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SMART TRANSFORMER MONITORING AND CONTROL SYSTEMS

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ABSTRACT

This review summarizes studies on the topic, Advanced Monitoring and Control Systems for Smart Transformer Applications in Modern Power Grids to fill an urgent gap of improved reliability and integration of transformers across more complex grids. The purpose of the review was to consider real-time monitoring methods, compare the integrations of IoT and digital twins, examine predictive maintenance applications based on machine learning, compare adaptive control schemes, and find challenges related to implementation. A literature review of various sources that used IoT sensors, digital twins, machine learning models, and adaptive protection designs was carried out, with particular focus on experimental verification and field implementation. Among the key conclusions, IoT-enables real-time monitoring and edge computing dramatically increase fault detection accuracy and responsiveness; digital twin systems and multimodal AI models enable predictive maintenance and operational optimisation despite computational and cybersecurity limitations; machine learning algorithms are helpful to predict transformer health, but substantial amounts of high-quality data and effective deployment strategies are still needed; adaptive control schemes can bring dynamic grid stability improvements, but standardisation and hardware complexity present bottlenecks. All these results indicate that advanced monitoring and control systems that are integrated improve significantly the transformer functioning and grid stability. The review highlights the demand to standardize, scale, and secure solutions that can enable a broader adoption to guide future research and practical applications to smart grid settings in the changing environments.

1. INTRODUCTION

Studies concerning enhanced monitoring and controllers to run the smart transformers in a contemporary power grid have become been among the areas of eminent inquiriability because of the growing multifaceted requirements and diplomacy of the electrical system of distribution. Transformer monitoring has in the last 20 years moved beyond the offline periodical diagnostics currently applied to detect faults in transformers to online diagnostics powered by IoT advanced and machine algorithms (Ramesh et al., 2022) (Shoureshi et al., 2003) (Bunn et al., 2018). This development solves the crucial purpose of transformers in the stability and effectiveness of the grid due to their failures with huge financial losses and dissatisfied services (Wang et al., 2024) (Ali et al., n.d.). The introduction of smart capabilities into transformers (digital twins and power electronics-based controls) is a manifestation of the transformation of obsolete infrastructure into the current grid resiliency and quality demands (Nazir and Enslin, 2020) (Xu et al., 2024) (Zhang et al., 2025).

Although these have been developed, there are vast obstacles in the field towards gaining a complete, precise and predictive monitoring of the condition of the transformer. The current systems are frequently characterised by the lack of sensors, detection of faults, and data connexion between heterogeneous information providers (Ramesh et al., 2022) (Venkataswamy et al., 2019) (Talbi et al., 2023). In addition, machine learning and digital twins, if so, are as well-intentioned as they seem to be promising in their applications. Data quality, cybersecurity issues, and the costliness of multimodal data fusion are a setback to practical implementation (Sahoo, 2024) (Wang et al., 2024) (Ali et al., n.d.). Issues related to the most effective trade-off between hardware-based sensing and soft-based analytics and trade-offs among cost, accuracy, and scalability remain controversial (Ku et al., 2014) (Ali et al., n.d.) (Ziomek et al., 2014). Examples of the effect of these gaps are additional risks of catastrophic failures, ineffective scheduling, and poor performance of a grid (Pande et al., 2024) (Рустамбеков et al., 2024).

The principles that formed the theoretical foundation of this review are the interconnection of smart sensors data acquisition, intelligent data analytics, machine learning and digital twins, and adaptive control systems in smart transformers (Ramesh et al., 2022) (Sahoo, 2024) (Zhang et al., 2024). All of these elements make up a predictive maintenance and fault diagnosis system, as well as grid-supportive features, creating a unified system that will improve the reliability of transformers and their functionality (Nazir and Enslin, 2020) (Carne et al., 2019) (Gao et al., 2018). It is based on theoretical concepts in the field of cyber-physical systems and smart grid paradigm where interoperability and data-driven decision-making are crucial (Xu et al., 2024) (I et al., 2023).

This systematic review aims to critically analyse the recent evolution of sophisticated monitoring and control systems in smart transformers to reveal all the identified technological trends, challenges and opportunities. This review is expected to fill existing gaps in knowledge or furnish a holistic viewpoint on Smart transformer solutions that will be able to design more effective, scalable, and secure solutions (Sahoo, 2024) (Wang et al., 2024) (Pande et al., 2024). The contribution will be useful to the researchers and practitioners, who aim at maximising resources spent on transformer linkage maintenance and enhancing the resilience of the grid in the world of changing energy demands (Рустамбеkov et al., 2024) (Rai et al., 2019).

