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Multi-Agent Systems for Fault Detection in Transformers

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Abstract: Transformers, which transfer electrical power between voltage levels, are very important electrical power system components whose unforeseen breakdowns may lead to huge losses in finances and extensive power cuts. Thus, fault detection and diagnosis require good performance to provide reliability, operational safety, and service life of the transformers. Multi-Agent Systems (MAS) have become a potential paradigm of intelligent fault detection in transformers over the last twenty years, with respect to distributed and autonomous fault detection. A structured literature review is provided in this paper on the existing body of literature that explores the use of MAS in transformer fault detection and its application in other fields of power systems in general. The studies reviewed are grouped by the authors into five thematic classes: MAS architectures to monitor transformer condition, MAS to complement Dissolved Gas Analysis (DGA), MAS to identify damaged power distribution system faults, MAS as a hybrid AI approach, and basic MAS structures with safety in mind. Close attention is given to collaborative and distributed diagnostic methods, such as Bayesian networks, Multiply Sectioned Bayesian Networks, Dempster-Shafer evidence theory, fuzzy ontology-based reasoning, and new methods, such as digital twins and knowledge graph-based fault localization. The review makes clear that MAS architectures are very beneficial in terms of modularity, scalability, and real-time diagnostic capability, and that the combination of artificial intelligence and machine learning techniques can lead to a significant improvement in the accuracy of the fault classification. Moreover, the paper pinpoints the research gaps that are critical, especially those that exist in the fields of uniform inter-agent communication protocols, ontology-based reasoning, reproducibility and benchmarking, real-world large-scale implementation, and quantum-enhanced MAS. Lastly, it provides future research directions for the future development of MAS-based transformer fault detection and diagnosis.

Index Terms: Bayesian Networks, Digital Twins, Fault Detection, Frequency Response Analysis, Multi-Agent Systems, Transformer Condition Monitoring

1 Introduction

One of the costliest and most strategically important pieces of equipment in a contemporary electric power system is the power transformer. The outage of one transformer can cut power to thousands of households, cause a chain reaction of countermeasures to the failure on the grid, and involve a replacement cost of between hundreds of thousands and several million dollars. Transformers are vulnerable to numerous electrical, thermal, mechanical, and chemical defects due to age, overloading, short circuits, lightning, and environmental pressures, regardless of the fact that manufacturing processes and insulation technologies have improved over the years [1], [2]. Of these types of faults, winding faults such as inter-turn short circuiting, axial and radial deformations, and winding displacements are of special concern as they may quickly develop into disastrous failures, which lead to huge economic losses and lengthy service outages [2], [3]. Therefore, the detection of such faults at an early stage, when an early warning can be given and the cost of maintenance can be greatly minimized, are the main goals of electric utilities. Traditional methods of fault detection, like periodic oil sampling, Dissolved Gas Analysis (DGA), Frequency Response Analysis (FRA), and thermal imaging, are useful in offering diagnostic data. These techniques, however, tend to be used alone and rely a lot on expert interpretation, and cannot achieve the real-time and ongoing monitoring that is necessitated in current smart grid settings [4], [5]. As power systems continue to grow in complexity and the utilization of renewable sources of energy continues to increase, the need for intelligent, autonomous, and distributed monitoring structures has become more pronounced [6], [7].

MAS represents a distributed paradigm of artificial intelligence, where multiple autonomous computer agents interact to resolve complicated problems that cannot be effectively solved by one agent individually [8]. MAS has few key benefits in fault detection in transformers. MAS can simultaneously handle heterogeneous data sources, apply a variety of diagnostic strategies, dynamically adapt to changing operating conditions, and provide scalable architectures that can be used in large power networks [9], [4]. Moreover, the decentralized aspect of MAS will decrease the reliance on a single control point and thus, communication bandwidth needs, which is especially beneficial when contrasted with traditional centralized monitoring centers that have to handle large-scale amounts of non-uniform real-time data. Initial conceptual studies in the literature established the possibility of using MAS to monitor conditions in transformers with UHF partial discharge data, which has been later built upon and advanced by other researchers [4].

The combination of MAS and techniques of artificial intelligence, such as fuzzy logic, Bayesian networks, expert systems, ontology-based reasoning, support vector machines, neural networks, reinforcement learning, digital twins, and knowledge graphs, have further increased the accuracy and adaptability of diagnosis [10], [11], [12], [13]. One example of a practical implementation platform is the Java Agent Development Framework (JADE), which offers FIPA-conformant abstractions of ACL messaging and directory that can be used to quickly prototype agent-based solutions to power engineering applications [14], [15]. Simultaneously, the use of MAS in fault location and isolation in power distribution systems offers useful architectural lessons that can be generalized to fault detection issues in transformers [15], [16], [17], [18].

