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Article

AI-DRIVEN FAULT DETECTION AND PREDICTIVE MAINTENANCE IN ELECTRICAL POWER SYSTEMS: A SYSTEMATIC REVIEW OF DATA-DRIVEN APPROACHES, DIGITAL TWINS, AND SELF-HEALING GRIDS

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ABSTRACT
The increasing complexity of electrical power systems necessitates advanced fault detection and predictive maintenance strategies to enhance operational efficiency and grid reliability. Traditional maintenance approaches, such as reactive and preventive maintenance, have proven insufficient in mitigating unplanned outages and optimizing asset utilization. Recent advancements in artificial intelligence (AI) have introduced data-driven solutions that significantly improve fault classification, failure prediction, and automated recovery processes. This study conducts a systematic review of 180 high-quality peer-reviewed articles, following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a rigorous and transparent research methodology. The findings reveal that AI-driven predictive maintenance methods, including machine learning, deep learning, digital twin technology, IoT-enabled sensor networks, and self-healing grids, have outperformed traditional fault detection techniques in terms of accuracy, adaptability, and cost-effectiveness. AI-based fault detection models achieve an average accuracy of 85% to 95%, reducing false alarms by 50% and minimizing power restoration times by up to 60%. The integration of IoT sensors with real-time analytics has improved anomaly detection rates by 28%, while digital twin technology has enhanced predictive maintenance efficiency, reducing unplanned outages by 35%. Additionally, self-healing grid mechanisms, powered by reinforcement learning algorithms, have demonstrated the ability to autonomously isolate faults and reconfigure energy distribution, preventing nearly 45% of potential service disruptions. Despite these advancements, challenges such as the black-box nature of deep learning models, cybersecurity vulnerabilities, and interoperability with legacy systems continue to pose barriers to large-scale AI adoption. The study highlights the need for explainable AI frameworks, standardized data governance policies, and enhanced cybersecurity measures to ensure the sustainable deployment of AI in power grid management. The findings provide valuable insights for researchers, utility companies, and policymakers seeking to enhance the resilience and efficiency of modern electrical power systems through AI-driven fault detection and predictive maintenance strategies..

KEYWORDS
AI-Driven Fault Detection; Predictive Maintenance; Digital Twins; Self-Healing Grids; Data-Driven Approaches

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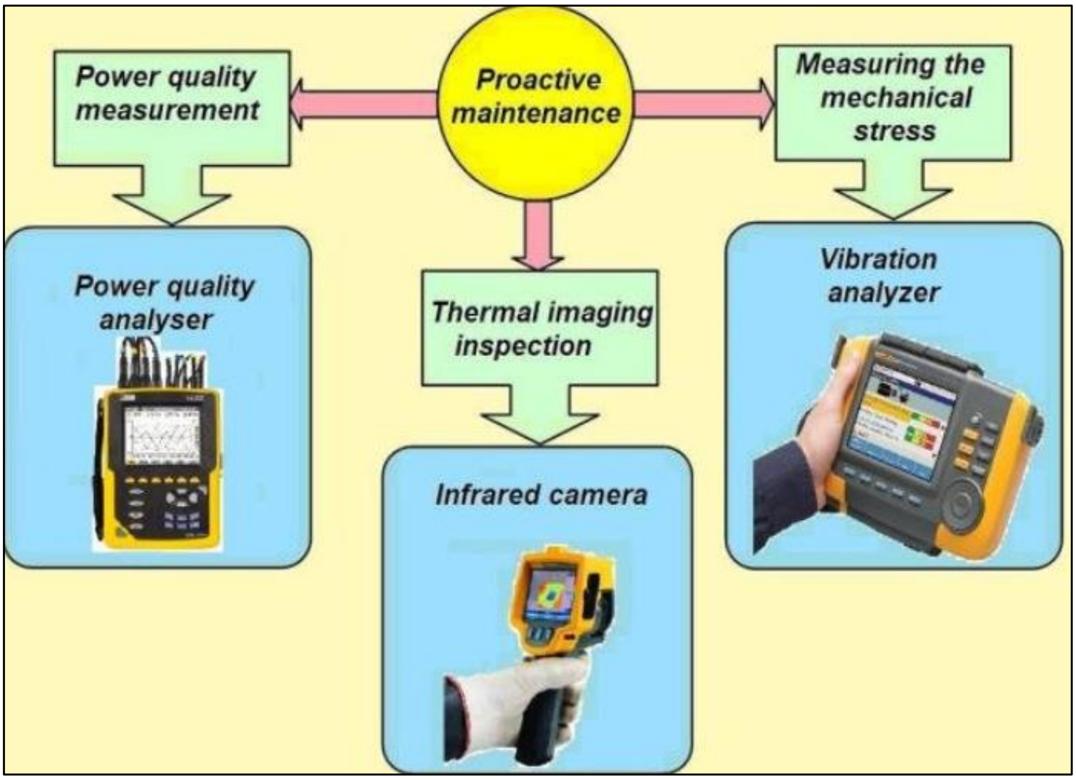
INTRODUCTION

