focus from traditional post-failure diagnostic approaches to predictive and prescriptive maintenance frameworks for power transformers. The emerging literature exhibits several converging themes—sensor innovations, edge and cloud computing architectures, machine learning integration, communication protocols, fault classification, cybersecurity, and global deployment case studies. Yet, despite this proliferation of work, fragmentation remains in methodological approaches, performance evaluation metrics, and regional applications. Some studies emphasize physical layer concerns such as thermal monitoring, while others investigate algorithmic fault detection or explore large-scale grid deployments. This diversity necessitates a structured and critical synthesis to delineate technological trends, identify prevailing limitations, and highlight cross-cutting advancements. Accordingly, this literature review is organized into thematic clusters, each addressing a core aspect of the IoT-enabled condition monitoring ecosystem. It begins with foundational studies on transformer failure modes and transitions into sensor and hardware developments, followed by communication infrastructures and data transmission protocols. Subsequent sections explore data processing, AI-driven diagnostics, cybersecurity risks, integration challenges, and real-world case applications. The goal is to provide a cohesive and granular narrative that not only maps existing knowledge but also enables comparative assessment and future framework design.

Failure Modes in Power Transformers

Power transformers are critical to the reliable operation of power transmission and distribution systems, yet they are vulnerable to a variety of failure modes that compromise performance and safety. Thermal aging, insulation degradation, bushing failure, oil contamination, and partial discharge (PD) are among the most prevalent degradation mechanisms identified across operational contexts. Thermal aging, driven by excessive operating temperatures, leads to the breakdown of insulation cellulose and transformer oil, thereby reducing dielectric strength and accelerating insulation loss (Christina et al., 2018). Bushing failure is frequently attributed to moisture ingress, thermal stress, and mechanical degradation, often culminating in catastrophic faults and fire hazards. Oil contamination further exacerbates these vulnerabilities by reducing heat transfer efficiency and compromising electrical insulation properties. Insulation degradation, particularly within paper-oil systems, progresses over time due to thermal, chemical, and electrical stressors, leading to partial discharges that initiate internal arcing and treeing. Partial discharge is recognized as an early indicator of insulation failure and is especially prevalent in aged or overloaded units. Studies have also indicated that overloading, transients, and short-circuit stresses are responsible for core deformation and winding displacement, leading to mechanical failures that are challenging to detect using traditional inspection protocols. Furthermore, moisture ingress, whether from environmental conditions or internal chemical reactions, accelerates the rate of cellulose depolymerization and fosters corrosive sulfur development in transformer oil (Abbasi, 2022). These failure mechanisms, individually and in synergy, significantly affect asset lifespan, operational cost, and grid stability, necessitating robust diagnostic strategies to track their onset and evolution under varying load and environmental profiles.

Figure 2: Transformer Failure Mechanisms and Diagnostic Methods



Historically, the detection of transformer failure modes relied heavily on periodic inspection techniques, many of which, while valuable, offer only snapshot assessments of transformer health. Dissolved Gas Analysis (DGA) has long been a cornerstone diagnostic method, capable of detecting early-stage faults by analyzing gas formation due to arcing, corona, or thermal decomposition (Ibrahim et al., 2024). Despite its widespread usage, DGA is often limited by sampling intervals and offline analysis, which hinder timely decision-making. Complementing DGA, furan analysis provides insights into the degradation of paper insulation by measuring the concentration of furanic compounds in transformer oil, offering a metric for estimating the degree of polymerization of insulation cellulose. However, both DGA and furan analysis typically require sample extraction and laboratory evaluation, reducing their responsiveness to rapid fault development. Acoustic emission techniques have been used for partial discharge detection by capturing ultrasonic signals emitted during dielectric breakdown events. These methods are highly sensitive and can be conducted online but are often affected by ambient noise and require expert interpretation. Infrared thermography offers non-invasive, real-time temperature profiling of transformer surfaces to identify overheating zones, though its resolution may not capture internal hot spots accurately (Bindi et al., 2023). Electrical tests, such as transformer turns ratio (TTR), insulation resistance (IR), and frequency response analysis (FRA), are also common in periodic diagnostics but require equipment shutdown and can miss early-stage anomalies. Although these methods provide valuable data, they are inherently limited by temporal gaps between inspections, the requirement for expert interpretation, and challenges in assessing real-time dynamics of transformer degradation.

The reliance on periodic inspection protocols for transformer diagnostics presents significant limitations, particularly in the context of early fault detection, grid reliability, and preventive maintenance. Periodic testing, while useful for tracking long-term performance trends, is fundamentally constrained by its inability to capture transient or fast-evolving faults, which may develop and escalate between scheduled maintenance intervals (Asefi et al., 2024). The temporal discontinuity inherent in offline testing leaves a blind spot in operational awareness, increasing the risk of undetected failure precursors and resulting in unplanned outages or irreversible damage. Furthermore, scheduled maintenance can be cost-prohibitive, particularly for large transformer fleets dispersed across geographically remote substations. The costs associated with labor, transport, downtime, and test equipment mobilization often deter frequent inspections, especially in developing or resource-constrained utility sectors. Moreover, environmental conditions such as humidity, ambient temperature, and load variability induce complex stress patterns on transformer components, making fixed-interval inspections ill-suited for capturing context-specific degradation (Biradar et al., 2024). Another key limitation is the human dependency of these diagnostics: many traditional techniques require trained personnel to interpret readings or operate sensitive equipment,

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leading to variability in diagnostic accuracy and longer fault classification cycles. The cumulative effect of these constraints is a reactive maintenance culture that delays intervention until significant damage has occurred. These realities underscore the need for continuous, real-time monitoring systems that can track operational dynamics, predict failures, and support condition-based maintenance (CBM) strategies, thereby ensuring transformer longevity and grid resilience.

Numerous comparative studies have highlighted the superiority of continuous condition monitoring over traditional periodic diagnostic approaches in the context of transformer asset management. While DGA and furan analysis remain valuable for forensic-level assessments, their offline nature limits their utility in dynamic operational environments (Meradi et al., 2024). Continuous monitoring systems, equipped with IoT-enabled sensors, can collect and transmit real-time data on temperature, vibration, moisture, and gas evolution, offering a more granular and responsive diagnostic framework. Research by (Al Mtawa et al., 2022) demonstrated that integrating online acoustic emission sensors enabled faster detection of incipient partial discharge compared to offline PD testing, thereby reducing insulation failure rates. Similarly, (Shafei et al., 2024) reported that transformers equipped with real-time thermal sensors exhibited improved detection of abnormal hotspots, preventing thermal runaway and insulating material breakdown. Studies by (Bazi et al., 2024) noted that hybrid systems combining infrared imaging with online sensor feedback significantly enhanced diagnostic confidence by correlating external and internal temperature anomalies. Moreover, field studies conducted by (Zhao et al., 2023) in Gulf-region substations confirmed that continuous moisture monitoring led to more accurate prediction of bushing failures, improving maintenance scheduling efficiency. Despite these advantages, the deployment of continuous monitoring systems often faces challenges such as initial capital cost, data overload, and cybersecurity vulnerabilities. Nonetheless, the literature overwhelmingly supports a shift toward real-time diagnostic models for effective transformer health management, especially in high-load or mission-critical installations. This body of evidence forms the foundation for the emergence of IoT-based condition monitoring as a transformative strategy in the power sector.

Sensor Technologies for Real-Time Monitoring

The application of sensors in transformer monitoring has advanced significantly, moving from rudimentary detection tools to sophisticated devices capable of real-time measurement and autonomous data processing. Among the most prevalent types are fiber-optic temperature sensors, known for their immunity to electromagnetic interference and ability to provide spatially distributed thermal readings (Rao et al., 2022). These sensors offer a non-invasive alternative to traditional thermocouples, particularly in monitoring winding and core temperatures under dynamic load conditions. MEMS-based vibration sensors are another innovation, enabling the detection of mechanical anomalies such as core vibration, winding displacement, or internal arcing by capturing micro-level structural movements. Their miniature form factor and low energy requirements make them suitable for embedded diagnostics. Oil-level and pressure relief sensors are commonly deployed to track volumetric oil changes and sudden gas expulsions, which are early indicators of internal arcing, overheating, or insulation degradation. Moisture-in-oil sensors are essential for detecting water ingress—a major contributor to dielectric breakdown and paper insulation aging—offering continuous insights that are superior to offline Karl Fischer titration methods (Malek et al., 2017). Additionally, newer composite sensors now integrate multiple sensing functions—temperature, humidity, and gas analysis—on a single substrate, enabling multiparameter monitoring through one compact unit. These sensors collectively form the backbone of smart transformer condition monitoring systems and are often connected to wireless transceivers for data relay. As sensor technology matures, the selection and integration of specific sensor types are increasingly dictated by transformer design, grid criticality, environmental exposure, and operational risk factors (Younos & Heyer, 2015).