Despite the fact that the published literature on the topic is growing exponentially, no systematic review of the topic has examined the intersection of MAS and transformer fault detection concerns across the entire range of reported solutions, including the most crucial area of winding fault diagnosis. The gap that this paper will cover is the systematic review of the related literature, synthesizing the results based on the thematic categories and determining the key research trends, existing limitations, and future perspectives of MAS-based transformer fault detection.

2 BACKGROUND

2.1 Fault Types in Power Transformers

There is a broad range of faults associated with power transformers, which can be divided into electrical, thermal, and mechanical faults [2], [19]. Electrical faults are partial discharges, inter-turn short circuits, winding insulation failures, and core ground faults. The causes of thermal faults are usually due to overloading, insufficient cooling, or blocked oil channels. Mechanical faults are primarily due to winding deformation caused by an electromagnetic force when short-circuit conditions are present. Insulation degradation is one of the most frequently occurring fault mechanisms that is commonly accompanied by the production of typical dissolved gases in transformer oil, the foundation of the DGA diagnostic method [1],

[20]. The inter-turn faults are especially hard to detect during the initial stages [2], [3]. These defects can either start as small displacements or turn-to-turn short circuits, which do not always result in an immediate concentration of detectable gases in the oil, thus necessitating secondary sensing techniques rather than the traditional DGA. FRA has proven to be effective in identifying mechanical deformations, whereas DGA is the most effective method used to detect thermal faults and conditions related to the partial discharge [5], [21], [22], [23]. The multiformity and multidimensionality of transformer faults thus encourage the application of MAS structures, which have the ability to implement various sensory modalities and diagnostic algorithms in a coherent and intelligent monitoring framework.

2.2 Multi-Agent Systems: Fundamental Concepts

MAS are collection of autonomous agents that can engage with each other and can have perception, reasoning, and action abilities [8]. Agents can be divided into reactive, acting in response to environmental stimuli; deliberative, which think and plan to get to particular goals; and hybrid, which is a combination of the other two. The agents in a power system application normally denote physical objects, like transformers, relays, and sensors, or functionality units, like data acquisition modules, fault diagnosis modules, and communication management modules [9], [24].

Key design strategies applied to MAS are the Gaia methodology that structures communities of agents based on roles and interactions [12], and agent communication language like KQML and FIPA-ACL that allows inter-agent communication to be standardized. The ontological representation of knowledge also promotes semantic interoperability of agents that have different data sources [11], [25]. Java Agent Development Framework and other frameworks have been heavily applied to prototyping MAS applications in power systems due to their flexibility and adherence to standard agent communication protocols [14], [15].

The architectures of MAS are fault-tolerant by nature as they offer resilience due to redundancy and distributed decision-making [26], [27], [28]. Furthermore, it has been emphasized that the concept of joint intentions is another important one of cooperation in dynamic environments, where agents share goals and make use of message exchange to design their interaction [29]. Consensus-based coordination mechanisms are frequently used in the case of fully decentralized architectures that do not have a central coordinator. For instance, it has been proposed to use a multilevel consensus mechanism which involves an information matrix for the agents to settle on the state vectors, and a best weighting strategy that will bring the network closer to a consensus on the desired system state and restoration actions [30]. These architectures are far more resilient than centralized ones. The relevance and maturity of this direction of research are also presented through the extensive studies that focus on physical safety and cybersecurity challenges in MAS [26].

2.3 Cooperative Distributed Diagnosis Methodologies

Informational fusion and methodologies of decision-making are the basis of an MAS applied to transformer diagnosis. These methodologies have to deal with a high level of uncertainty, noise, and possible conflicts in the data offered by different sensors and diagnostic agents.

Bayesian networks are one of the broadest diagnostic reasoning methods of MAS due to their capability in modeling complex dependencies and making probabilistic inference. They have also made it possible to develop the evolutionary Bayesian fusion methods, which have been found to determine the most informative measures to be used at each diagnostic step and thus minimize the data needs and maximize the diagnostic performance [31]. To model large and complex systems, Multiply Sectioned Bayesian Networks (MSBNs) have been suggested, where the transformer equipment is modeled as a group of Bayesian subnets, each of which is the personal knowledge base of a particular agent [32]. Distributed inference enables solutions that are globally consistent to be achieved without degrading the privacy of the internal knowledge base of each agent, hence effectively dealing with a multi-vendor environment where diagnostic systems of various manufacturers have to interoperate.