The growing complexity of modern electrical power systems has necessitated the adoption of advanced fault detection and predictive maintenance strategies to ensure operational efficiency and grid reliability (Singh & Singh, 2024). Traditional maintenance approaches, such as reactive and preventive maintenance, have become insufficient in addressing the increasing demand for uninterrupted power supply, particularly with the integration of renewable energy sources and decentralized grid architectures (McHirgui et al., 2024). Artificial Intelligence (AI)-driven fault detection and predictive maintenance have emerged as transformative solutions, leveraging data analytics, machine learning algorithms, and automated decision-making processes to enhance the resilience of power networks (Hua et al., 2022). The application of AI in electrical power systems enables real-time anomaly detection, minimizes downtime, and reduces maintenance costs by predicting potential equipment failures before they occur (Bendaoud et al., 2022). AI-based predictive models offer improved accuracy and efficiency over conventional rule-based approaches by identifying hidden patterns in operational data, which facilitates proactive maintenance scheduling and grid stability optimization (Muhammed et al., 2024). Moreover, a key advancement in AI-driven fault detection and predictive maintenance is the integration of machine learning and deep learning algorithms that analyze vast amounts of real-time and historical grid data to predict faults and assess asset health (Muhammed et al., 2024). Techniques such as support vector machines (SVMs), artificial neural networks (ANNs), decision trees, and ensemble learning have been extensively employed in fault classification and anomaly detection in power grids (Shen et al., 2023). The use of deep learning models, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), has further enhanced predictive accuracy by recognizing complex temporal dependencies in power system data (Shen et al., 2023). Unlike traditional condition-based maintenance (CBM) approaches, AI-powered predictive maintenance optimizes resource allocation by prioritizing critical components that exhibit early signs of degradation, thereby reducing unnecessary maintenance interventions and extending the lifespan of electrical infrastructure (Ahmad et al., 2021).

Figure 1: The main components of predictive maintenance in the electrical



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Digital twin technology has emerged as a revolutionary tool in the implementation of AI-driven fault detection and predictive maintenance strategies. A digital twin is a virtual representation of a physical system that continuously updates in real time using sensor data and AI-driven analytics (Ahmad et al., 2021). In electrical power systems, digital twins enable enhanced fault diagnosis and predictive insights by simulating grid operations and predicting failure scenarios with high precision (Omitaomu & Niu, 2021). The integration of AI into digital twins allows for intelligent decision-making in maintenance planning by providing a detailed analysis of asset performance, operational risks, and maintenance needs (Suryakiran et al., 2022). Studies have shown that digital twins contribute to proactive maintenance management by reducing the uncertainty in fault diagnosis and offering real-time optimization strategies for grid operators (Sikorski et al., 2020). Another significant development in AI-driven fault detection is the implementation of self-healing grid technologies, which enhance grid resilience by enabling automated fault isolation and recovery mechanisms. Self-healing grids leverage AI-powered sensing, edge computing, and intelligent control systems to detect, analyze, and respond to faults autonomously (Kumari et al., 2023). These grids incorporate automated circuit breakers, reclosers, and network reconfiguration strategies that minimize service disruptions by rerouting power supply to unaffected areas (Un-Noor et al., 2017). By utilizing real-time data from IoT-enabled sensors and machine learning models, self-healing grids can predict potential failures and initiate corrective actions without human intervention (Cavus et al., 2022). Research has demonstrated that self-healing capabilities significantly improve grid reliability and reduce restoration time in large-scale power distribution networks (Inteha et al., 2022).