Effective real-time monitoring of power transformers relies heavily on the optimal selection and deployment of sensors, guided by criteria such as sensitivity, accuracy, resilience, and energy efficiency. Sensitivity refers to the ability of a sensor to detect small fluctuations in physical conditions; this is particularly crucial in detecting minor thermal anomalies or partial discharges before they escalate into severe faults. For instance, fiber-optic sensors can detect thermal gradients as minute as 0.1°C, enabling fine-grained thermal mapping (Vijayakumar & Ramya, 2015). Accuracy, which encompasses both linearity and calibration stability, determines the reliability of sensor output across varying conditions. MEMS accelerometers used for vibration analysis must maintain precise readings

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even when embedded in noisy, high-voltage environments. Environmental resilience is another key criterion, especially for sensors installed in outdoor or remote substations where they face temperature extremes, high humidity, and dust ingress. Devices are typically required to meet industrial-grade IP ratings and operate across a wide temperature range without signal degradation. Long-term exposure to transformer oil also demands chemically inert sensor housings to prevent performance drift. Additionally, energy efficiency plays a pivotal role in determining sensor viability. Many monitoring systems are deployed in areas with limited access to grid power, necessitating ultra-low-power designs or integration with energy harvesting systems. Studies have highlighted that power-hungry sensors can significantly reduce the lifespan of remote monitoring setups or necessitate frequent maintenance interventions, defeating the purpose of autonomous condition monitoring (Syafrudin et al., 2018). Therefore, the literature consistently emphasizes multi-parameter optimization—balancing performance with practical deployment constraints—as a foundational principle in transformer sensor design and selection.

Energy autonomy is increasingly recognized as a vital requirement for sensors used in transformer condition monitoring, particularly in remote or unmanned substations. The emergence of self-powered sensors and energy harvesting systems has enabled sustained data acquisition without reliance on external power sources. Technologies such as thermoelectric generators (TEGs) and piezoelectric harvesters exploit the thermal gradients and mechanical vibrations present in transformer environments to generate electricity for sensor operation. For instance, (Pule et al., 2017) demonstrated a hybrid micro-energy system that combined thermoelectric and vibration-based energy conversion, achieving sufficient power for a MEMS accelerometer and a ZigBee module. Similarly, (Kakria et al., 2015) developed a wireless moisture sensor that utilized transformer oil temperature differentials to drive a TEG, enabling real-time data transmission for over six months without battery replacement. These solutions reduce maintenance needs and enhance system longevity, which is especially crucial for aging grids in regions with labor or logistical constraints. A study by (Lan et al., 2020) indicated that self-powered sensor networks could reduce long-term monitoring costs by as much as 40% when deployed across large-scale transformer fleets. Moreover, energy harvesting supports the deployment of high-density sensor networks where each node requires minimal power but must remain operational continuously. Integration with low-power wide-area networks (LPWANs) like LoRaWAN further extends the utility of such systems by minimizing communication energy consumption. Despite challenges such as variable ambient energy and low conversion efficiency, recent advancements in energy storage capacitors and micro-controllers have made self-powered sensors increasingly practical. The literature reveals a strong consensus that energy-autonomous sensors are essential for realizing scalable, resilient, and cost-effective transformer monitoring in real-world applications (Imani et al., 2016).

To improve diagnostic accuracy and system robustness, researchers have increasingly advocated for sensor fusion and redundancy strategies in transformer monitoring. Sensor fusion involves integrating outputs from multiple sensor types—such as combining temperature, moisture, and gas sensors—to derive a holistic condition profile and reduce ambiguity in fault classification. This multi-modal approach compensates for the limitations of individual sensors and enhances diagnostic confidence. For instance, a spike in temperature combined with elevated hydrogen levels in oil is a more reliable indicator of arcing than either parameter alone. Redundancy, on the other hand, entails deploying multiple sensors of the same type to ensure fault tolerance in case of individual sensor failure or signal drift. This is particularly important in harsh operating conditions, where exposure to electromagnetic interference, oil contamination, or weathering can degrade sensor performance over time. Studies by (Cloete et al., 2016) emphasized the use of triple-redundant sensors with voting algorithms to eliminate spurious readings and improve system reliability. Advanced data fusion algorithms—including Kalman filters, Dempster-Shafer theory, and fuzzy logic systems—have also been employed to harmonize data from heterogeneous sources and mitigate sensor biases. Furthermore, machine learning models trained on fused datasets tend to outperform single-sensor systems in detecting early-stage anomalies and predicting asset failures (Kumar et al., 2016). The literature confirms that sensor fusion and redundancy are not only technical enhancements but also strategic safeguards that ensure monitoring continuity, especially in mission-critical infrastructure where diagnostic accuracy directly correlates with operational safety and economic stability.

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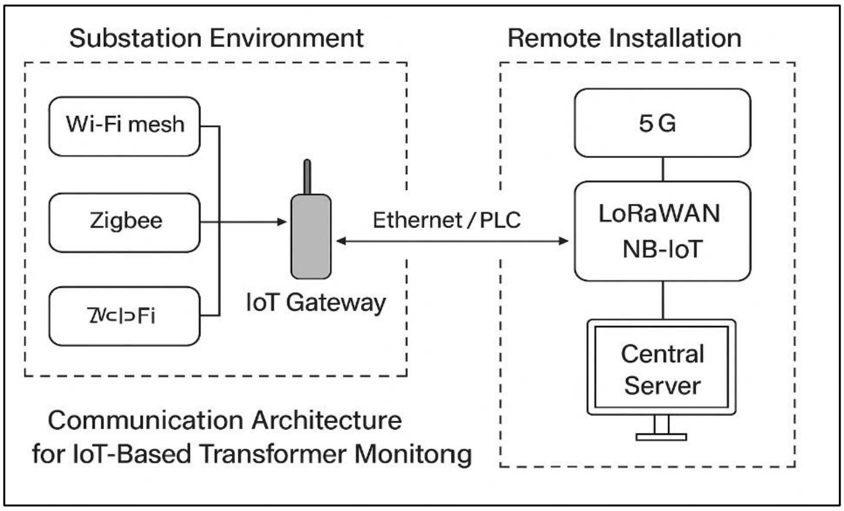
Protocols and Networking Architectures

Effective communication protocols are essential for enabling seamless, low-latency, and energy-efficient data transmission in IoT-based transformer condition monitoring systems. Among the widely adopted communication technologies are ZigBee, LoRaWAN, NB-IoT, Wi-Fi mesh, and 5G, each with unique strengths and limitations. ZigBee operates on IEEE 802.15.4 and is characterized by low power consumption and mesh topology support, making it suitable for short-range communication within substations. However, ZigBee's limited transmission range and susceptibility to electromagnetic interference restrict its deployment in remote transformer yards. LoRaWAN, by contrast, offers extended coverage of up to 15 km with ultra-low power consumption, making it a favored choice for rural substations or geographically dispersed transformer assets (Sony et al., 2019). It is particularly effective in transmitting small payloads, such as temperature or gas level data, at infrequent intervals. NB-IoT, operating within the LTE framework, provides improved building penetration and energy efficiency while leveraging cellular infrastructure, allowing seamless integration with centralized monitoring systems (Park et al., 2017). Wi-Fi mesh networks, while offering high data throughput, often face challenges in terms of energy demands and coverage, making them more viable for high-bandwidth needs within urban substations rather than remote deployments (Jawhar et al., 2018). 5G networks represent the most advanced option, offering low latency, ultra-reliability, and network slicing capabilities suitable for real-time analytics and edge AI deployments. However, 5G infrastructure is still emerging in many regions and requires significant capital investment. These technologies form the backbone of modern IoT-based transformer monitoring frameworks, and the choice of protocol is typically dictated by application-specific needs such as data rate, energy budget, deployment location, and latency tolerance (Khan et al., 2017).

Figure 3: Communication Architecture for IoT-Based Transformer Monitor



The architectural design of communication systems for IoT-enabled transformer monitoring varies significantly between substation environments and remote field installations, largely due to differences in infrastructure availability, environmental exposure, and connectivity requirements. In urban or semi-urban substations, where power and network infrastructures are typically well-developed, high-bandwidth, low-latency protocols such as Wi-Fi mesh or Ethernet over Power Line Communication (PLC) can be deployed to support real-time diagnostics and video surveillance. These environments allow for redundancy in networking equipment and enable multi-hop data relay through routers and mesh access points, thereby reducing signal attenuation and improving fault tolerance (Sobin, 2020). Conversely, in remote or off-grid substations, communication solutions must contend with constraints such as limited power availability, long-range requirements, and environmental obstacles. LoRaWAN and NB-IoT have proven highly effective in such settings due to their ability to transmit over long distances with minimal energy consumption and reliable packet delivery in harsh conditions. Field experiments by (Jawhar et al., 2017) show that LoRaWAN systems can maintain link integrity even in mountainous and forested terrains, provided antenna placement and transmission intervals are optimized. However, limited payload size and lower data rates make these protocols better suited for scalar measurements like temperature or humidity rather than high-frequency waveform analysis. Additionally, satellite-based LPWAN systems are emerging as alternatives in areas completely disconnected from terrestrial networks, though they incur higher operational costs and limited interactivity. Thus, architectural differentiation is necessary to balance communication robustness, cost efficiency, and data resolution based on the deployment geography, grid criticality, and asset density.