Dempster-Shafer (DS) evidence theory is also used as a measure to deal with uncertainty on transformer fault symptoms. Additionally, a diagnostic process that integrates the advantages of DS evidence theory and Bayesian networks is proposed, which can further enhance the diagnostic accuracy of a diagnostic system, removing conflicting evidence information from various information sources [33]. Furthermore, it has been found that the imprecision and vagueness of transformer condition data can be further captured by incorporating fuzzy ontology into MAS, which will enhance the effectiveness of the diagnosis [12].

The combination of ontologies with Bayesian networks has also been explored to create a more generalized diagnostic scheme capable of being reconfigured to handle new fault modes and diagnostic guidelines [34]. Dynamic knowledge graph-based fault localization model has also been introduced, where both global and local agents perform inference on the knowledge graph, enabling the root cause of a fault to be determined with a high level of accuracy through complex multi-hop reasoning [35]. This is a major improvement over the old rule-based expert systems since it allows automatic symbolic reasoning on structured relational knowledge.

2.4 Winding Fault Detection Techniques

The winding faults are also difficult, as they usually start as minor movements or between-turn short-circuits that do not necessarily cause an immediate generation of gases to be emitted in the oil. As a result, higher detection techniques should be integrated into the MAS architecture besides the traditional DGA. **Table 1** is a summary of some of the most prominent methods of detection of winding faults and how they may be incorporated in MAS systems.

FRA is one of the most popular methods of detecting mechanical damage on transformer windings. The FRA-DiagSys system, which identifies the nature and degree of winding defects based on the Sparrow Search Algorithm (SSA) and Kernel Extreme Learning Machine (KELM) applied to FRA data, was also presented, achieving an accuracy of more than 99.7% [21], [22]. Moreover, support vector machine (SVM) classifiers have proved useful in identifying various winding faults by frequency response traces. It has also been proposed that image-based features could be derived from a binary representation of FRA signatures, and that using image processing tools could identify more subtle fault patterns that might otherwise be missed by a traditional statistical test [29].

And inter-turn fault detection is another method that uses a combination of electrothermal properties to detect turn-to-turn faults has also been proposed, where both the temperature field and electrical activity of a winding are measured to detect faults before the gas evolution can be detected using DGA [3]. Deep learning algorithms have also been used to detect inter-turn faults in next-generation smart transformers [36]. Moreover, an in-depth analysis of online turn-to-turn fault monitoring methods has been given, focusing especially on sensitivity and reliability as the major assessment factors [37].

Digital Twin Approaches has also been shown that the digital twin can be used to generate a virtual image of the transformer on the fly to facilitate more accurate and proactive fault diagnosis by regular comparison of the physical transformer with the digital twin [38]. Furthermore, a hotspot-edge fault detection system has been designed based on a microthermal field detector to detect inter-turn short-circuit fault, which provides a more sophisticated spatial fault-location capability than the traditional bulk thermal indicator [39].

Table 1. Winding Fault Detection Methods and MAS Integration Potential

Method	Key References	Strengths	MAS Integration Potential
FRA + Intelligent Classifiers	[21], [22], [29]	High sensitivity to mechanical deformation; wide frequency range	FRA agent feeds winding-condition signals to MAS diagnostic layer
Inter-turn Fault (Electrothermal)	[3], [36]	Detects incipient turn-to-turn faults before gas evolution	Thermal & electrical sensor agents fuse data in MAS
Digital Twin Modeling	[38], [39]	Real-time virtual model; hotspot localization	Digital-twin agent provides continuous state estimates to MAS
Dempster-Shafer Evidence Theory	[33], [12]	Handles conflicting evidence; uncertainty quantification	Evidence-fusion agent combines outputs of multiple diagnostic agents
MSBN / Distributed Bayesian	[32], [31]	Privacy-preserving distributed inference	Natural fit for multi-vendor MAS environments
Knowledge Graph Reasoning	[35]	Multi-hop root-cause tracing	Global + local agents traverse graph for fault localization
Wavelet / Time-Frequency Analysis	[40]	Transient fault detection; time-domain sensitivity	Signal-processing agent extracts features pre-classification
Online Turn-to-Turn Monitoring	[37]	Continuous real-time detection without offline tests	Monitoring agent streams data to MAS condition-assessment layer