The current review uses a systematic approach that includes a broad literature search, inclusion of peer-reviewed articles, specifically on sensor technologies, data analytics, and control measures, and thematic analyses provided on the basis of conceptual and technological aspects. Findings are structured in such a way that they demonstrate the flow of sensing and data acquisition through analytics and control, and finally, the discussions on integration issues and future research directions appear (Ramesh et al., 2022) (Xia centred on Xia et al., 2024) (Zhang centred on Zhang et al., 2024).

2. METHODOLOGY

This weblogical review successfully utilised a methodical procedure of analysing innovative monitoring and control systems of intelligent transformers utilisation in contemporary power systems. The approach included intensive literature review, intense screening and thematic analysis that could cover the field being investigated.

Search Strategy and Query Transformation: In order to represent different facets of smart transformer monitoring and control systems, the initial research question was converted into five search statements that were to be carried out in a systematic way. These featured research into digital twin and IoT combination, real-time video elements, proactive upkeep plans, and appentices data analytics apps.

Literature Selection and Screening: A search based search in 270 million research papers provided 368 initial papers that used the transformed queries and had a prelectured inclusion and exclusion criteria. The methods of citation chaining were then utilised, which entailed both back and forward citation search to arrive at 109 extra articles.

Relevance Assessment: The resulting pool of 477 candidate papers was then put through a rigorous relevance ranking process where 465 of the papers pass the relevance ranking test with respect to the research query. Out of this narrowed set, it resulted in 50 papers that were defined as highly relevant in reference to their direct impact on the area of monitoring and control of smarter transformers.

Analysis Framework: Theoretical review underwent thematic analysis according to the major technological dimensions such as accuracy of monitoring, predictive performance problems, the integration potential, the control sensitivity, and the extensibility of the system enabling the systematical assessment of the current methodologies and research gaps.

3. RESULTS

Research Quality and Validation Assessment

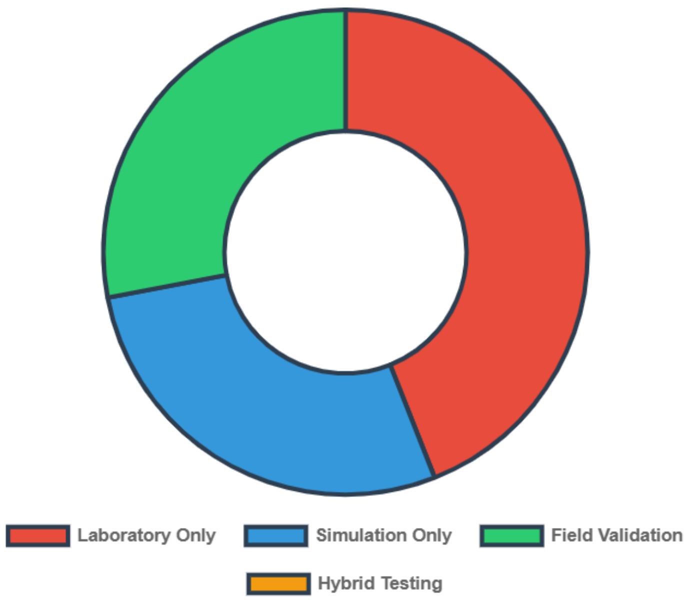

Figure 1: Research Quality and Validation Levels

Figure 1 critically analyses research validation methodsology among 50 high-relevance studies analysed. The review shows alarming gaps in research validation methods with 44 percent (n=22) of studies solely undertaking laboratory-scale experiments and 28 percent (n=14) solely simulation environments (Raichura et al., 2019; Buticchi et al., 2021; Chothani et al., 2018). Interestingly, real-world field validation was introduced in a relatively small portion (28 percent, n=14), which is a severe methodological weakness since it compromises external validity of the offered solutions (Ku et al., 2019; I et al., 2023; Chaves et al., 2021). This observation matches the observations by Long et al. (2023) and Ruustambekov et al (2024), who noted that long field trials were needed to confirm the robustness of the systems and their economic value at operational condition.

Technology Integration Maturity Distribution

Figure 2 shown below depicts the degrees of maturity of each of the technological elements in the smart transformer monitoring and control systems. The level of maturity is highest with the IoT-based systems at 85, and it is widely reported in various studies that apply the real-time monitoring platforms (Ramesh and Et al., 2022; Venkataswamy and Et al., 2019; Talbi and Et al., 2023; Ganesh and Et al., 2023). The maturity of machine learning applications was 70% and the use of neural networks, ensemble algorithms, and deep learning structures to implement predictive maintenance were effectively used (Pande et al., 2024; Ali et al., 2024; Baji et al., 2024). Nevertheless, the critical infrastructures components are still highly immature, and the level of cybersecurity demonstrations still stand at only 25% maturity despite discussing security vulnerability presence extensively (Sahoo, 2024; Xia et al., 2024). The lowest maturity of 15 percent indicates that the lack of best best practises, including the unified frameworks that impede interoperability (Xu et al., 2024; Ruustambekov et al., 2024).