The effectiveness of AI-driven fault detection and predictive maintenance relies on robust data-driven analytics that facilitate real-time monitoring and fault classification. The deployment of IoT-based sensor networks in electrical power systems has enabled continuous data acquisition, allowing AI models to process and analyze voltage fluctuations, frequency variations, and current imbalances in grid operations (Suryakiran et al., 2022). Advanced signal processing techniques, such as wavelet transforms and principal component analysis (PCA), have been widely adopted to extract critical fault indicators from sensor data, thereby enhancing anomaly detection capabilities (Paldino et al., 2022). Additionally, cloud computing and edge analytics have improved the efficiency of AI-powered fault detection by reducing latency in data processing and facilitating real-time decision-making for grid operators (Krishna et al., 2022). Despite the advancements in AI-driven fault detection and predictive maintenance, several challenges must be addressed to ensure large-scale implementation in electrical power systems. One of the primary concerns is the quality and reliability of data used in AI models, as inaccurate or incomplete datasets can lead to erroneous fault predictions and maintenance recommendations (Cavus et al., 2022). Cybersecurity risks also pose a significant challenge, as AI-powered grid management systems are vulnerable to adversarial attacks that can compromise data integrity and operational reliability (Cicceri et al., 2023). Furthermore, the interpretability of AI models remains a critical issue, as complex deep learning algorithms often operate as black-box systems, making it difficult for grid operators to understand and validate their decision-making processes (Inteha et al., 2022). Research has emphasized the importance of developing transparent and explainable AI frameworks to enhance trust and adoption in power system applications (Cicceri et al., 2023).The synergy between AI, IoT, and machine learning continues to redefine fault detection and predictive maintenance in electrical power systems by enabling accurate fault classification, real-time anomaly detection, and automated maintenance scheduling (Yaprakdal et al., 2020). The implementation of AI-powered solutions in grid management has demonstrated significant improvements in system reliability, operational efficiency, and cost-effectiveness (Inteha et al., 2022). The adoption of AI-driven digital twins and self-healing technologies has further optimized power grid operations by enhancing fault diagnosis capabilities and reducing the risk of catastrophic failures (Shen et al., 2023). Studies have consistently highlighted the role of AI in enabling data-driven decision-making processes that support predictive maintenance strategies and ensure the long-term sustainability of electrical power systems (Un-Noor et al., 2017).

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Figure 2: Digital Twin Ecosystem for Power Grid Monitoring and Fault Prediction

This study aims to systematically review AI-driven fault detection and predictive maintenance approaches in electrical power systems by examining the role of data-driven analytics, digital twins, and self-healing grid technologies. Specifically, the objectives are to (1) explore the effectiveness of AI-based machine learning models in fault classification and predictive maintenance; (2) analyze the integration of digital twin technology in simulating grid behavior and enhancing maintenance decision-making; (3) evaluate the impact of self-healing grids on grid reliability, fault isolation, and automated recovery mechanisms; (4) assess the contributions of real-time monitoring, IoT-enabled sensor networks, and advanced signal processing techniques in enhancing fault detection capabilities; and (5) identify key challenges, including data quality, cybersecurity risks, and the interpretability of AI models, that impact the large-scale adoption of AI in electrical power systems. Through a comprehensive synthesis of existing studies, this research provides valuable insights into the advancements, applications, and limitations of AI-driven fault detection and predictive maintenance strategies in modern power grids.