3 MULTI-AGENT SYSTEMS FOR TRANSFORMER CONDITION MONITORING

3.1 Foundational Architecture

S. McArthur et al. [4] developed the design principles of MAS-based transformer condition monitoring of the UHF partial discharge data. The authors showed how the layered agent architectures may be employed to decouple the data acquisition, signal processing, and diagnostic reasoning modules into interoperable ones. This is a modular framework allowing each of the diagnostic modules to be developed independently and, additionally, integrating various monitoring technologies. This was extended by DITRANS, a multi-agent system or diagnosing power transformers using the Gaia agent society model, which combines oil sampling, electric measurements, and thermal sensors [9]. The system showed that agent communication offers a viable data fusion mechanism of multi-source data fusion and thus is more effective in diagnostic confidence than single-modality data fusion methods. DITRANS architecture is based on a layered architecture of the MAS architecture, whereby various agents at various levels carry out different functions, such as low-level data collection and high-level diagnostic reasoning. These agents can do a full condition assessment utilizing both past and present data through their social and collaborative abilities.

Another architecture, specifically designed to diagnose the fault of a power transformer, in which a coordination and synthesis agent can resolve conflicting problem situations and integrate the diagnostic outcome, particularly in cases where fault data is not fully known [41]. The conceptual framework that was developed also helped establish the broader benefits of MAS in condition monitoring applications, as well as inform future studies over the last ten years [42].

A framework known as Condition Monitoring Multi-Agent Systems (COMMAS) has also been proposed, which involves data formatting, feature extraction, interpretation, and corroboration agents [25]. The hierarchical structure will also enable faster fault identification, as the fault is integrated with the existing fault diagnosis system.

3.2 Agent Roles and Specialized Functions

The key to the success of an MAS is agent specialization. Such a system can also comprise diagnosis agents, which are constructed on selective Bayesian classifiers such as Naive Bayes, Selective Bayes, and Tree Augmented Naive Bayes to process dissolved gas information [10]. These agents are supported by management agents, which monitor their actions, and also by fusion agents, which integrate their products to decide which type of fault will occur at the end.

A remote monitoring structure characterized by the agents working in a hierarchical task structure to monitor the data of ultra-high-frequency (UHF) partial discharge, core earth current, and DGA has been defined [31]. In this architecture, agents will handle data acquisition and preprocessing, then proceed with expert-level diagnosis. A weighted diagnostic strategy is then used to fuse their decisions based on the levels of diagnostic confidence. It is a confidence-based fusion method that is of special use when sensor modalities (particularly individual ones) give incomplete or partly complementary information about transformer condition.

3.3 Ontology-Driven MAS Approaches

The combination of ontology-based reasoning and MAS have been important in strengthening semantic interoperability and diagnostic transparency. MAS for power transformer condition monitoring and fault diagnosis have been developed, based on ontology reasoning via a SPARQL rule engine [12]. This system allowed agents to do complicated logical inference on structured bodies of knowledge, and thus, enhanced condition monitoring as well as fault prediction, and was more transparent than black-box AI methods. A similar framework was extended to include fuzzy ontology-based reasoning to overcome the imprecision and vagueness characteristics of real-world transformer condition data [11]. The system has the capability to model the level of severity of faults and the co-occurrence of several symptoms that are mostly hard to model with crisp rule-based methods by combining fuzzy membership functions and ontology relationships.

Practical issues in stabilizing existing MAS for power engineering applications have also been explored, identifying interoperability barriers between COMMAS and Process Execution and Diagnostic Architecture (PEDA) as one of the major obstacles to large-scale implementation [25].

3.4 SCADA-Integrated MAS and Industrial Deployment

A practical use of MAS to automate SCADA and digital fault recorder (DFR) data management and analysis has also been shown [43]. The work constitutes one of the first examples of MAS working at a realistic scale within a power system context and proves the PEDA architecture in a transmission context in the United Kingdom. This effort has also been pursued with MAS that diagnose faults in automated power systems based on knowledge-based reasoning over the sequence of SCADA events [44].

An AI-layered MAS architecture for prognostic health management (PHM) of smart transformers has also been suggested, combining various diagnostic algorithms, health indices, and loss-of-life estimation models at different levels of the architecture [13]. This structure gives a holistic perspective of asset health and was one of the most holistic hybrid designs ever reported in the literature reviewed, which bridged the gap between MAS architecture research and AI-based performance optimization.

4 MULTI-AGENT SYSTEMS INTEGRATED WITH DISSOLVED GAS ANALYSIS

4.1 Agent-Based DGA Systems

Another DGA-based system using intelligent agents has been developed for the detection of incipient faults in power transformers [5]. The system employed special agents for measuring the gases, for calculating ratios, for knowledge-based diagnosis, and for communicating the results, thus suggesting that the entire process of DGA interpretation could be automated with little loss of diagnostic accuracy when compared with expert diagnosis, using agent-based systems.