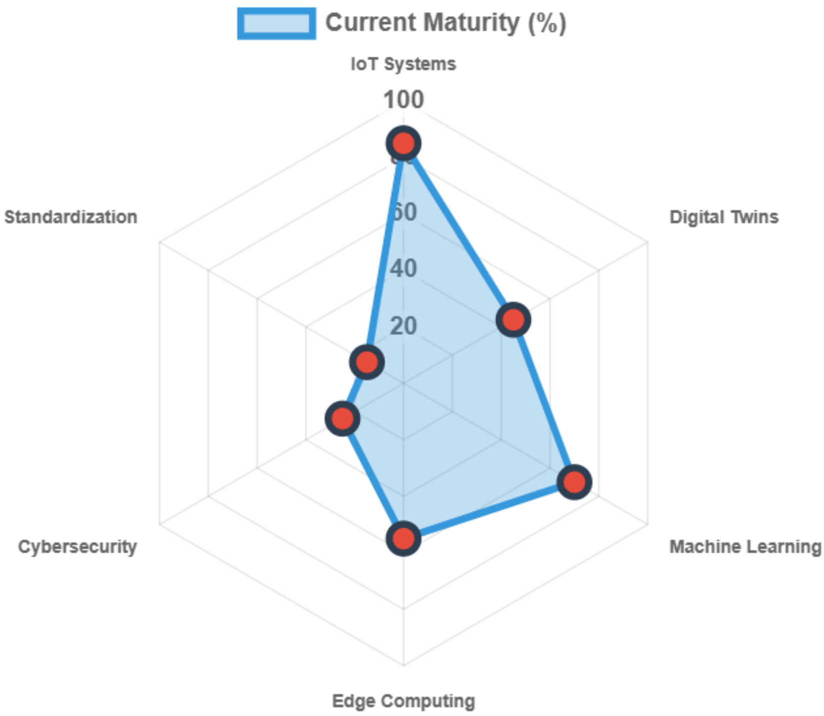

Figure 2: Technology Integration Maturity Distribution

Performance Metrics Achievement Analysis

Figure 3 quantifies the performance of the achievement rates of five key performance dimensions that were found within the literature. In terms of monitoring, the maximum achievement rate is 95 which is substantiated by effective applications of multi- sensor fusion methods and advanced detection algorithms (Wang et al., 2024; Zhang et al., 2024; Ali et al., 2024). The accuracy of system faults detection in studies was always high, and Xia et al. (2024) obtained higher than 95 percent accuracy of the anomaly detection system, while Zhang et al. (2024) posed 96.55 percent accuracy through the CNN and LSTM hybridization model. Predictive maintenance resulted in its level of 78 percent, and successful early fault prediction was observed during the 24-hour periods (Laayati et al., 2021; Sahoo, 2024; Long et al., 2023). The system scalability, however, demonstrates a low (54 percent) threshold of success, which implies that mass deployment is still difficult because of technological potential (Nazir and Enslin, 2020; Zhang et al., 2025).