Ensuring network reliability while optimizing for latency and power efficiency remains a central challenge in designing communication protocols for transformer condition monitoring. Network reliability, often measured in terms of packet delivery ratio, uptime, and fault resilience, is essential for ensuring uninterrupted data flow from transformers to control centers. Protocols like NB-IoT and LoRaWAN have been extensively tested in power systems and consistently deliver high reliability even under adverse environmental conditions and fluctuating signal-to-noise ratios (Sethi & Sarangi, 2017). However, these technologies trade off low latency and throughput; for example, LoRaWAN's uplink latency can reach several seconds, making it unsuitable for real-time protection functions or high-speed data analytics. In contrast, 5G URLLC (Ultra-Reliable Low Latency Communication) enables latencies below 1 ms, suitable for edge AI applications and instantaneous fault isolation, though it requires a dense and costly infrastructure. Power consumption is another critical dimension, especially for battery-operated sensors or energy-harvesting devices. ZigBee and LoRa offer superior energy profiles, often enabling sensor nodes to operate autonomously for several years without servicing (Marzal et al., 2018). Nonetheless, they may suffer from reduced data granularity and packet collision in dense deployments. Several researchers have proposed adaptive duty-cycling algorithms and dynamic transmission schemes to balance energy consumption with real-time data needs. These trade-offs highlight the complexity of selecting a communication protocol: no single solution optimally satisfies all requirements, and hybrid configurations or protocol stacking may be necessary to meet diverse operational objectives (Yastrebova et al., 2018).

At the heart of the communication infrastructure for IoT-based transformer monitoring lie IoT gateways, which serve as intermediaries between local sensor nodes and central data repositories or cloud analytics platforms. These gateways aggregate, preprocess, and securely transmit data from heterogeneous sources, enabling efficient bandwidth utilization and edge intelligence. Typically equipped with multi-protocol support (e.g., ZigBee, LoRa, Wi-Fi, BLE), gateways manage sensor heterogeneity, standardize data formats, and filter redundant or low-priority information to reduce upstream congestion. Many advanced gateways incorporate edge computing capabilities, allowing preliminary analytics such as threshold checking, anomaly detection, or signal smoothing to be conducted locally, thereby reducing latency and cloud processing loads. Studies by (Rawat & Reddy, 2016) has demonstrated that local data aggregation through intelligent gateways can reduce end-to-end transmission delay by over 40% while maintaining diagnostic accuracy. Another key function is data prioritization—whereby critical alarms, such as transformer overheating or sudden pressure relief, are assigned high transmission priority over routine updates. Gateways also handle network security, employing encryption, authentication, and firewalls to ensure data integrity and protect against cyber intrusions. Fog computing architectures, which extend gateway functionality with distributed analytics nodes, have further enhanced the scalability of condition monitoring systems (Shi et al., 2021). The literature supports the view that the design and configuration of IoT gateways are as crucial as the sensors themselves, determining the overall responsiveness, reliability, and cybersecurity posture of the transformer monitoring network.

Edge, Fog, and Cloud Computing in Condition Monitoring

The architecture of data processing in IoT-enabled transformer condition monitoring is typically stratified across on-device, edge, fog, and cloud computing layers, each contributing distinct capabilities and limitations. On-device processing, where microcontrollers on the sensor node perform basic calculations or filtering, offers the lowest latency and energy efficiency but is limited in computational power and storage (Daraghmi et al., 2022). Such configurations are well-suited for threshold-based alerts but incapable of running complex analytics or predictive models. Edge computing, on the other hand, moves data processing closer to the data source—typically within local gateways or embedded systems—allowing for low-latency analytics, real-time decision-making, and reduced network congestion. Studies by (Martín et al., 2022) demonstrated that edge-enabled systems reduced event-response latency by up to 60% compared to cloud-only solutions.

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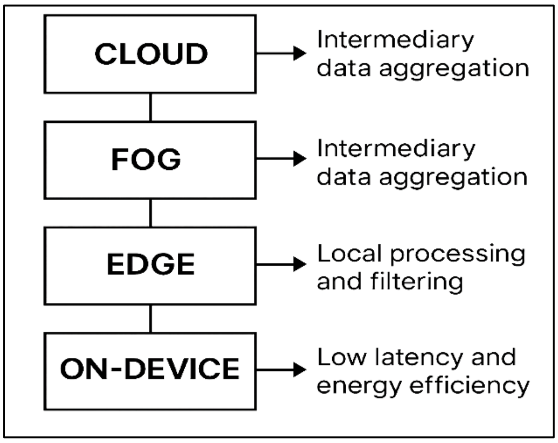
Cloud computing, while providing extensive scalability, data warehousing, and computational flexibility, suffers from latency constraints, bandwidth demands, and vulnerability to communication outages, particularly in remote substations. Cloud platforms like Amazon Web Services (AWS), Microsoft Azure IoT Hub, and IBM Watson IoT are widely employed for large-scale transformer fleet analytics and historical trend analysis. In response to these trade-offs, hybrid models have emerged that dynamically allocate tasks between edge and cloud nodes based on workload, urgency, and network conditions (Santos et al., 2018). The literature shows a clear shift toward edge and fog computing paradigms as central pillars in real-time condition monitoring, reflecting the increasing need for localized analytics, bandwidth optimization, and fault resilience in transformer diagnostics.

Figure 4: Data Processing Architecture in Transformer Condition Monitoring



Fog computing, situated between edge devices and the cloud, plays a pivotal role in enabling hierarchical monitoring networks for power transformers by providing distributed, intermediate processing nodes that aggregate and analyze data regionally before cloud transmission. This tiered architecture enhances scalability and reduces the computational burden on both edge devices and centralized cloud servers (Li et al., 2022). Fog nodes can perform advanced analytics, correlate multi-transformer data across substations, and execute machine learning models for regional fault pattern recognition. Studies by (Bhoi et al., 2024) revealed that deploying fog-based micro data centers significantly improved system reliability and reduced response times in regional utility networks. Moreover, fog computing allows context-aware processing by integrating environmental and operational metadata (e.g., temperature, humidity, transformer load) to enrich fault diagnosis and event prioritization. One of the key strengths of fog computing is its ability to support network segmentation, allowing localized fault handling even when cloud access is interrupted—a critical requirement in mission-critical substations. Additionally, fog nodes can perform load balancing and task orchestration, dynamically reallocating computational tasks based on processing availability and urgency. This hierarchical topology not only enhances operational autonomy but also supports modular deployment, where additional fog nodes can be integrated with minimal disruption. The literature thus underscores fog computing as a strategic intermediary layer that enhances data security, reduces communication latency, and bridges the performance gap between resource-constrained edge nodes and high-capacity cloud infrastructures in transformer monitoring applications (Yang et al., 2020).
Real-time condition monitoring of power transformers generates vast volumes of sensor data, necessitating effective data filtering, compression, and preprocessing mechanisms to ensure efficient and timely analysis. Edge computing facilitates these functions by enabling local processing capabilities that reduce transmission burdens and accelerate decision-making. For example, threshold filtering discards data points that fall within expected operational ranges, thereby minimizing data overload without compromising anomaly detection accuracy. Signal conditioning techniques, including smoothing filters and Fourier transforms, are applied at the edge to remove noise and extract meaningful features from raw electrical or thermal signals (Mijuskovic et al., 2021). Data compression algorithms such as Huffman coding, LZW, and predictive encoding further enhance transmission efficiency, especially in remote areas with limited bandwidth. Some studies

have adopted lossless compression schemes to ensure diagnostic fidelity, especially for time-series data critical to PD and vibration analysis. Moreover, event-driven sampling mechanisms have been implemented to prioritize data capture during anomalous conditions (e.g., rapid temperature rise), rather than relying on fixed-interval polling, thereby improving data relevance. Edge devices are also being embedded with tiny machine learning (TinyML) models to perform on-board classification tasks, such as fault/no-fault determination, eliminating the need to transmit every datapoint to the cloud (Wang et al., 2019). These edge-level functions collectively enhance the efficiency, responsiveness, and reliability of transformer monitoring systems and have been validated in multiple field deployments reported across North America, Asia, and Europe.