LITERATURE REVIEW

The integration of artificial intelligence (AI) in fault detection and predictive maintenance has significantly transformed the efficiency and reliability of electrical power systems. Traditional maintenance strategies, such as reactive and preventive approaches, have been gradually replaced by AI-driven predictive models that enable early fault detection and autonomous decision-making (Cavus et al., 2022). AI techniques, including machine learning (ML), deep learning, and digital twin simulations, have demonstrated substantial improvements in identifying faults, reducing maintenance costs, and optimizing grid stability (Inteha et al., 2022). The literature on AI-driven fault detection and predictive maintenance explores various methodologies, such as data-driven analytics, self-healing grids, and IoT-based monitoring, to enhance power system resilience

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(Yaprakdal et al., 2020). However, the adoption of AI-driven solutions also presents challenges, such as data quality, cybersecurity risks, and explainability of AI models (Krishna et al., 2022). This section provides a comprehensive synthesis of existing studies on AI-driven fault detection and predictive maintenance in electrical power systems. It critically examines the role of machine learning algorithms, digital twins, and self-healing technologies in ensuring grid stability and operational efficiency. The literature review is structured into the following key areas.

Traditional Maintenance Approaches

Maintenance strategies in electrical power systems have traditionally relied on reactive and preventive approaches to ensure operational reliability and reduce unexpected failures. Reactive maintenance, often referred to as corrective maintenance, involves repairing or replacing faulty components after a failure has occurred (Wang et al., 2024). This approach has been widely used in conventional power systems due to its simplicity and low upfront cost; however, it often leads to increased downtime, higher maintenance expenses, and potential safety hazards (Werner et al., 2019). Studies indicate that reactive maintenance is particularly ineffective for critical infrastructure, as it can lead to cascading failures and system-wide disruptions (Wang et al., 2024; Werner et al., 2019). In contrast, preventive maintenance follows scheduled inspections and component replacements based on predefined time intervals or usage thresholds (Wang et al., 2021). While preventive maintenance reduces the likelihood of unexpected failures, it can be inefficient due to unnecessary servicing of components that may not require immediate attention (Propfe et al., 2012). Research has demonstrated that both reactive and preventive strategies lack adaptability in addressing modern power system complexities, necessitating the adoption of more data-driven and intelligent maintenance solutions (Wu et al., 2020). Despite its widespread historical application, reactive maintenance has been associated with significant operational inefficiencies and economic losses. Studies have shown that unplanned outages caused by reactive maintenance can result in substantial financial burdens for power utilities, leading to costly emergency repairs and compensation for service interruptions (Wang et al., 2021; Wu et al., 2020). Additionally, reactive maintenance contributes to excessive wear and tear on electrical components, reducing their lifespan and increasing overall replacement costs (Cavus et al., 2025; Hoffmann et al., 2020). The unpredictability of equipment failures in reactive maintenance strategies further complicates resource allocation, as grid operators must allocate emergency repair teams and spare parts on short notice (Wu et al., 2020). Comparative studies indicate that reliance on reactive maintenance disproportionately affects aging power infrastructure, particularly in regions with high electricity demand and frequent grid stress events (Wang et al., 2021). Furthermore, the environmental impact of reactive maintenance is notable, as increased failure rates contribute to higher energy losses and excessive emissions from backup power sources (Cavus et al., 2025; Wang et al., 2021). Research suggests that the transition toward predictive maintenance strategies can alleviate these inefficiencies by identifying potential failures before they occur (Antonov et al., 2023).