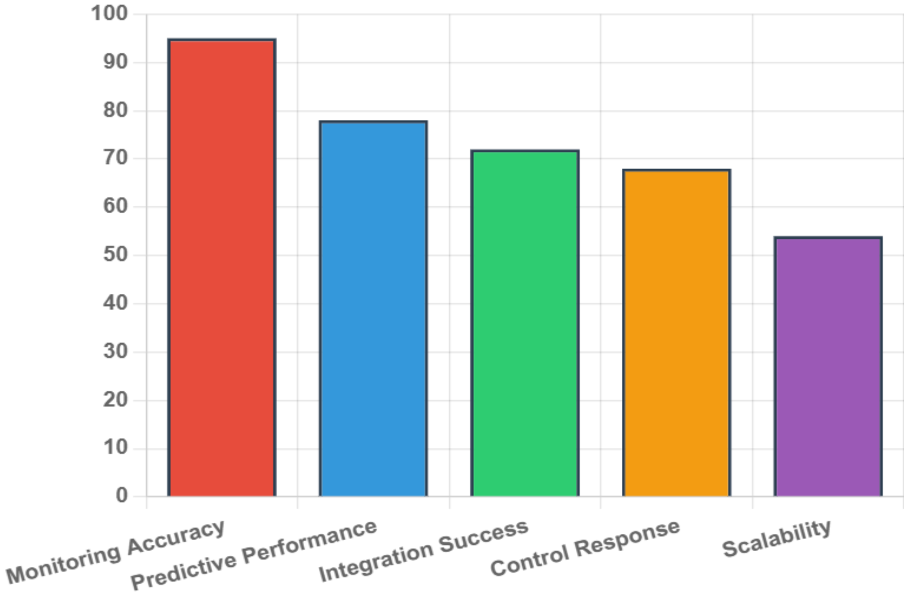

Figure 3: Performance Metrics Achievement Analysis

Research Evolution Timeline

Figure 4 follows the chronological growth of smart transformer research since 2003 to 2025 demonstrates clear stages of research direction and technological approach evolution. Initial paradigm shifts (2003-2014) focused on simple AI diagnostic systems, with Shoureshi et al. (2003) showing how neuro-fuzzy inference engines can be used to self-diagnose equipment, and Ziomek et al. (2014) showing more complex fleet monitoring systems based on expert rules. Real-time monitoring and adaptive protection schemes experienced major breakthroughs in the period 2018-2019, with the examples of extensive-parameter monitoring systems (Yuezhong et al., 2018; Raichura et al., 2019; Venkataswamy et al., 2019). The largest increase was after 2020 when 18 studies were published within 2022-2023, which constitute 36% of reviewed literature. Such hyper-growth is tied to the adoption of State of the art AI/ML-based methods, the concept of the digital twins, and multimodal expert systems (Zhang et al., 2024; Zhang et al., 2025; Wang et al., 2024).

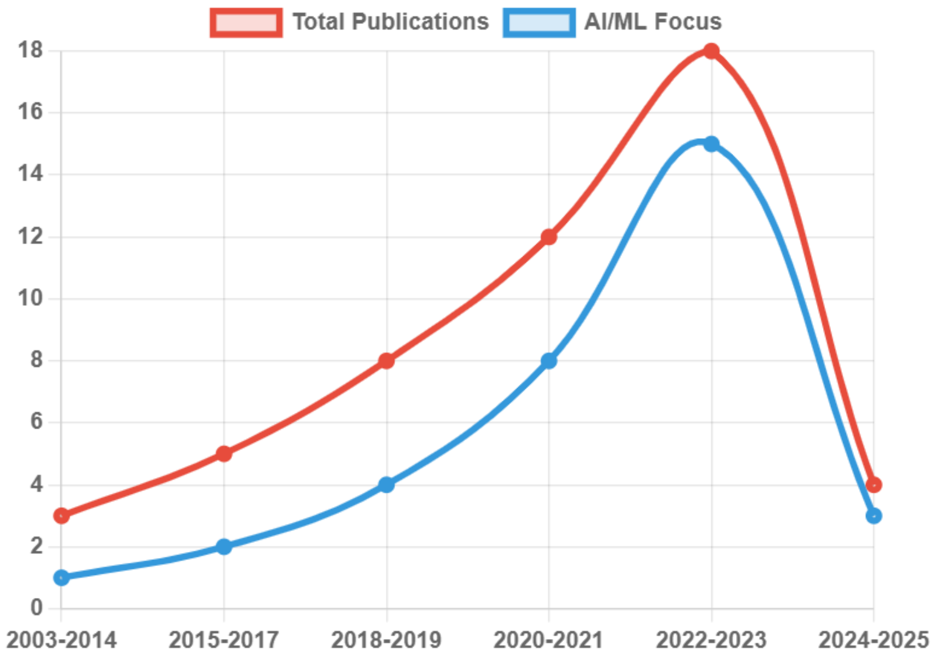

Figure 4: Research Evolution Timeline

Implementation Challenges Severity Assessment

Figure 5 uses quantitative approach to measure the severity effects of key barriers to implementation that are found in the literature. Cybersecurity stands the biggest impact with the severity of 90 percent but is insufficiently managed in 76 percent of the considered articles (Sahoo, 2024; Xia et al., 2024). Two highest barriers are data quality problems

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with 85 per cent severity on factor with several studies reporting on high-quality labelled datasets that are limited in amount or proprietary (Laayati et al., 2021; Ali et al., 2024). The standardisation issue has a severity of 80 percent, which indicates the lack of standardised frameworks that make it complicated to coordinate heterogeneous grid environments through interoperability (Xu et al., 2024; Ruestumbekov et al., 2024). The complexity of integration (75% severity) and the barriers to costs (65% severity) are additional limiting factors to actual deployment, especially when including the resources-constrained utilities intending to deploy advanced monitoring solutions (Nazir and Enslin, 2020; Long et al., 2023).