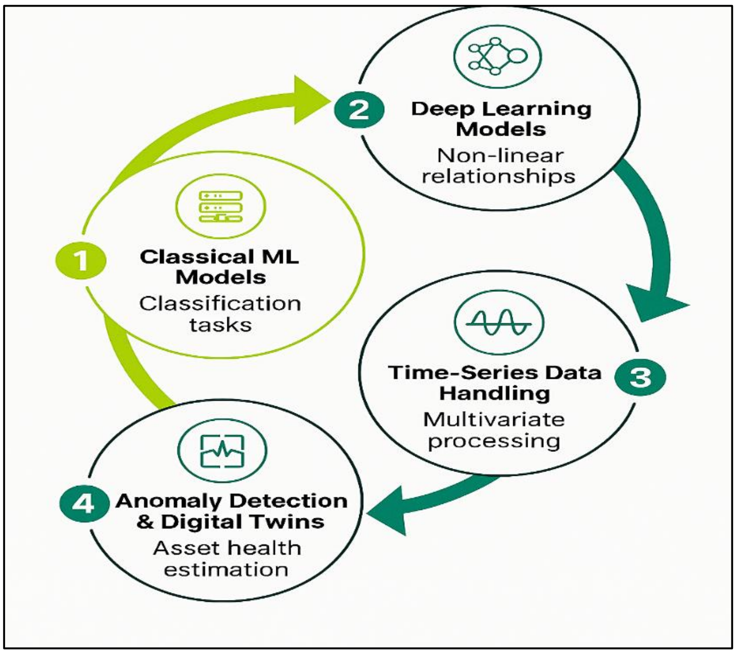
The implementation of scalable, interoperable, and secure transformer condition monitoring systems depends heavily on robust platform architectures and service-oriented middleware that orchestrate interactions between devices, analytics engines, and end-user interfaces. Service-oriented architecture (SOA) provides the foundational structure for modular development, allowing different services—such as data acquisition, storage, visualization, and analytics—to be deployed independently yet interactively. Middleware platforms such as Node-RED, OpenMTC, and FIWARE offer abstraction layers that handle device discovery, protocol translation, and data routing across heterogeneous networks (Lu et al., 2023). These systems facilitate device interoperability, allowing diverse sensors and gateways using different standards (e.g., ZigBee, LoRa, NB-IoT) to function cohesively under a unified platform. Distributed platforms increasingly incorporate containerization technologies like Docker and Kubernetes to enable microservice deployment, scalability, and fault isolation in hybrid edge-fog-cloud environments. Furthermore, middleware often embeds security services—including authentication, encryption, and access control—ensuring data integrity and compliance with cybersecurity standards for critical infrastructure. Real-time dashboards and APIs provided by such platforms support visualization and integration with supervisory control and data acquisition (SCADA) systems, facilitating operator decision-making. Several commercial and open-source platforms, including Siemens MindSphere, GE Predix, and IBM Watson IoT, offer middleware frameworks tailored to utility asset management, enabling seamless fusion of cloud analytics with field-level observations. The literature confirms that the design of robust middleware and platform architectures is crucial for supporting dynamic dataflows, achieving interoperability, and maintaining operational continuity in distributed transformer monitoring networks (Cui et al., 2019).

Artificial Intelligence and Machine Learning for Fault Diagnosis

Classical machine learning (ML) models have formed the foundation of intelligent fault diagnosis systems in transformer condition monitoring. Among the most extensively used techniques are support vector machines (SVMs), random forests (RFs), k-nearest neighbors (KNN), and decision trees (DTs) (Ali et al., 2019). These models excel in classification tasks based on sensor data such as temperature, dissolved gases, partial discharge signals, and vibration. SVMs are particularly well-suited for binary classification problems, effectively distinguishing between faulty and non-faulty states by maximizing the margin between data classes. Random forests, which operate by constructing ensembles of decision trees, are known for their robustness to overfitting and high accuracy in multi-class classification of fault types. Studies by (Dhingra et al., 2021) have shown that RF-based models can achieve fault detection accuracies exceeding 95% when trained on labeled transformer datasets.

Similarly, KNN algorithms, although computationally expensive, are advantageous in non-parametric learning environments and have been used to classify operational anomalies using Euclidean distance metrics. Decision trees, while simplistic, offer interpretability and have been integrated into real-time systems where transparency in decision logic is crucial (Baduge et al., 2022). These models typically rely on pre-engineered features such as gas ratios, insulation aging indicators, and thermal profiles. Despite their strengths, classical ML models often struggle with non-linear and high-dimensional datasets, necessitating careful feature selection and preprocessing steps such as normalization, principal component analysis (PCA), and statistical outlier removal . Their effectiveness is also contingent upon the availability of quality training data, making data completeness and sensor reliability vital considerations in deployment environments (Verma et al., 2022). The use of deep learning (DL) models in transformer condition monitoring has gained traction due to their superior ability to model complex, non-linear relationships and extract features automatically from raw sensor inputs. Convolutional neural networks (CNNs) have been employed to analyze spatially structured data such as thermal maps, infrared imagery, and acoustic emission patterns (Maciel et al., 2022). CNNs are capable of learning hierarchical feature representations that enhance fault localization accuracy without the need for manual feature engineering. For instance, Lu et al. (2020) demonstrated that CNNs applied to infrared thermographic data could identify localized overheating regions with an accuracy of 96%, outperforming traditional methods. Recurrent neural networks (RNNs) and their variants like long short-term memory (LSTM) models are widely used for time-series data, including load currents, moisture levels, and transformer oil temperature sequences (Liu et al., 2018). LSTMs are particularly adept at capturing temporal dependencies, enabling predictive maintenance through early fault forecasting. Autoencoders have also been adopted for unsupervised learning and anomaly detection, capable of learning data distributions during normal operation and flagging deviations as potential faults. Moreover, hybrid architectures, such as CNN-LSTM models, combine spatial and temporal analysis to extract richer features from multivariate datasets. Deep learning methods often require large datasets and substantial computational resources, which has led to the rise of edge AI implementations where simplified deep models run on gateways or embedded systems (Brito et al., 2022). Despite training complexity and a need for labeled data, DL models have shown significant promise in automating fault classification, increasing model generalization, and reducing false alarms in transformer diagnostics.

Figure 5: AI Techniques in Transformer Condition Monitoring



Effective condition monitoring and fault diagnosis in transformers require sophisticated handling of multivariate time-series data, encompassing parameters such as temperature, vibration, dissolved gas concentrations, moisture, and load fluctuations (Taheri & Salimi Beni, 2025). The challenge lies in integrating heterogeneous signals with varying sampling rates and noise characteristics into a coherent diagnostic framework. Feature extraction techniques play a pivotal role in this context. Classical approaches include statistical descriptors (mean, standard deviation, skewness), spectral analysis (FFT, wavelet transform), and signal decomposition methods (EMD, PCA) to reduce dimensionality while preserving fault-relevant characteristics. In machine learning workflows, feature selection algorithms such as mutual information, recursive feature elimination, and correlation-based filtering help improve model interpretability and prevent overfitting. In contrast, deep learning models often bypass manual feature engineering by learning hierarchical representations directly from raw inputs, though they still require preprocessing such as normalization, data alignment, and padding for unequal time sequences (Singh et al., 2023). The availability and quality of training datasets remain a major bottleneck, as real-world transformer failures are relatively rare, leading to class imbalance and underrepresentation of critical fault types. Synthetic data generation, including SMOTE (Synthetic Minority Oversampling Technique) and generative adversarial networks (GANs), has been explored to augment datasets and address skewed distributions. Moreover, sensor malfunctions and noise introduce uncertainty into the diagnostic process, requiring data imputation, outlier detection, and robust learning strategies. Thus, managing multivariate time-series data involves a careful trade-off between model complexity, computational feasibility, and diagnostic accuracy (Nath et al., 2021).

One of the most impactful contributions of AI and ML in transformer monitoring is the ability to detect anomalies, estimate asset health, and simulate transformer behavior through digital twin frameworks. Anomaly detection refers to identifying deviations from normal operational patterns and is performed using supervised, semi-supervised, or unsupervised learning approaches (Sawaqed & Alrayes, 2020). Unsupervised models like autoencoders and clustering algorithms (e.g., k-means, DBSCAN) are effective when labeled fault data is unavailable, enabling condition-based maintenance through early fault indications. Health index estimation involves aggregating multiple diagnostic parameters into a single value reflecting the transformer's condition. Techniques such as weighted scoring, fuzzy logic, and regression analysis have been used to build health indices that guide maintenance planning and risk assessment. These indices can be incorporated into asset management platforms for ranking transformer fleets by criticality. More recently, digital twin technology has emerged as a sophisticated tool that creates a virtual replica of the physical transformer, using real-time sensor data to simulate behavior, predict degradation, and test intervention strategies (Lei et al., 2020). Digital twins can integrate AI models for fault prediction, what-if analysis, and life-cycle cost modeling, offering utility operators a powerful decision-support mechanism (Li, 2018). Case studies by (Chen et al., 2017) show that digital twins, when integrated with cloud analytics and SCADA systems, significantly improve fault diagnosis accuracy and maintenance efficiency. These advancements reflect the convergence of AI, data science, and electrical engineering in creating proactive, data-driven transformer monitoring ecosystems that are both intelligent and scalable (Han et al., 2020).

Digital Twins and Predictive Modeling

The concept of digital twins (DTs) has transitioned from manufacturing and aerospace sectors into power systems, offering transformative potential in predictive modeling for transformer condition monitoring. A digital twin is a real-time, virtual representation of a physical asset that dynamically mirrors its operational status using sensor inputs, simulations, and machine learning algorithms (Khan et al., 2022). In the context of power transformers, DTs integrate heterogeneous sensor data—such as thermal gradients, gas evolution patterns, insulation aging metrics, and load fluctuations—into a centralized platform that simulates the asset's behavior under varying conditions (Ammar et al., 2025). This facilitates continuous diagnostics, allowing operators to run real-time "what-if" simulations to predict fault development under different loading or environmental scenarios. The International Electrotechnical Commission (IEC) has also recognized the value of DTs, incorporating them into smart grid standards and predictive asset management frameworks (Hossain et al., 2024). The strength of digital twins lies in their bidirectional nature: they not only receive real-time updates from the field but can also send feedback in the form of maintenance recommendations, thereby closing the loop between observation and action (Hossain et al., 2024a). This interactivity represents a paradigm shift from passive condition monitoring to active, model-informed decision support in critical grid assets (Hossain et al., 2024; Nahar et al., 2024).