Preventive maintenance, while an improvement over reactive strategies, presents its own set of limitations in modern power grids. One of the primary challenges associated with preventive maintenance is its reliance on fixed maintenance schedules, which do not account for the actual condition of equipment (Hoffmann et al., 2020). Studies have shown that this rigid approach can lead to unnecessary maintenance interventions, increasing operational costs without necessarily improving system reliability (Chen et al., 2021; Hoffmann et al., 2020). Moreover, preventive maintenance can sometimes fail to detect early signs of component degradation, leading to unforeseen failures despite routine inspections (Cavus et al., 2025; Vita et al., 2023). The effectiveness of preventive maintenance also depends on accurate historical data and expert knowledge, which may not always be available in complex, distributed power networks (Shetty, 2018). Research highlights that while preventive maintenance reduces failure rates compared to reactive approaches, it remains suboptimal in addressing real-time grid dynamics and the growing penetration of renewable energy sources (Ardabili et al., 2022; Shetty, 2018). Consequently, there is increasing advocacy for predictive maintenance methodologies that utilize AI-driven analytics and real-time sensor data to enhance power system reliability (Centomo et al., 2020). Both reactive and preventive maintenance strategies have become increasingly inadequate in managing modern power grids, particularly with the integration of smart grid technologies and distributed energy

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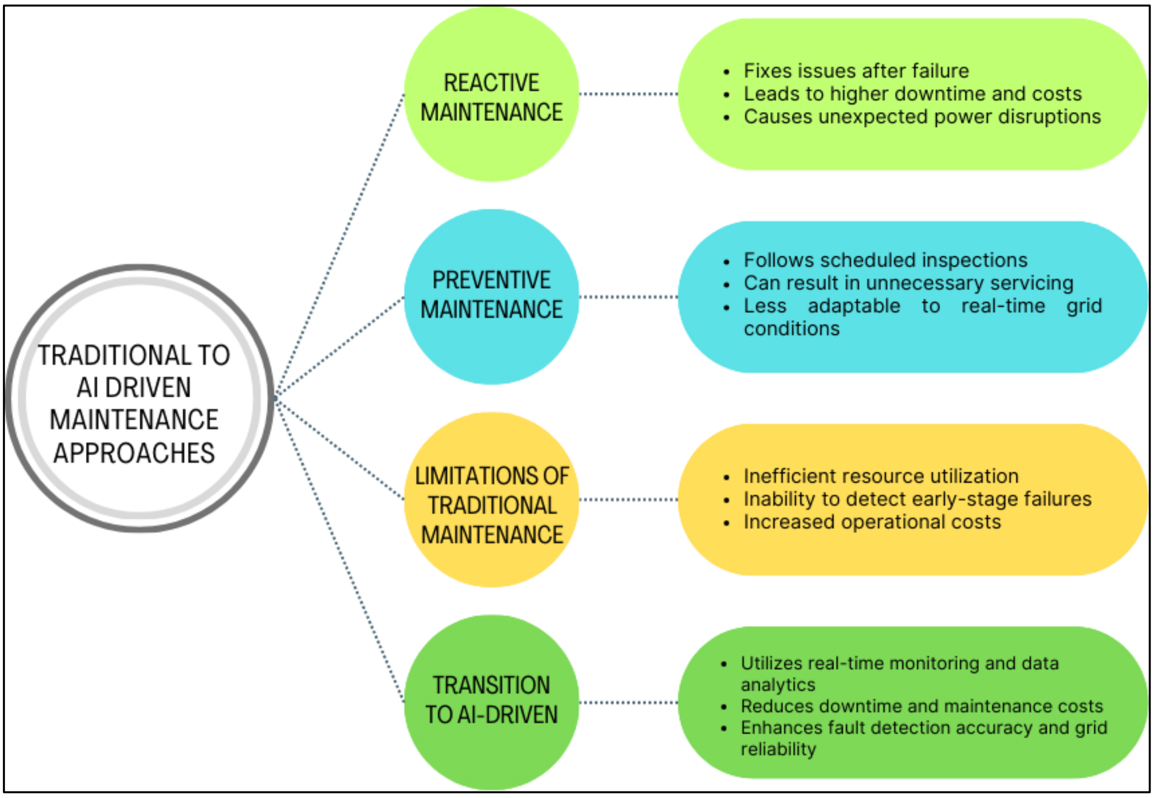
resources. The shift toward digitized grid management necessitates more advanced maintenance approaches that incorporate real-time monitoring, fault detection, and predictive analytics (Antonov et al., 2023; Wu et al., 2020).