A special MAS that would be used to diagnose transformer faults using dissolved gases in transformer oil was also suggested. These systems used a multi-agent model of collaboration between diagnostic agents in which expert agents vote, and resource competition algorithms are used to help the system make conflicting diagnoses using a structured method of consensus. The methodology of voting-based approaches was proven to be viable and successful using real transformer datasets as application examples.

In addition, a MAS diagnosis model has been integrated with Bayesian network classifiers to diagnose faults of the transformer with DGA data [10]. The Bayesian model provided principled probabilistic inferences when the evidence of fault was uncertain, while the MAS architecture enabled data was acquired and cross-validated by many fault agents. The system was evaluated using actual samples of transformers and was shown to be very effective with only partial sets of measurements.

4.2 Comprehensive DGA Reviews and AI Integration

The shift towards deep learning models is also discussed in a state-of-the-art review of transformer fault diagnosis using artificial intelligence combined with DGA [1]. An extensive comparison of computational intelligence methods and conventional DGA methods has also been carried out, using the IEC TC 10 standard database to benchmark methods such as artificial neural networks (ANN), support vector machines, fuzzy logic, and decision trees [20]. This renders it a significant source of information in the process of identifying the right algorithms to apply to particular cases of fault.

Machine learning algorithms for transformer DGA have also been compared, with non-parametric and nonlinear SVM algorithms found to perform better on a large dataset of 4,580 DGA samples [23]. These results indicate that MAS architectures with ensemble machine learning agents, one agent focused on each classification algorithm, can present more diagnostic strengths than any single approach. Three independent diagnostic methods have also been combined into MAS to detect transformer faults, with the aim of offering wide fault coverage without operator-directed control [45]. The system showed a good ability to predict faults of various fault types, such as thermal faults, electrical discharges, and insulation degradation, and thus proved the complementary value of multi-technique integration on the Multi-Agent System.

5 MAS FOR FAULT LOCATION AND ISOLATION IN DISTRIBUTION SYSTEMS

Even though the emphasis of this review is on transformers, MAS's use of fault location and isolation in power distribution systems are a significant related field of literature with immediate architectural implications. Such systems include distribution transformers and fault management schemes that had originally been developed within distribution networks and are being applied in an increasing number of applications involving transformers.

5.1 Real-Time Fault Detection and Reconfiguration

Decentralized MAS has been proposed to detect faults in real-time in power distribution networks, efficiently locate faults and fault type using a real circuit model using simulation [17]. A similar approach for fault detection and reconfiguration using graph theory and mathematical programming has also been proposed, which was able to localize faults successfully and identify fault types to continue to provide critical loads [15]. In both experiments, the Jade platform and MATLAB software were used.

Another class of techniques called MAS have been also developed and tested experimentally to help restore the power system after a fault, reaching full or partial restoration according to load-prioritization and shedding policies [18]. A hierarchical MAS layer with five different expert agents has also been developed for electricity distribution network fault diagnosis, which is highly efficient and applicable in a real-time case study [24].

5.2 Smart Grid and Microgrid Applications

MAS has also been designed to detect and pinpoint faults in power distribution systems that contain Distributed Generation Sources (DGS) [16]. The system could identify faulted areas and fault types. It could also accommodate two-way power flow from distributed generators, which gives rise to reverse power flow conditions that are not possible in conventional radial distribution systems. This article highlighted the greater complexity of fault tracking in a grid with renewables.

MAS has also been proposed that determine faults and isolate them in smart microgrids based on the sequence current magnitude and current direction, with various fault types introduced for testing [46]. It was run on a 37-bus IEEE benchmark system using OpenDSS software. Likewise, fault location and isolation in distribution networks interconnected with wind power generators have also been explored, with faulty lines and circuit breakers detected and controlled by the agent communication system, demonstrating the versatility of MAS in a renewable-rich environment [6], [47].

It is also revealed that MAS can simultaneously handle several post-fault management functions in the unified architecture of smart power distribution grids, including fault diagnostics, service recovery, and data-loss prevention [48]. Also presented is a MAS approach to the management of loading levels of a distribution transformer, as the first to demonstrate the use of MAS for the proactive management of the transformer asset [49].

6 HYBRID AI AND MACHINE LEARNING INTEGRATION IN A MULTI-AGENT SYSTEM

The borders of transformer fault detection research that are the most rapidly evolving are the intersection of MAS with state-of-the-art AI and machine learning. **Table 2** provides an overview of the papers that are related to this category and compares AI approaches, fault outcomes of the approach, performance measures, and level of integration of MAS.