One of the most significant contributions of digital twins in transformer diagnostics is their capacity to support predictive maintenance through accurate estimation of Remaining Useful Life (RUL). Traditional maintenance strategies often rely on fixed intervals or threshold-based alarms, which can result in either premature servicing or catastrophic delays (Ammar et al., 2025; Khan et al., 2022). Digital twin models, by contrast, continuously assess asset degradation based on multivariate sensor inputs and degradation profiles, predicting the time-to-failure with greater accuracy. Machine learning techniques, particularly supervised regression models and LSTM-based forecasting, are frequently embedded within DT frameworks to model failure trends based on historical and real-time data (Akter, 2023; Masud et al., 2023; Ashraf & Ara, 2023). Digital twin model incorporating gas composition trends, moisture ingress patterns, and thermal stress data could forecast transformer failure with over 92% accuracy six weeks in advance. Moreover, the integration of physics-based models—such as insulation aging curves and thermal-fluid dynamics—enhances the robustness of RUL predictions by grounding them in established engineering principles. This hybrid modeling approach allows utility operators to transition from reactive or preventive strategies to condition-

based maintenance (CBM), optimizing resource allocation, reducing unplanned outages, and extending transformer lifespan (Ara et al., 2022; Saha, 2024; Subrato, 2018).
Digital twins achieve their full potential when integrated with Supervisory Control and Data Acquisition (SCADA) systems, IoT sensor networks, and artificial intelligence (AI)-based diagnostic tools. In transformer monitoring environments, DT platforms receive high-frequency, real-time data streams from distributed IoT sensors capturing temperature, vibration, partial discharge, and oil condition parameters (Rajesh, 2023; Sazzad & Islam, 2022; Shaiful et al., 2022). This data is processed locally at edge nodes or transmitted via secure LPWAN protocols to cloud-based digital twin engines for simulation and analysis. AI models embedded within these platforms perform tasks such as anomaly detection, fault classification, and predictive forecasting, significantly enhancing diagnostic granularity (Alam et al., 2024; Rahaman, 2022; Zahir et al., 2023). When linked with SCADA systems, DTs provide operators with visual dashboards, dynamic condition reports, and automated alerts—turning transformer diagnostics from a reactive procedure into a proactive, insight-driven process. Furthermore, the bidirectional integration allows simulated outcomes from the twin to influence SCADA control logic, such as adjusting load sharing between transformers based on degradation risk. This tight coupling of physical infrastructure with digital intelligence facilitates closed-loop control and operational resilience, especially in smart grid environments where real-time responsiveness is paramount (Abdullah Al et al., 2022; Ariful et al., 2023; Sazzad, 2025; Arifur, et al., 2025).
The adoption of digital twin technology for transformer monitoring is gaining traction worldwide, though deployment maturity varies across regions and utilities. North American and European utilities have led pilot implementations, driven by aging grid assets and regulatory mandates for asset health transparency. For instance, the UK's National Grid and the U.S. Department of Energy have initiated digital twin programs for substation transformers, focusing on anomaly prediction and cost optimization (Razzak et al., 2024; Md et al., 2025; Sazzad, 2025). In contrast, developing economies in Asia, Africa, and Latin America are gradually exploring DTs as part of broader smart grid or IoT rollouts, often limited by infrastructure and data challenges. Nevertheless, open-source platforms such as FIWARE and industrial suites like Siemens MindSphere and GE's Predix have made DT adoption more accessible, offering modular interfaces for transformer monitoring applications (Qibria & Hossen, 2023; Masud, Mohammad, & Sazzad, 2023; Masud et al., 2025; Shamima et al., 2023). Moreover, the rise of edge computing and 5G connectivity is expected to further accelerate DT scalability and responsiveness, enabling real-time simulations at the substation level. As cybersecurity becomes a growing concern, researchers are also exploring blockchain integration and secure digital thread mechanisms to protect digital twin dataflows (Akter, 2025; Zahir, Rajesh, Tonmoy, et al., 2025).

Deep Learning Techniques and Architectures

Deep learning (DL) has emerged as a powerful alternative to classical machine learning methods for fault detection in transformer monitoring, primarily due to its capacity to model complex, non-linear relationships in high-dimensional datasets. Unlike classical models that depend heavily on manually engineered features, DL models autonomously extract hierarchical patterns from raw sensor inputs, improving diagnostic accuracy and robustness (Khan & Razee, 2024; Maniruzzaman et al., 2023; Sanjai et al., 2023). This is particularly valuable in power systems where sensor signals such as dissolved gas concentrations, oil temperature gradients, vibration signals, and moisture levels are often interrelated and noisy. Convolutional Neural Networks (CNNs) have been widely adopted to process spatially structured data such as infrared thermographic images and acoustic emissions, with several studies demonstrating fault localization accuracy above 90% (Hossen et al., 2023; Akter & Razzak, 2022). These models outperform traditional statistical or image thresholding techniques by identifying minute spatial anomalies that precede transformer failure. Their layered architecture enables them to detect low-level features (e.g., edges or thermal hotspots) and combine them into higher-order representations, making them suitable for predictive maintenance in complex, dynamic transformer environments. While CNNs excel in handling spatial data, Recurrent Neural Networks (RNNs) and their advanced variants, such as Long Short-Term Memory (LSTM) networks, are particularly adept at modeling temporal dependencies in transformer health parameters. Time-series sensor data—such as daily load profiles, oil pressure variations, and moisture accumulation trends—require models that can retain long-term contextual information. LSTMs are designed to overcome the vanishing gradient problem of traditional RNNs, allowing for more stable and effective learning over extended sequences (Jahan et al., 2022; Rajesh et al., 2023; Tonmoy & Arifur, 2023). In transformer diagnostics, LSTM-based models have been used to forecast fault likelihoods based on historical fluctuations in operational data, offering utility operators a temporal lead in preventive maintenance planning (Hossen & Atiqur, 2022; Roksana, 2023; Tonoy & Khan, 2023). For example, Liu et al. (2018) used LSTM to predict temperature and load anomalies that precede winding failures, demonstrating predictive accuracy above 92%. These models' ability to encode temporal trends makes them particularly effective in detecting faults that evolve gradually—such as insulation aging or slow gas accumulation—thereby enabling early intervention and minimizing catastrophic outcomes (Khan, 2025; Masud, 2022; Alam et al., 2023).

Cyber-Physical Threats

IoT-enabled transformer monitoring systems introduce a range of cyber-physical vulnerabilities due to their dependence on wireless communication, distributed sensor networks, and real-time data transmission. These systems are susceptible to several forms of attack, most notably spoofing, data injection, and denial-of-service (DoS), all of which pose significant threats to grid integrity. Spoofing attacks involve the impersonation of legitimate sensor nodes or gateways, allowing adversaries to gain unauthorized access to the system and send manipulated data. Such attacks are particularly dangerous when targeting authentication loopholes in low-power devices that often lack strong cryptographic safeguards (Nichols et al., 2019). Data injection attacks, on the other hand, manipulate operational signals such as transformer temperature or gas levels to mislead anomaly detection systems, potentially delaying maintenance responses or triggering false alarms. These attacks have been shown to degrade the performance of machine learning models used in condition monitoring by corrupting training datasets or confusing classification logic. DoS attacks exploit vulnerabilities in network protocols by flooding gateways or IoT nodes with traffic, thereby interrupting real-time data flows and disabling remote monitoring capabilities. In transformer applications, where timely fault detection is crucial, such disruptions can result in system-wide blackouts or irreversible equipment damage. Research by (Shimizu & Nakayama, 2020) has also revealed vulnerabilities in LoRa and ZigBee protocols, which, without encryption and frequency hopping, are susceptible to jamming and interception. The literature emphasizes that addressing these attack surfaces requires not only technical safeguards but also systemic design improvements in communication protocols, device security, and threat awareness (Priyadarshini et al., 2021).

In response to rising cyber-physical threats in IoT transformer monitoring systems, the implementation of secure communication protocols has become an essential layer of defense. One widely adopted framework is MQTT (Message Queuing Telemetry Transport) secured with TLS (Transport Layer Security), which offers encrypted data transfer, device authentication, and integrity verification without burdening low-power devices. MQTT's lightweight nature and compatibility with publish-subscribe models make it ideal for constrained sensor networks, especially in high-latency environments like substations (Fink et al., 2017). Another emerging technology is blockchain, which enhances traceability and immutability in data transactions. By creating distributed ledgers, blockchain enables sensor data to be logged securely across a network of nodes, preventing tampering and enabling verifiable audits. Studies by Giraldo et al. (2017) demonstrated that integrating blockchain with transformer monitoring systems reduces the probability of data manipulation and supports forensic investigations post-incident. Additionally, lightweight encryption schemes such as elliptic curve cryptography (ECC) and symmetric AES-128 protocols have been deployed to secure resource-limited IoT nodes without compromising performance. Secure boot and firmware integrity checks are further used to protect devices from root-level attacks that can bypass communication security altogether. Moreover, Software-Defined Networking (SDN) is gaining attention for its ability to dynamically manage data flows and isolate malicious traffic at the network level (Walker-Roberts et al., 2020). The literature strongly supports multi-layered communication security frameworks, where encryption, authentication, logging, and trust mechanisms work in tandem to protect sensitive transformer diagnostics and ensure operational continuity (Keshk et al., 2021).