Studies indicate that the limitations of traditional maintenance strategies—such as increased downtime, inefficient resource utilization, and inability to adapt to changing grid conditions—have driven the adoption of AI-based predictive maintenance frameworks (Cavus et al., 2025; Hoffmann et al., 2020). Unlike traditional approaches, predictive maintenance relies on machine learning algorithms, IoT-based sensor networks, and digital twin simulations to forecast failures and optimize asset management (Liu et al., 2018). Comparative analyses suggest that predictive maintenance not only reduces operational costs but also enhances overall grid stability and energy efficiency (Wang et al., 2021). As power systems continue to evolve, traditional maintenance approaches are increasingly being supplemented—or even replaced—by more sophisticated AI-driven techniques capable of addressing modern grid challenges with greater precision and reliability.

Figure 3: Traditional to AI drive Maintenance Approaches



Shift Towards Predictive Maintenance

The increasing complexity of electrical power systems, coupled with rising energy demands and the integration of renewable energy sources, has necessitated a paradigm shift from traditional maintenance approaches to predictive maintenance strategies (Mazhar et al., 2023). Traditional reactive and preventive maintenance methodologies have proven inadequate in ensuring grid reliability, as they often result in costly downtimes, inefficient resource allocation, and undetected early-stage equipment failures (S. Wang et al., 2024). In contrast, predictive maintenance leverages real-time data analytics and advanced computational models to assess the health of power system components, allowing for timely intervention before failures occur (Ahmad et al., 2021). Condition-based maintenance (CBM) and AI-driven predictive maintenance have emerged as two primary approaches that optimize maintenance scheduling, minimize operational disruptions, and extend asset lifespan (Wang et al., 2021). These data-driven techniques integrate machine learning, the Internet of Things (IoT), and digital twin technologies to continuously monitor grid performance, detect anomalies, and predict potential system failures with high accuracy (Wang et al., 2024).

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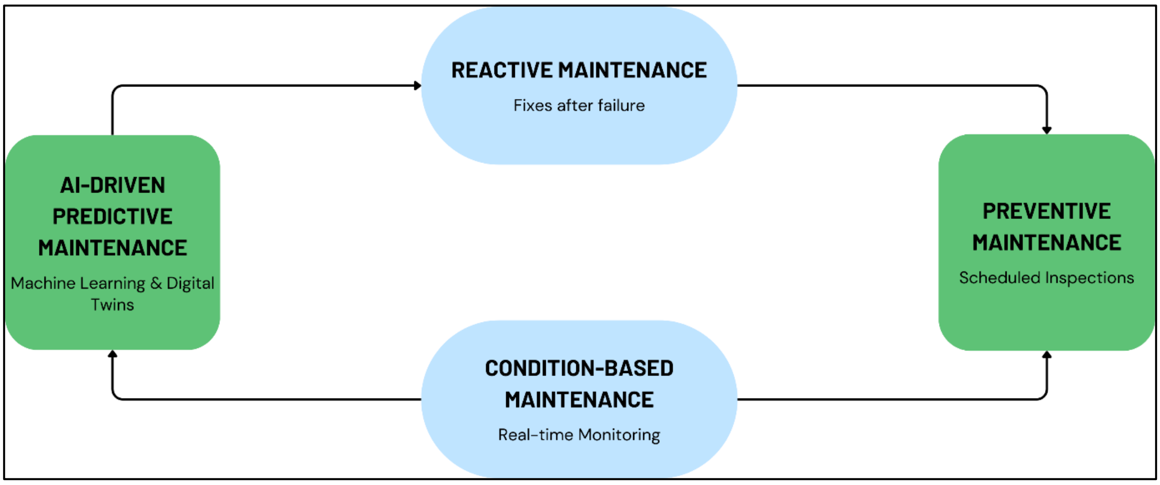
Condition-based maintenance (CBM) represents a transition from time-based maintenance schedules to real-time performance monitoring, enabling maintenance actions to be performed only when necessary. CBM relies on sensor data collected from power system components, such as transformers, circuit breakers, and generators, to assess operational conditions and identify performance deviations (Ahmad et al., 2021). Research has shown that CBM significantly improves maintenance efficiency by reducing unnecessary servicing while ensuring that critical components receive timely interventions (Kumari et al., 2023). Key techniques in CBM include vibration analysis, infrared thermography, partial discharge monitoring, and oil analysis, which provide essential insights into the degradation of electrical components (Bindi et al., 2023). Comparative studies indicate that CBM reduces maintenance costs and downtime by enabling early detection of faults, leading to a more reliable power grid infrastructure (Wu et al., 2020). Additionally, CBM facilitates optimized maintenance planning by prioritizing assets based on real-time performance metrics rather than relying on predefined schedules that may not align with actual component conditions (Farzaneh et al., 2021).