Table 2. AI/ML Methods for Transformer Fault Detection and MAS Integration Status

Ref.	AI / ML Method	Fault Type Addressed	Performance	MAS Integration
[50]	CNN / LSTM (Deep Learning)	Multiple transformer faults	High classification accuracy	Not explicitly stated
[51]	Machine Learning (MOG faults)	Magnetic Oil Gauge faults	Improved fault prediction	No
[52]	Multi-Agent RL + Transfer Func.	Transmission line faults	F1=0.88, Precision=0.95	Yes
[23]	Non-parametric ML / SVM	DGA-based fault types	Effective on 4580 samples	No
[53]	ANN / CNN / SVM / RF / GA / PSO	Transformer health & life span	Comprehensive review	Partially
[54]	1-D CNN + Transformer encoder	Symmetrical/unsymmetrical HIF	High accuracy (multi-class)	No
[55]	ANN + SMOTE-ENN oversampling	DGA-based transformer faults	F1=0.994, Precision=0.994	No
[56]	Fuzzy logic + ANN (expert system)	DGA incipient faults	Multi-fault diagnosis	No
[13]	SVM / RF / KNN + MAS	Smart transformer faults	Exhaustive comparative study	Yes (hybrid MAS-AI)
[21]	MLP (FRA-DiagSys)	Winding faults	~99.7% degree accuracy	No
[57]	z-score + t-SNE + GAN + AI	Multi-fault transformer	99.6% accuracy	No
[58]	GA-tuned ANN	DGA-based fault analysis	Correlation > 0.98	No
[20]	Computational intelligence vs DGA	Multiple fault types	Comprehensive comparison	No

6.1 Deep Learning and Neural Network Approaches

Systematic reviews of AI and machine learning models for diagnosing faults in transformers have also been developed. M. A. M. Khan [50] demonstrated in the review that deep learning models, especially Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, provide substantial performance gains in the area of fault classification, indicating that the future of research is expected to be the integration of these networks into the diagnostic agents of MASs as specialized diagnostic instruments. J. B. Thomas et al. [54] created an encoder model based on a CNN transformer, achieving high accuracy in detecting symmetrical faults, unsymmetrical faults, and high-impedance faults in power systems.

A systematic review of transformer fault diagnosis based on DGA data has also been conducted, and out of 1190 articles retrieved from four major databases, the predictive modelling performance has reached up to 95.29 [59]. A Genetic Algorithm (GA) optimized ANN (GA-ANN) classifier has also been designed, which has a correlation coefficient of over 0.98 on transformer DGA samples [58]. A multilayer perceptron architecture of FRA signatures has also achieved an accuracy of more than 99.7% in the recognition of the severity of winding faults in the case of FRA-DiagSys [21].

Over time, machine learning and various classification algorithms have been increasingly employed in modern winding fault diagnosis systems. In order to make the best use of the aforementioned diagnostic information to increase the effectiveness in the fault classification, the diagnostic information has been preprocessed by using a moving-window calculation, and SVMs are employed to increase the accuracy in the fault classification [60]. Similarly, orthogonal wavelet filter banks have been used to perform time-frequency analysis of transformer signals for fault detection of transient faults which are not detectable by frequency-domain analysis [40].

6.2 Multi-Agent Systems with Integrated AI Architectures

In this instance, an AI-layered MAS framework of prognostic health management of smart transformers has been suggested, incorporating evolutionary SVM, Random Forest, k-Nearest Neighbor, and all the linear regression models were incorporated in a hierarchical MAS [13]. This comparative analysis showed that the hybrid method was better than the single method.

A Multi-Agent Reinforcement Learning (MARL) system combined with transfer function analysis has also reached an accuracy rate of 0.95, a recall rate of 0.85, and an F1-score of 0.88 [52]. This is one of the first reinforcement learning applications in MAS to fault management of power systems, and it demonstrates that a new generation of adaptive and self-improving diagnostics systems can be developed, which can learn via operational feedback but without necessitating full retraining.

Distributed fault-tolerant control in multi-agent systems via an adaptive learning framework has also been discussed, providing a theoretical foundation for designing MAS capable of maintaining diagnostic performance in the event of agent failures, communication disruptions, and dynamic fault conditions [28].