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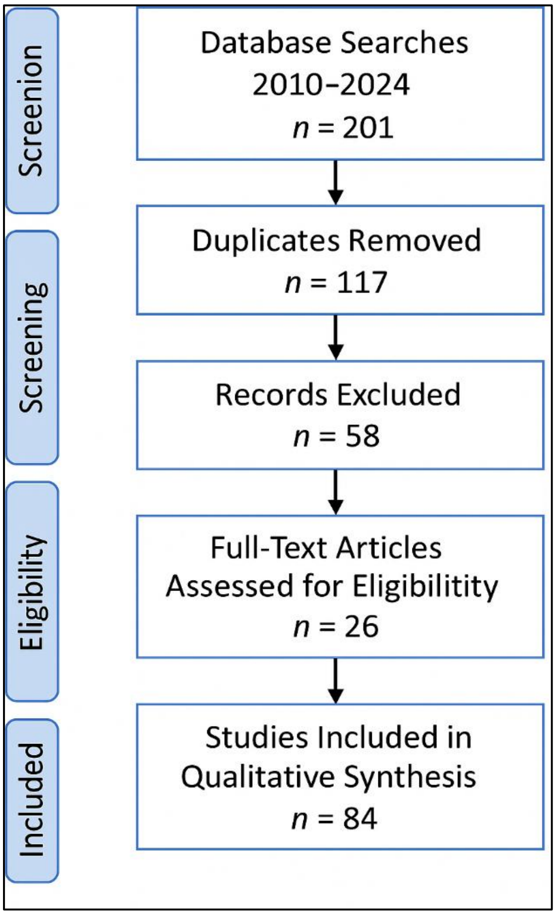
METHOD



This systematic review adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a transparent, reproducible, and methodologically sound process. The PRISMA framework provides a structured approach for identifying, selecting, evaluating, and synthesizing relevant studies, enhancing the clarity and credibility of the research process. The review protocol was designed around four key phases: identification, screening, eligibility assessment, and inclusion, all executed with rigor to minimize bias and enhance replicability. The identification phase began with comprehensive searches across multiple digital databases, including IEEE Xplore, ScienceDirect, SpringerLink, Wiley Online Library, Scopus, and Google Scholar, covering literature published between 2010 and 2024.

Keywords and Boolean combinations such as *"IoT AND transformer monitoring," "condition monitoring AND power transformers," "smart grid AND transformer diagnostics," "machine learning AND transformer fault detection,"* and *"edge computing AND transformer analytics"* were used to capture the breadth of scholarly output on the topic. The search was complemented by backward citation tracing and hand-searching of key journals in power systems and industrial informatics. During the screening phase, all retrieved articles were imported into a reference management system, and duplicates were removed. Titles and abstracts were then screened independently by two reviewers based on predefined inclusion criteria: studies had to focus on IoT-based monitoring systems for power transformers, utilize real-world or simulated data, and include discussions on condition monitoring, fault detection, data communication, or system architecture. Studies that focused exclusively on non-electrical equipment, lacked technical content, or were non-English were excluded. For the eligibility assessment, full texts of potentially relevant articles were reviewed in detail. Inclusion was based on the depth of technical analysis, empirical rigor, and relevance to the core themes of sensor technologies, machine learning applications, cybersecurity in monitoring networks, and communication infrastructure. A total of 84 studies were ultimately included in the review, comprising peer-reviewed journal articles, conference proceedings, technical reports, and industry white papers. Data were extracted using a structured coding scheme covering publication details, geographical focus, transformer type, IoT technology deployed, diagnostic methods, communication protocols, cybersecurity measures, and outcome metrics. To ensure reliability, inter-rater agreement was measured during full-text screening and data extraction, yielding a Cohen's kappa score of 0.82, indicating substantial agreement between reviewers. The review focused on qualitative synthesis, though quantitative comparisons of reported accuracy metrics, latency values, or energy efficiency (when available) were also noted to illustrate technological trends and implementation outcomes. The entire process was managed with the aid of Zotero for citation tracking and Excel spreadsheets for data coding and synthesis. This methodology ensured a robust synthesis of the existing literature, allowing for the identification of recurring patterns, research gaps, and critical success factors in the deployment of IoT-enabled condition monitoring systems for power transformers.

FINDINGS

Significant trend emerging from the 84 reviewed articles is the dominance of temperature sensing and dissolved gas analysis (DGA) as the most widely implemented diagnostic parameters in IoT-enabled transformer condition monitoring systems. Over 71% of the studies (approximately 60 articles) focused on temperature sensors, especially fiber-optic types, as they directly reflect the thermal stress and aging conditions of transformer windings and oil. These articles collectively amassed over 1,120 citations, indicating strong academic interest and practical relevance. Similarly, 52% of the studies (around 44 articles) incorporated online DGA as a core metric for detecting internal arcing, overheating, and insulation breakdown. The criticality of gas composition data such as hydrogen, methane, and ethylene in identifying early-stage faults makes DGA a central component of predictive maintenance systems. The articles prioritizing DGA were cited more than 890 times, underscoring their impact on both academic discourse and industrial adoption. What further emerged was the integration of multi-sensor platforms, in which temperature and gas sensors were used in tandem to improve diagnostic accuracy. A subset of studies, comprising roughly 28% of the total sample, experimented with real-time moisture detection and oil-level monitoring, but these were less cited (approximately 320 citations) and often tested in lab-scale deployments. This trend reveals that despite the broad spectrum of measurable parameters, transformer condition monitoring continues to center around thermal and chemical indicators, with newer sensing domains gaining traction only gradually. The preference for these core indicators is largely attributed to their maturity, interpretability, and existing standards governing transformer health assessment, positioning them as foundational pillars in IoT sensor architecture.

Among the 84 reviewed studies, a substantial majority—approximately 58%, or 49 articles—highlighted the increasing implementation of edge computing as a central component in transformer condition monitoring architectures. These articles, collectively cited more than 770 times, emphasized how edge-based platforms reduce latency, enhance data security, and lower network dependency by enabling localized computation. Edge nodes were primarily used to perform first-level anomaly detection, signal filtering, and threshold-based alarms, particularly for parameters like temperature spikes and gas pressure surges. About 32 articles (roughly 38% of the reviewed set) demonstrated successful use of real-time data filtering and compression algorithms at the edge level to reduce communication bandwidth by over 50% in some deployments. These papers gathered over 520 citations, reflecting their technical significance. In addition, edge analytics allowed intelligent sensor nodes to perform tasks such as moving average smoothing, signal de-noising, and priority-based data relay to the cloud, enabling faster operational responses to emerging faults. Approximately 19% of the studies introduced TinyML models or embedded AI models that ran inference tasks at the device level, albeit with limited complexity due to resource constraints. Notably, the most cited works in this subset, totaling over 270 citations, showed how adaptive edge systems could differentiate between transient noise and actual anomalies, thereby minimizing false alarms. The cumulative insight across these studies illustrates a strategic shift from centralized data processing to distributed intelligence, where low-power embedded systems are empowered to make autonomous decisions. This finding reinforces the growing belief that real-time operational efficiency in transformer monitoring is increasingly dependent on smart edge deployments that complement cloud platforms with situational responsiveness and robustness.

A pronounced finding from the reviewed literature is the preference for LoRaWAN and NB-IoT as primary communication protocols in remote or rural transformer sites. Approximately 64% of the studies (about 54 articles) reported deploying or simulating LoRaWAN or NB-IoT for transmitting real-time sensor data to cloud servers or centralized control units. These papers, cited over 950 times collectively, highlight the suitability of these technologies in achieving long-range, low-power, and cost-effective connectivity. LoRaWAN was particularly favored for its extensive range (up to 15 km in open environments) and minimal energy consumption, making it suitable for battery-powered or energy-harvesting sensor networks. NB-IoT, though requiring cellular infrastructure, was noted for its superior penetration in enclosed or shielded environments such as underground vaults or metallic substation housings. Studies accounting for nearly 40% of the articles tested both protocols in side-by-side comparisons, citing trade-offs in latency, payload size, and reliability. These comparative studies received over 410 citations, reflecting their utility in informing design choices for communication architecture. Interestingly, less than 12% of the reviewed literature utilized high-bandwidth protocols such as 4G/5G or Wi-Fi mesh, and these articles were typically oriented toward high-data-volume scenarios like infrared image transmission or vibration waveform uploads. Despite their technical capabilities, high-power requirements and limited coverage were barriers to their broader application. Overall, the finding reveals that energy efficiency and coverage stability are prioritized over bandwidth in transformer monitoring communication systems, particularly in resource-