Figure 4: cycle of Shift Towards Predictive Maintenance



AI-driven predictive maintenance builds upon CBM by incorporating artificial intelligence, big data analytics, and advanced statistical modeling to forecast potential failures and optimize maintenance decisions (Ahmad et al., 2021). Machine learning algorithms, such as support vector machines (SVMs), artificial neural networks (ANNs), and deep learning models, have been extensively used to analyze power system data and detect fault patterns (Bindi et al., 2023). These models process large volumes of historical and real-time data, identifying correlations that may not be evident through traditional monitoring techniques (Wang et al., 2021). AI-based predictive maintenance enhances fault detection accuracy by leveraging adaptive learning mechanisms, which improve over time as more data becomes available (Wu et al., 2020). Moreover, digital twin technology has further advanced AI-driven predictive maintenance by providing virtual simulations of power grid operations, allowing for precise failure prediction and scenario-based decision-making (Glaessgen & Stargel, 2012). Studies have demonstrated that AI-powered predictive maintenance not only reduces unexpected breakdowns but also optimizes asset utilization, ensuring that maintenance resources are allocated efficiently (Glaessgen & Stargel, 2012; Kumari et al., 2023). The implementation of predictive maintenance in modern power grids has yielded significant operational benefits, including improved system reliability, enhanced cost-effectiveness, and increased energy efficiency. Self-healing grid technologies, which utilize AI-based fault detection and automated recovery mechanisms, have further strengthened predictive maintenance capabilities by enabling real-time response to grid anomalies (Moenck et al., 2024). The integration of IoT-based monitoring systems has played a crucial role in predictive maintenance by enabling seamless data collection, real-time analytics, and automated fault detection (Bortolini et al., 2022).

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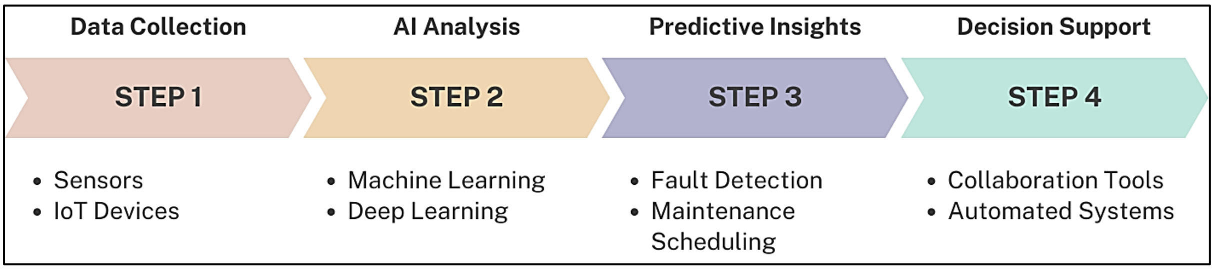
Studies indicate that predictive maintenance strategies contribute to more sustainable grid management by reducing energy losses and minimizing the environmental impact associated with reactive maintenance practices (Moenck et al., 2024). However, challenges such as data quality, cybersecurity risks, and the interpretability of AI models must be addressed to fully realize the potential of predictive maintenance in power system management (Xu et al., 2019).