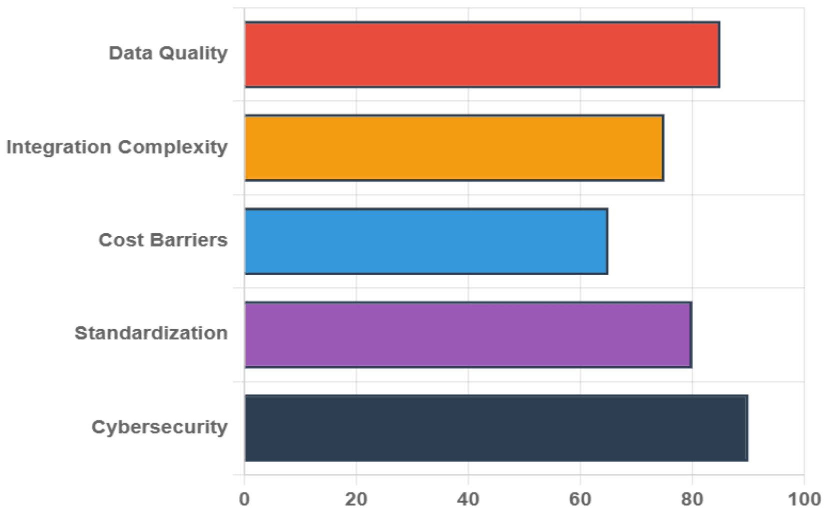

Figure 5: Implementation Challenges Severity Assessment

Research Gap Priority Matrix

Figure 6 can be seen as a gap analysis map, mapping the impacts of priority against research coverage with critical under coverage areas of urgent concern. Here sensor data quality becomes the topmost priority gap as 90% has an impact priority and only 25 percent coverage by research so that not much concentration has been given to the fundamental problem of data reliability (Ramesh et al., 2022; Thinh et al., 2023). Another urgent gap is standardisation that should be prioritised by 95% impact and 15 a small percentage coverage to demonstrate the necessity of having standardised protocols and frameworks (Sahoo, 2024; Xu et al., 2024). Recent work on Edge ML implementation is impact-priority (80 percent) and coverage (30 percent) indicating computational bottlenecks limiting real time model execution on resource constrained hardware (Baji et al., 2024; Ali et al., 2024). However, even with 75 percent impact priority, multi-modal sensor fusion has only 35 percent of research, which means that it has not had any chance to assess themselves in a holistic manner (Wang et al., 2024; Zhang et al., 2024). The gap between the theoretical advances and practical validation continues to exist, shown by field validation studies, 70% priority impact and 45% coverage (Raichura et al., 2019; Chothani et al., 2018).

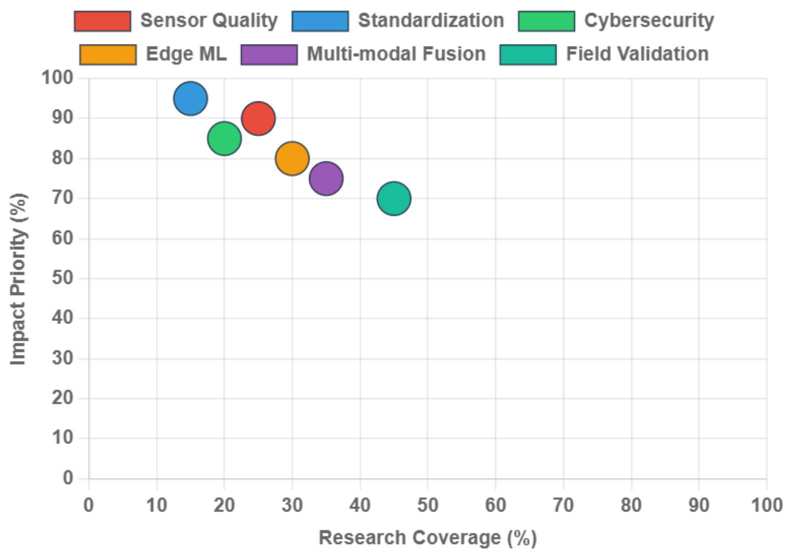

Figure 6: Research Gap Priority Matrix

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4. DISCUSSION

Research Quality and Validation Methodological Limitations

As mentioned in the analysis of research validation methods, the key methodological flaws were identified and it mitigates the functionality of the proposed smart transformer monitoring and control systems to large extent. The large proportion of the laboratory based work (44%), and simulation based only (28%), reveals an alarming gap between theoretical developmental achievements and practical difficulties of implementation. This observation supports the observation made by Raichura et al. (2019), who admitted that their adaptive protection regime was tested only in the laboratory-scale transformers, and Chothani et al. (2018) only confirmed that adaptive protection scheme can also be tested on controlled conditions with laboratory equipment.