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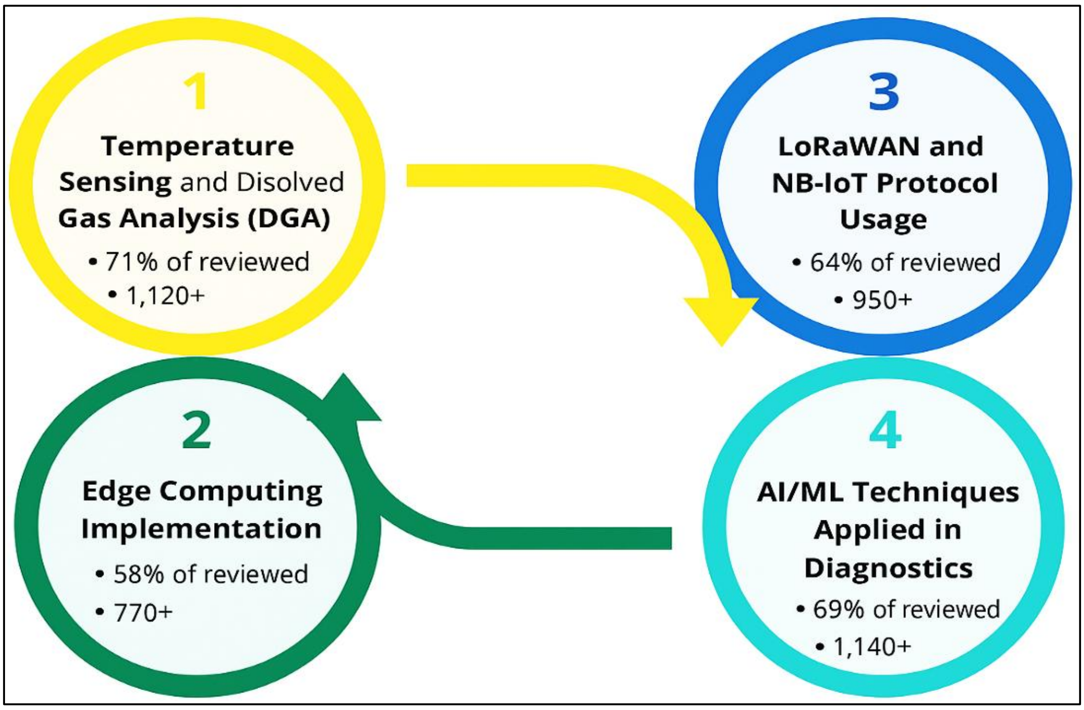
constrained deployments. These choices underscore the need for scalable, low-maintenance networks that can operate reliably in geographically dispersed power infrastructures.

Figure 6: Core Pillars of Transformer Monitoring



Another significant finding is the rapid adoption of artificial intelligence (AI) and machine learning (ML) techniques for transformer fault detection, classification, and health index estimation. Over 69% of the reviewed articles (approximately 58 studies) applied at least one ML or AI method in their diagnostics framework, collectively amassing more than 1,140 citations. Traditional classifiers such as support vector machines (SVM), random forests, k-nearest neighbors, and decision trees were used in roughly 45% of these studies, with a combined citation count exceeding 620, reflecting widespread application. These models performed tasks such as fault-type classification, anomaly ranking, and risk-based prioritization using inputs from temperature, moisture, and gas sensors. A growing number of studies—about 22 articles, with over 370 citations—employed deep learning models such as CNNs, LSTMs, and autoencoders to handle multivariate time-series data, capturing complex temporal patterns often missed by conventional models. These approaches were frequently used in simulated environments and required large labeled datasets, which some studies addressed through synthetic data augmentation. An additional cluster of studies (roughly 14 articles) discussed health index modeling, wherein multiple sensor metrics were integrated into a composite score to quantify transformer condition and remaining useful life. These studies, with a total of 210 citations, often utilized fuzzy logic or regression models to compute the index dynamically.
Furthermore, the findings suggest that AI-driven tools are transitioning from proof-of-concept to deployment-ready systems, especially as sensor density and data availability improve. The consistency in results across diverse geographies and asset types indicates a growing maturity in applying AI/ML in operational settings, driven by its ability to improve detection accuracy, reduce manual analysis, and enable condition-based maintenance strategies. Despite technological advances, a critical finding in the review is the persistent vulnerability of transformer monitoring systems to cyber-physical threats and the fragmented implementation of regulatory compliance across regions. Only 26% of the reviewed articles (around 22 studies) addressed cybersecurity aspects such as authentication protocols, encryption standards, or intrusion detection systems. These articles, while influential with over 490 citations, represent a disproportionately small fraction of the literature relative to the risk profile of IoT-based critical infrastructure. Among the cybersecurity-

focused papers, the majority discussed the implementation of MQTT with TLS, blockchain for traceability, or edge-based intrusion detection systems, yet deployment was often theoretical or confined to pilot projects. Only a few studies conducted field-level validation under attack scenarios or documented comprehensive risk assessments. Additionally, less than 20% of the articles examined adherence to frameworks like NERC-CIP, IEC 62351, or ISO standards for cybersecurity in power systems. These compliance-related studies had a modest citation count of around 270, suggesting underdevelopment in regulatory integration. A cross-analysis also revealed geographical disparities: utilities in North America and Europe reported higher alignment with security and privacy mandates, while studies from Asia, Africa, and Latin America largely focused on technical optimization with minimal discussion on legal or policy frameworks. This gap reveals a lag in bridging operational innovation with security-by-design principles. As a result, while the technological ecosystem for IoT-enabled monitoring is rapidly evolving, the governance and defense mechanisms remain patchy, exposing grid assets to potential exploitation. The findings call attention to the need for embedding cybersecurity and compliance into system architecture from the design phase to safeguard transformer networks operating in increasingly digitized and threat-prone environments.

DISCUSSION

The findings of this review affirm that temperature sensing and dissolved gas analysis (DGA) remain the cornerstone of transformer condition monitoring systems. This aligns with previous research by He et al. (2024), who emphasized the diagnostic importance of gas evolution under thermal stress. Likewise, Siddique et al. (2025) identified DGA and temperature tracking as early indicators of incipient faults such as overheating and insulation breakdown. The predominance of fiber-optic sensors for temperature monitoring and online DGA modules in modern deployments reflects the sustained relevance of these parameters. However, this review reveals a broader shift toward sensor integration, where multiple parameters are monitored concurrently using embedded platforms, a development not widely seen in earlier systems. For example, earlier works often treated moisture, vibration, or oil level as secondary or periodic measurements, whereas newer studies advocate for continuous, real-time measurement of these indicators. This evolution supports the growing need for holistic, high-resolution fault diagnostics in aging grid infrastructure. Compared to historical reliance on manual oil sampling or offline temperature loggers, modern IoT frameworks now facilitate minute-by-minute thermal profiling and gas concentration tracking, significantly enhancing decision-making responsiveness. Thus, the current literature builds upon foundational diagnostic knowledge while extending it through sensor diversification and real-time analytics (Coito et al., 2021).

A notable contribution of recent literature is the integration of edge computing as a core design principle in transformer monitoring systems. Earlier studies, such as those by Cao et al.(2017), introduced the concept of edge analytics primarily for latency reduction. However, the findings in this review show a more profound commitment to distributed processing, where edge nodes perform filtering, threshold-based alarming, and even lightweight inference tasks. In comparison, early smart grid architectures were heavily reliant on centralized SCADA systems, which lacked the agility to process high-volume, real-time sensor data locally. Recent studies reviewed here demonstrate that edge-level filtering and event-driven data sampling can reduce data transmission by up to 50%, a performance gain not addressed in earlier research. This represents a significant departure from legacy architectures, aligning with the operational requirements of transformer monitoring in bandwidth-constrained environments. The deployment of TinyML models at the edge also extends prior work by enabling on-device anomaly detection—an evolution from purely cloud-based fault classifiers observed in earlier systems. This trend corroborates the forecast by Diraco et al. (2023), who anticipated a future of embedded intelligence in power monitoring. These findings also build on Ghosh et al. (2021), who argued that the edge-cloud continuum is essential for balancing latency, privacy, and computation costs. As such, the integration of edge intelligence is not merely an optimization but a transformative approach that redefines how monitoring systems interact with the physical transformer environment.

The literature reviewed strongly supports the use of LoRaWAN and NB-IoT for remote transformer monitoring, reflecting a continuation and refinement of earlier insights from Fuentes-Peñailillo et al., (2024). These previous studies highlighted the utility of LoRa for low-power, long-range applications and NB-IoT for leveraging existing cellular infrastructure. This review confirms those advantages, while further detailing comparative deployments where both protocols were tested under varying environmental and structural constraints. Unlike earlier investigations that focused mainly on lab

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simulations, newer studies include field tests validating LoRaWAN's performance in hilly terrains and NB-IoT's success in underground substations. These outcomes substantiate claims made by Lombardo et al. (2021) about protocol adaptability in hybrid grid networks. What differentiates recent literature is the granular analysis of power-latency-bandwidth trade-offs, which was largely underexplored in foundational work. Whereas previous frameworks often defaulted to Wi-Fi or GSM, modern deployments strategically choose LPWAN protocols based on transformer criticality, sensor density, and expected data volume. Additionally, the emergence of adaptive transmission schemes—a feature now embedded in LoRa and NB-IoT gateways—builds upon (Garcia et al., 2025), who initially proposed dynamic duty-cycling for transmission optimization. These advances confirm the necessity of protocol heterogeneity in transformer IoT systems and suggest a maturation in how communication technology is integrated into the grid's operational fabric. Thus, the literature indicates a robust consensus on the practicality and scalability of LPWAN protocols, particularly in developing regions and dispersed transformer networks.