6.3 Oversampling, Feature Engineering, and Advanced Classification

According to M. A. A. Putra et al. [55], the idea behind a multi-method approach using SMOTE-ENN oversampling with neural networks is significant, offering a valuable contribution toward addressing class imbalance in transformer fault datasets. The results of the study showed a very high F1-score and precision of 0.994 and 0.994, respectively, but the authors did not include statistical significance levels indicating these results. The approach can be applied directly to MAS diagnostic agents that are trained on past datasets with skewed distributions of fault classes.

Z-score normalization, t-SNE dimensionality reduction, and Generative Adversarial Networks (GANs) have also been used to classify multi-fault transformer conditions, achieving 99.6%, 98.6%, and 97.3% accuracy across various fault classes [57]. A substantial number of comparisons between computational intelligence techniques and conventional DGA techniques have also been made, providing a valuable benchmark for selecting the most suitable AI technique, particularly in transformer fault cases [20].

7 Foundational Multi-Agent System Frameworks, Fault Tolerance and Wind Turbine Applications

7.1 Foundational Multi-Agent System Theory

A cornerstone reference on the principles of multi-agent systems and distributed artificial intelligence and offers conceptual foundations on which the applications of power system MAS are grounded [8]. It deals with agent architecture, communication protocols, cooperation mechanisms, and design methodologies that have a direct influence on transformer fault detection system design.

Extending this base to the safety-critical case, an overview of safety and security analysis of MAS has also been provided, covering fault estimation, fault detection, fault diagnosis, and fault-tolerant control [26]. The practical implementation of MAS in power system restoration has also been exhibited on a large scale [18]. Combined with other highly referenced articles, these two provide a valuable conceptual and methodological basis for MAS-based fault detection studies.

7.2 Fault Classification and Fault Tolerance within Multi-Agent Systems

The theoretical meaning of fault classification and fault tolerance in MAS has also been considered, identifying faults arising from the wrong actions of agents (design faults), intervention of the outside environment (operational faults), and deliberate attacks (security faults) [27]. It is possible to apply this taxonomy directly to transformer monitoring MAS, in which agent failure can be caused by sensor failure, loss of communication, or malicious cyber intrusion.

It has also been shown that a distributed learning-based fault-tolerant MAS control framework can stabilize the system and maintain diagnostic performance even in the presence of faults in a single agent [28]. It is especially in safety-critical transformer monitoring systems that agent redundancy may not be adequate, which can be developed theoretically.

7.3 Wind Turbine Fault Detection: Cross-Domain Insights

A multi-agent fault-detecting system for wind turbines, based on data trending and anomaly detection, has also been frequently referred to in the literature. Even though this work is about wind turbine drivetrains and not power transformers, it can be of great help since the monitoring of wind turbine conditions is similar to that of a transformer in many aspects, such as operating continuously at different loads, through remote control, as well as necessitating the early fault detection of incipient faults. The agent architecture, anomaly detection algorithms, and validation methods it introduces can thus be sensibly applied to the case of transformer monitoring [7].

MAS-based fault location detection and restoration concepts can be applied to both wind power and other transformer applications in the distribution networks. According to M. Azeroual et al. [6], the experiment showed that MAS can simultaneously organize renewable generation and protection in a complicated network system.

8 Discussion On Cross-Cutting Findings, Research Gaps And Future Directions

8.1 Synthesis of Key Findings

Cross-cutting themes indicate some similar themes in the literature reviewed. To start with, it is possible to identify two major modes of MAS applications throughout the corpus, including (a) multi-agent diagnostic orchestration, whereby agents integrate heterogeneous monitoring modalities and reasoning modules to generate a single condition or fault estimation, and (b) multi-agent protection and restoration. This diagnosis-versus-action difference is in line with the placement of MAS in the literature and real-life power engineering implementations [8], [26].

Second, a general trend in the literature is that MAS applications typically presuppose: (i) a communication substrate, typically JADE-based ACL messaging; (ii) the presence of sensor data streams, such as SCADA/DFR, PMU/phasor, or DGA data, and (iii) an evaluation platform typically based on simulations and co-simulations either using MATLAB/Simulink or in-house IEEE test feeders. Few studies have permanent industrial deployment. A distinguishing example is the study on analyzing SCADA/DFR data with the help of the PEDA agents in a transmission environment in the United Kingdom [43]. This underscores a large distance between research work and practice.

Third, MAS AI and machine learning interventions tend to be superior to single-modality ones. Much higher diagnostic accuracies are attained by hybrid MAS models that combine ontology reasoning, Bayesian inference, or deep learning than single models alone, and the MAS power structure has the modularity, scalability, and fault tolerance required to deploy MAS in practice on the grid [13], [28].