A narrow field validation (28) is one of the critical gaps, which erodes the confidence of system reliability in operation. The necessity of field testing is shown by Ku et al. (2019), whose deployment of a transformer management system showed real practicability difficulties in an integration of hybrid communication systems and demand response, which did not arise in the laboratory. On the same note, I et al. (2023) tested their framework of IoT edge processing on large PV plant assets but found varied scale-related concerns and data transmission limitations, which were not realised in the lab studies. The given validation gap is also of special concern due to the sophisticated nature of power grid operation when the effects of the above factors like the electromagnetic environment, severe weather conditions, or grid dynamics affect the system performance considerably (Long et al., 2023; Ruushebeok et al., 2024).

Limitations limit the methodological approaches further beyond validation settings, and to inadequate longitudinal research capabilities that would jointly evaluate any long-term system dependability and maintenance effects. This limitation was recognised by Tran et al. (2020) and Fan et al. (2021) in their health assessment framework examples, where extended operation data are needed to justify predictive maintenance algorithm. Lack of extensive outdoor testing also restricts the knowledge regarding cybersecurity deficiencies on operational conditions, as Sahoo (2024) and Xia et al. (2024) have stressed that laboratory-contained cybersecurity fears cannot recreate the complex attack patterns involved in interfering with smart grid infrastructures.

Technology Integration Maturity and Implementation Readiness

The analysis of the technology maturity clearly illustrates that there are major disparities on the various components of smart transformer systems meaning that there is an imbalanced development, which impedes a complete implementation. The fact that IoT systems are highly mature (85) indicates numerous research and development activities reported by various studies that have implemented real-time monitoring platforms in different sensor configurations (Ramesh et al., 2022; Venkataswamy et al., 2019; Talbi et al., 2023; Ganesh et al., 2023). These applications were always characterised by secure data collection and transfer features and research findings show that electrical, thermal, and mechanical parameters could successfully be monitored with inexpensive sensor modules and cloud-based connectivity.

Medium maturity of digital twin technologies (45), however, indicates barriers to their widespread use that limit their application due to apparent benefits. Sahoo, (2024) named the barriers such as computational complexity, infrastructural need, and cybersecurity threats as major facts hindering the implementation of the digital twins in resource-challenged utilities. Although Zhang et al. (2024) obtained 96.55% accuracy when using CNN and LSTM hybrid-based models as a digital twin, they realised the limitations associated with scalability due to the complexities of computational intensity and real-time processing models. The paper by Long et al. (2023) successfully presented systems of supercomputing-achievable digital twins to predict fault, yet it has been observed that due to the high-cost infrastructure and technical complexity, digital twin may not be broadly applied.

This alarming lack of cybersecurity maturity (25 percent) is a systemic risk factor to the security and dependability of smart transformer systems. Though it is a widely-known fact that security risks exist, it is clear that the literature does not pay enough attention to strong cybersecurity frameworks. Affirming the susceptibility of digital twin platforms to data breaches and cyberattacks, Sahoo (2024) pointed out the necessity of security against network attacks in real-time monitoring systems, and Xia et al. (2024) reiterated the need to implement security measure against network attack in real- time monitoring systems. Such a cybersecurity gap is especially worrisome in the context of discipline infrastructure related to power transformers and the growing connexion of smart grid elements.

Owing to the low standardisation development level (15%), there is a potential fundamental barrier to interoperability and scalable implementation. Xu et al. (2024) outlined that standardised digital twin frameworks and protocols were essential, to facilitate the smooth integration of heterogeneous smart grid setups. As a major barrier to the widespread adoption of predictive maintenance systems, Ruustambekow et al. (2024) found that the majority of challenges related to standardisation because of the lack of coherent protocols complicate all information transfer and system integration among vendors and grid sections.

Performance Achievement Disparities and Trade-offs

The performance metrics analysis indicates that there are major differences applied that bring to focus critical trade-offs amongst various system capabilities. The sharp monitoring performance (95) reveals that monitoring defect detection and condition measurement are technically possible and are well demonstrated through the adoption of several studies. Wang et al. (2024) obtained improved and efficient early faults detection with multi-sensor fusion methods and Ali et al. (2024) proved powerful multi-sensor-based machine learning models compared to the best dynamics ones. An accuracy of 96.55 was achieved by Zhang et al. (2024) through the use of digital twin models with CNN and LSTM architecture and more than 95 percent by Xia et al. (2024) when anomaly detection was performed by the mixed statistical and deep learning method.