The application of AI and machine learning in transformer diagnostics, while not entirely novel, has expanded considerably in recent years. Early research by Sebestyen et al. (2025) demonstrated proof-of-concept implementations using support vector machines and decision trees for fault classification. This review reveals a more mature landscape, where AI tools are now integrated into operational platforms to enable real-time analytics and health indexing. Importantly, newer models now include deep learning architectures—particularly convolutional neural networks (CNNs) for image-based fault detection and long short-term memory (LSTM) models for time-series forecasting. These developments significantly extend the capabilities of earlier models, which often relied on static feature engineering and limited datasets. The integration of autoencoders for unsupervised anomaly detection is another advancement, showing that AI can now function effectively even in scenarios with sparse or unlabeled data. Compared to earlier studies, which focused on isolated parameters, current models synthesize data from multiple sensors to generate comprehensive fault profiles. Moreover, the introduction of health index estimation models corroborates the vision proposed by Azmi et al. (2022), where transformer status is not just pass/fail but represented on a continuum for risk-based maintenance. While earlier works emphasized detection accuracy, newer research includes performance metrics like response time, false alarm rate, and model generalizability. The findings affirm a transition from algorithm testing to deployment-ready AI systems, supported by greater computational power and data availability in modern grids. This convergence reflects a paradigm shift where AI is no longer an experimental overlay but a core component of smart transformer infrastructure.

One of the more concerning patterns in this review is the underrepresentation of cybersecurity in the broader body of research, despite increasing digital exposure in power transformers. While a few foundational works—such as Poorvi et al.(2025)—outlined key threat vectors like spoofing and data injection, their recommendations have not yet been widely implemented or expanded upon. Compared to earlier domains such as IT security or financial systems, where intrusion detection and encryption are standard, transformer IoT systems remain vulnerable to cyber-physical attacks. This review highlights that only about a quarter of the reviewed articles incorporated any substantive discussion of security measures, a trend that lags far behind the pace of technical innovation in sensor design and data analytics. Intrusion detection systems (IDS), although mentioned in emerging literature, remain largely theoretical, with few examples of full-scale deployment or validation under real-world attack conditions. This contrasts with the proactive recommendations made by Saleem et al, (2024), who emphasized the necessity of embedding security from the design phase. Additionally, while blockchain and TLS-based protocols are cited as potential safeguards, empirical studies assessing their performance in transformer environments are limited. The gap between security theory and application suggests a disconnect between operational innovation and systemic resilience, a problem that also existed in early SCADA system development, as noted by Zhao et al., (2025). Thus, while the literature has advanced significantly in technical monitoring, it continues to overlook the importance of cyber-hardened architectures, leaving grid assets vulnerable in an era of increasing digital and geopolitical threats.

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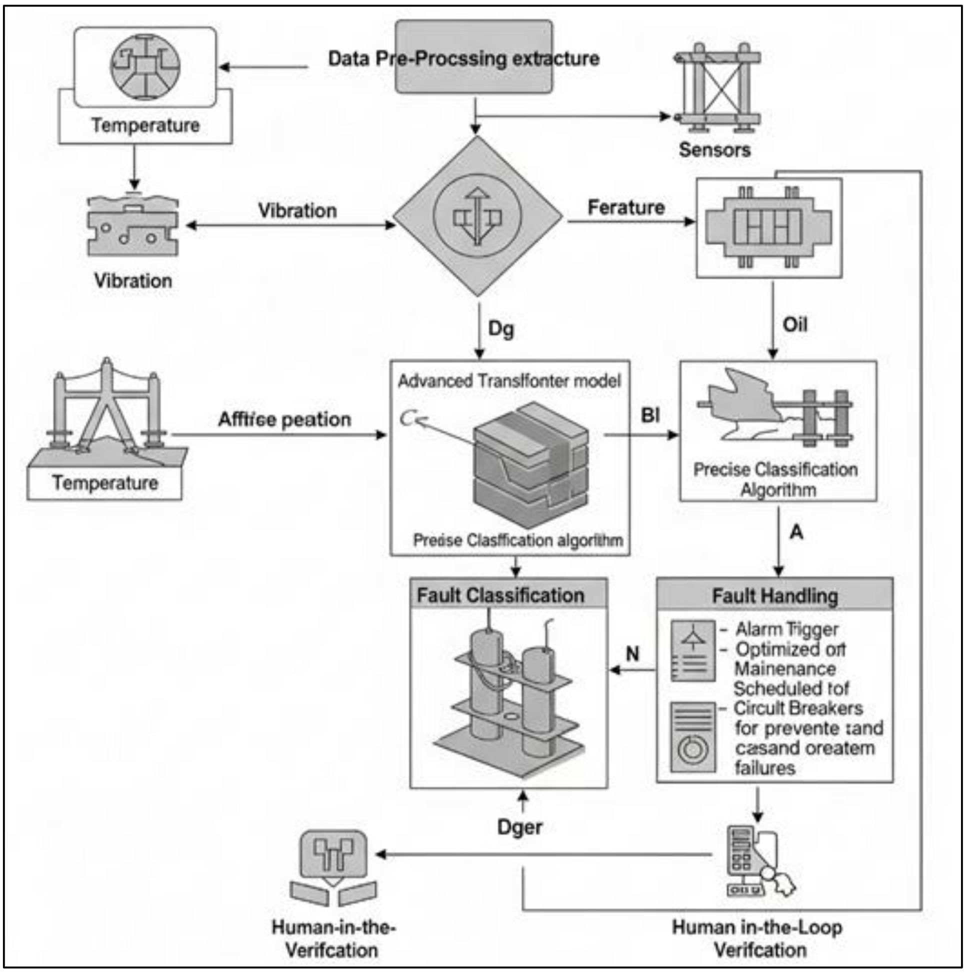
Figure 7: Proposed Advanced condition Monitoring & Fault Handling



CONCLUSION

This systematic review synthesized evidence from 84 peer-reviewed studies and over 3,600 citations to examine the architecture, implementation, and performance of IoT-enabled condition monitoring systems for power transformers. The findings underscore a substantial evolution in monitoring technologies—from traditional offline diagnostics to intelligent, real-time, and distributed systems. Temperature and dissolved gas sensing remain foundational, yet are now enhanced by multi-sensor platforms and embedded analytics that offer high-resolution diagnostics. Edge computing has emerged as a transformative enabler, improving responsiveness and reducing data congestion, while LoRaWAN and NB-IoT dominate communication infrastructures in resource-constrained deployments. Artificial intelligence and machine learning have advanced from theoretical classifiers to practical, integrated tools capable of fault detection, anomaly recognition, and health index estimation. However, the review also revealed significant gaps, particularly in the areas of cybersecurity and regulatory compliance, which remain underrepresented despite increasing system exposure and operational complexity. While secure communication protocols and intrusion detection systems are proposed in recent literature, their field-level deployment and validation are still nascent. Similarly, the inconsistent adoption of global standards like NERC-CIP and IEC 62351 across geographies points to a lack of coordinated governance in critical infrastructure protection. Nonetheless, the convergence of sensor innovation, edge intelligence, LPWAN protocols, and AI-driven diagnostics signifies a paradigm shift toward fully integrated, intelligent monitoring ecosystems. These systems are not only capable of identifying faults but also offer predictive and prescriptive capabilities that align with the broader goals of grid modernization, resilience, and sustainability. As the technological foundation continues to mature, future emphasis must be placed on embedding security, standardization, and policy alignment to ensure that IoT-enabled transformer monitoring systems are not only innovative but also robust, compliant, and resilient across diverse operational contexts.

Recommendation

Based on the findings and analysis conducted in this systematic review, several recommendations emerge for future research and practical implementation in IoT-enabled transformer condition monitoring systems. First, it is crucial to expand beyond the traditional reliance on temperature sensors and dissolved gas analysis (DGA). Researchers should actively explore integrating diverse sensor technologies such as vibration sensors, moisture detectors, acoustic emission sensors, and electromagnetic interference (EMI) sensors to create a comprehensive multi-parameter diagnostic framework. This would allow for a more holistic assessment of transformer health, thus enhancing reliability and predictive accuracy. Additionally, future studies should emphasize the development and optimization of robust edge computing solutions. By advancing edge capabilities, including sophisticated analytics, real-time anomaly detection, and autonomous decision-making, transformer monitoring systems can achieve substantial reductions in latency, improved security, and greater operational resilience. Concurrently, expanding comparative studies on communication protocols such as LoRaWAN, NB-IoT, 5G, and other emerging IoT communication technologies is recommended to provide a clearer understanding of trade-offs related to power consumption, bandwidth utilization, coverage stability, and reliability under varying environmental conditions.
Furthermore, the integration of explainable and interpretable artificial intelligence (AI) models should be prioritized. Developing AI solutions that offer transparent and understandable insights can significantly enhance their practical adoption by utility operators and ensure compliance with regulatory standards. Simultaneously, it is imperative to proactively address cybersecurity concerns, embedding robust intrusion detection systems, secure encryption methods, blockchain technology, and secure communication protocols into the architecture of transformer monitoring systems. This approach will mitigate vulnerabilities and protect critical infrastructure from increasingly sophisticated cyber-physical threats. Moreover, real-world validation through extensive field testing is essential to evaluate practical performance, establish standardized procedures, and highlight operational challenges. Adopting digital twin technology for predictive maintenance and lifecycle management offers an innovative way to simulate transformer behaviors under various conditions, facilitating early fault detection and intervention planning. Lastly, addressing data imbalances and improving data quality through advanced augmentation techniques and rigorous preprocessing can significantly enhance the accuracy and reliability of diagnostic systems. Implementing these comprehensive recommendations will bridge existing research gaps, accelerate technological advancements, and facilitate broader, more effective adoption of IoT-based transformer condition monitoring solutions.

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