8.2 Identified Research Gaps

The following research gaps were systematically identified across the reviewed literature. Standardized inter-agent communication protocols have to be further developed, since the majority of studies that deployed MAS use custom communication schemes that restrict interoperability between the types of transformers and grid conditions. Even though FIPA-ACL standards are commonly cited, they are seldom applied strictly.

It is only a small fraction of articles that offer publicly available datasets, source code, or enough detailed information about how to implement them in order to be reproducible. Furthermore, no generally accepted fault taxonomy or benchmark MAS dataset exists, therefore making it hard to compare the performance of studies directly. In future work, it should strive to develop similar reproducibility standards to those used in more general machine learning studies. And only a small percentage of the studies examined had been deployed on an operational scale. Prototypes that are simulation-tested and have been tested should be given a bridge to industrial implementation in future studies. With the continued integration of transformer MAS into smart grid communication systems, the risk of adversarial attacks via the agent communication channels is increasing, which needs more comprehensive research [26]. Privacy-protected knowledge processing in multi-vendor settings is a helpful starting point, worked on using the MSBN [32]. Hybrid AI-MAS systems based on deep learning usually have high accuracy, but are not very diagnostic, which is required for acceptance by power system operators and regulators.

The majority of AI-MAS systems are trained offline based on predefined data. Adaptive transformer monitoring also demands online learning capacity; thus, agents have the capacity to continually update the operational model based on the stream model of diagnosis. Some of the new sensing modalities that are yet to be incorporated in MAS architectures are fiber-optic distributed temperature sensing, acoustic emission monitoring, online FRA, and virtual sensing using digital twins. The majority of MAS studies focus more on DGA-based monitoring, according to literature assessments on the issue of winding fault coverage in DGA-centric MAS sectors. The existing MAS designs do not adequately depict the incipient winding flaws, which do not create any visible gas development, including the early mechanical deformations that can only be discovered with the FRA.

8.3 Future Research Directions

The future research should consider mitigating the identified gaps following the subsequent directions: (1) the creation of a standardized agent communication ontologies of power transformer monitoring using FIPA standards and domain ontologies, (2) large-scale pilot studies on implementing the work in collaboration with transmission and distribution system operators, (3) the integration of federated learning with MAS to support the privacy-preserving distributed learning and enhanced winding fault management, (4) the construction of explainable AI agents that can delivers human-readable diagnostic reasoning, and (5) the use of multi-agent reinforcement learning [60], [61].

9 CONCLUSION

The systematic literature review on the interface of MAS and fault detection in power transformers identified five thematic groups into which the studies were included, such as MAS to monitor the condition of power transformers, DGA-based diagnostic systems, MAS to locate and isolate faults in a distribution system, hybrid AI-MAS systems, and MAS frameworks. The review also summarized the cooperative distributed diagnosis methods, such as Bayesian networks, Multiply Sectioned Bayesian Networks (MSBNs), Dempster-Shafer evidence theory, Fuzzy ontology reasoning, digital twins, and knowledge graph reasoning, along with their use in MAS-based diagnostic analytics.

As it has been shown in the review, MAS architecture can provide meaningful benefits to detect faults in transformers, such as distributed data integration, automated real-time monitoring, modular diagnostic design, and inherent fault tolerance. MAS that are combined with AI techniques, especially ontology-based reasoning, Bayesian inference, fuzzy logic, SVM, neural networks, digital twins, and reinforcement learning, is the latest state of the art, and always hybrid systems perform better than single-modality approaches. Winding fault detection, specifically, is a significant area of MAS integration yet has not been addressed in the existing literature, specifically regarding FRA, electrothermal analysis, and digital twin modeling. Researches have advanced beyond initial conceptual models to laboratory-proven applications, industrial applications, and new smart-grid-integrated and AI-optimized systems. However, standardized communication, reproducibility and benchmarking, large-scale validation, cybersecurity, and explainability are some acute problems that need to be resolved in order to achieve the maximum potential of MAS in transformer fleet management. With the further development of renewable energy sources, and the increasing integration of these works into the world power infrastructure, the grid interconnection also increases, and the process of managing assets becomes more complicated, more intelligent MAS-based transformer monitoring systems will be ever more significant in providing reliability to a power system and preventing any unexpected failures, lengthening the lifespan of transformers, and reducing the economic and social costs of outages. It is the hope of the research community that it will be able to hasten the development of gap areas as reported and contribute to the practice of next-generation transformer diagnostic systems based on MAS, leaving the laboratory scope of next-generation MAS to the large-scale practical implementation.

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