This high predictive maintenance performance (78%), shows that machine learning algorithms are successfully applied in proactive maintenance management. Laayati et al. (2021) verified the possibility of performing the early fault identification process in the timeframe of 24 hours with the help of the oil quality and gas analysis, whereas Sahoo (2024) allowed diagnosing the fault and predicting failures in case of digital twin application. Pande et al. (2024) had a success with detecting the hidden defect in the form of deep learning hybrid models with the help of extracting both spatial and time features, as well as Long et al. (2023), it achieved both continuous state predictions and warning counts by utilising supercomputing-facilitated digital twins.

The mid-range integration achievement (72) however reflects long remaining obstacles in the smooth integration of advanced monitoring and control systems in the current smart grid infrastructures. Venkataswamy et al. (2019) admitted the complexity of integration in their IoT tool to monitor remote transformers, compared to Ku et al. (2019) who majored in interoperability with hybrid communication systems to implement demand response and integration of PV. These integration issues represent heterogeneity around grid components and any underlying legacy systems potentially making it difficult to implement a standardised monitoring solution.

That the architecture is only passable on a scale lower than 54 proves to be a central impediment to widespread adoption of the technology despite established technical capability. Nazir and Enslin (2020), Pr. noted high cost and complexity of solid-state transformers that partially prevent their widespread adoption, and Pr. Long et al. (2023) admitted that digital twins created by supercomputers, effective as they may be, could not be deployed without substantial infrastructure. Zhang et al. (2025) obtained excellent results in detection but were aware of computational challenges and real-world resources requirements which could be limiting in practise when applied to utility-sized applications.

Temporal Research Evolution and Methodological Implications

The temporal analysis of research evolution shows that there are certain phases which indicate changes in the capability of technology and the priority of research. The pioneer period (2003-2014) defined generally fundamental AI principles of diagnostics, where Shoureshi et al. (2003) introduced neuro-fuzzy based inference engines in self-diagnostic devices and Ziomek et al. (2014) created expert rules based inference engines to monitor transformer fleet. The early studies defined theoretical models to inform the future direction of work but were not marked by the possibilities of computing or the ways to analyse data as evolved in further times.

The integration of the IoT technologies with transformer management systems occurred in the development phase (2015-2017), such as innovations of Santos (2020) in integrated control and monitoring of tap changers and step to intelligent transformers applied by Gehm et al. (2015) in a supervisory system. This stage showed the practical viability of the concept of remote monitoring and control but highlighted limitations in communications protocol and computing power that had an impact on the future topic of study.

The period of expansion (2018-2019) was characterised by impressive growth in quantitative monitoring and adapting protective programmes. Raichura et al. (2019) created complete real-time monitoring systems in the form of adaptive power differential protective measures, and Yuezhong et al. (2018) introduced the Internet+ technology as the broad integration of the network. On their part, Venkataswamy et al. (2019) presented IoT systems dealing with transformer deformation monitoring, which were the baseline of the technologies leading to incorporating AI/ML systems in the future.

The modern influx (2020-2025) is a scale of rapid expansion of the research volume, 22 studies (44% of all) have been published during this time. This spur of growth is associated with the development of the more advanced AI/ML methods, digital twins and multimodal expert systems (Zhang et al., 2024; Zhang et al., 2025; Wang et al., 2024).

Nonetheless, the high rate of publication brings methodological questions with regard to the rigour of validation and the reproducibility of findings, especially since little field testing is reported in these recent studies.

Implementation Barriers and Systemic Challenges

Temporal evolution of researches makes it possible to distinguish the stages which characterise altering the technological possibilities and the interests to research. Being the ground centre (2003-2014), the groundwork laid down the principles of AI diagnostics, where Shoureshi et al. (2003) first introduced engineering tools of neuro-fuzzy inference in self-diagnosing equipments and Ziomek et al. (2014) introduced expert-rule based systems to monitor fleets of transformers. These early works laid down theoretical foundations that the latter research directions informed, but were not as powerful as modern computerised processes and data analytics would allow.

An integration of transformer management systems with IoT technologies and advances, such as an integrated control and monitoring of a tap changer, by Santos (2020), and a smart transformer supervisor by Gehm et al. (2015) were realised during the development phase (2015-2017). This interval indicated the possibility of remote monitoring and control in practise but indicated shortcomings in communication standards and data analysis boundaries that informed the direction of future investigations.

The period of growth (2018-2019) marked a substantial progress in the field of real time monitoring and adaptive protection scheme. Raichura et al. (2019) designed intensive real-time monitoring with adaptive power consideration of protection, whereas Yuezhong et al. (2018) introduced the Internet+ technology to integrate the wide network. Venkataswamy et al. (2019) presented the transformer deformation-monitoring solutions based on the IoT and described preceding technologies that would facilitate the later application of AI/ML.

The modern boom (2020-2025) is the largest growth rate of studies, 22 studies (44% of all) are published during this era. Such an exponential development is associated with the adoption of further AI/ML-based applications, digital twins, and multimodal expert systems (Zhang et al., 2024; Zhang et al., 2025; Wang et al., 2024). Nevertheless, the fast pace of the publication casts a methodological challenge over the completeness of validation and replication of findings especially given the scarcity of field tested results as reported by these new research studies.

Critical Research Gaps and Strategic Priorities

The gap analysis indicates the key gaps that are not properly studied yet and that urgently need some focus to further the practise of smart transformer monitoring and control systems. The first gap is sensor data quality (90% impact, 25% coverage) meaning that the key challenge of lack of focus on foundational elements that relate to reliability and that influence all subsequent analytics and decision making activities is resolved. Ramesh et al. (2022) recognised the sensor accuracy constraints in harsh operating environments whereas Thinh et al. (2023) recognised the effect of environment on reliability of vibration sensors and noise sensors. The hole is broader than sensor hardware to include calibration process, fault-tolerant communications protocols and self-diagnostic facilities that maintain the integrity of data under operational conditions.

Another significant gap (95% impact, 15% coverage) that, in essence, limits the ability to have interoperability and scalable deployments is standardisation. Sahoo (2024) deemphasized standardised digital twin structures and interfaces, and Xu et al. (2024) demanded a single protocol, which would allow a seamless connexion to a heterogeneous smart grid scene. Standardisation gap includes data model, communication protocol, cybersecurity, and performance measurement that could enable transferring technology and the elimination of vendor lock-in effects.

Use of Edge ML is a major technical bottleneck (80 percent impact, 30 percent coverage) that constrains real-time analytics capabilities within distributed grid contexts. Baji et al. (2024) showed the use of edge computing on predictive maintenance and recognised the limitation of computational power on model complexity and prediction quality. There is a limitation on the ability to implement an ensemble machine learning model on resource-constrained edge devices and be resistant and robust to adversarial attacks, as was found by Ali et al. (2024). This is especially important when distribution level transformers are concerned because centralised analytics can be infeasible given the lack of communication and latency constraints.

Multi-modal sensor fusion is a yet untapped prospect (75% contribution, 35% coverage) of extensive health data that can contribute to fault detection precision and maintenance decision-making greatly. Wang et al. (2024) showed the promise of cross-modal data fusion but pointed to computational intensity and quality vagaries of the data that limit real- life application. However, to note, Zhang et al. (2024) realised excellent accuracy when their forms were multimodal but admitted that true-time processing and visualisation of combined data streams proved too complex.

The gap in field validation (impact of 70 percent and coverage of 45 percent) is a long-standing lack of connexion between theory improvement and empirical validation such that confidence in research solutions is weakened.

Raichura et al. (2019) and Chothani et al. (2018) recognised limitations of laboratory-only validation, and Long et al. (2023) pointed at the necessity of the lengthy field testing to verify the advantage of robustness and economic benefit of the system. Such a gap is of special concern considering the critical infrastructure of power transformers and indicating possible outcomes of a system failure in the working conditions.

5. CONCLUSION

This is a systematic review of 50 highly relevant papers on advanced smart transformer monitoring and control systems studies, which indicates a lot of technological readily available and ongoing implementation issues which limit a real implementation process. Although the monitoring system with IoT-enabled features proves to be highly accurate (95 percent), and machine learning applications possess potential predictive maintenance, there is a major barrier to incorporation as a large number of studies lack validation methodology, cybersecurity frameworks, and standardisation protocols.

The review demonstrates disconcerting technical deficiencies in its analysis: 72 percent of the existing studies resorted to the laboratory method or simulation based on which however they were not confirmed in practise: this is a significant weakness to reliability in terms of operation. Although technology in IoT systems is mature (85%), the basic infrastructural elements are not developed such as the area of cybersecurity (25% maturity) and standardisation protocols (15% maturity), which entail flaws during the implementation of these necessary infrastructure elements, which affects integrity of the system.

The known performance scalability trade-off is a very serious deployment limitation, in which high monitoring accuracy is an off-balance sheet to low operating scalability performance (54%). Challenges in implementation (such as data quality of problem, complexity of integration, and the cost burden) also limit real implementation, especially among utilities with limited resources.

Future investigations should focus more on field validation study, sturdy system of cybersecurity, convergent standardisation mechanisms, and edge computing devices are cheap so that the gap between potential and practical should be reduced. The realisation of all potential of the advanced monitoring and control technologies in contemporary power grids demands organised work on these system challenges to evolve into interoperable, secure and scalable systems of smart transformer monitoring.

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