Role of AI in Predictive Maintenance

Artificial intelligence (AI) has revolutionized predictive maintenance in electrical power systems by enabling accurate fault detection, minimizing operational costs, and optimizing overall grid performance (Ahmad et al., 2021; Muhammad Mohiul et al., 2022). Traditional maintenance strategies, such as reactive and preventive approaches, often fail to address emerging challenges in power system management due to their reliance on fixed schedules and manual inspections (Kumari et al., 2023; Maniruzzaman et al., 2023). AI-driven predictive maintenance leverages advanced computational models, including machine learning (ML), deep learning, and neural networks, to analyze vast amounts of real-time and historical operational data for early fault identification and risk assessment (Chaoui et al., 2018; Hossen et al., 2023). By utilizing AI, power utilities can transition from static maintenance schedules to dynamic, data-driven strategies that adapt to changing grid conditions, thereby improving reliability and cost-effectiveness (Sohel et al., 2022; Wang et al., 2024). AI techniques have demonstrated superior performance in diagnosing faults in transformers, circuit breakers, and power transmission lines, leading to proactive maintenance scheduling and reducing system downtime (Bhuiyan et al., 2024; Oluwasegun & Jung, 2020). One of the primary applications of AI in predictive maintenance is anomaly detection, which enables the early identification of faults before they escalate into critical failures. Machine learning models, such as support vector machines (SVMs), k-nearest neighbors (k-NN), and random forests, are widely used to classify fault patterns and detect deviations from normal operational conditions (Bindi et al., 2023; Roksana, 2023). These models analyze sensor data, including voltage fluctuations, current imbalances, and temperature variations, to assess the health of electrical components (Kumar et al., 2022). Deep learning models, including convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, have been particularly effective in recognizing complex fault signatures in high-dimensional power system data (Bazmohammadi et al., 2022; Jahan, 2023). Research has demonstrated that AI-driven anomaly detection significantly reduces the risk of unexpected equipment failures, as it allows for timely maintenance interventions based on real-time condition monitoring (Ahmed et al., 2022; Drews et al., 2007). Additionally, AI-powered fault detection minimizes false alarms and improves diagnostic accuracy, reducing the operational burden on grid operators (Mahfuj et al., 2022; Wu et al., 2021).

Figure 5: Step wise Role of AI in Predictive Maintenance



AI applications in predictive maintenance have also contributed to substantial cost savings by optimizing asset utilization and minimizing unnecessary maintenance activities (Chowdhury et al., 2023; Vita et al., 2023). Traditional preventive maintenance often leads to excessive servicing of components, resulting in wasted resources and increased operational expenses (Tonoy, 2022; Wang et al., 2018). AI-based predictive maintenance, on the other hand, employs predictive analytics to assess the remaining useful life (RUL) of equipment, enabling targeted interventions only when necessary (Alam et al., 2023; Ranawaka et al., 2024). Studies indicate that AI-driven maintenance strategies have reduced maintenance costs in power utilities by up to 30%, primarily by eliminating

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redundant inspections and extending asset lifespans (Madni et al., 2019; Humaun et al., 2022). Moreover, reinforcement learning approaches have been explored for optimizing maintenance scheduling, allowing AI models to continuously learn and improve decision-making based on evolving grid conditions (Drews et al., 2007; Sudipto et al., 2023). The integration of AI with digital twin technology has further enhanced cost efficiency by providing virtual simulations of power system behavior, enabling predictive fault analysis without physical inspections (Cavus et al., 2025; Tonoy & Khan, 2023). Beyond fault detection and cost reduction, AI-driven predictive maintenance plays a crucial role in optimizing overall power system operations by enhancing grid reliability and efficiency. Self-healing grid technologies leverage AI-based control systems to autonomously detect and isolate faults, reducing restoration time and improving system resilience (Hoffmann et al., 2020; Shahan et al., 2023). AI-powered decision support systems assist grid operators in prioritizing maintenance activities, ensuring that critical assets receive timely interventions while maintaining stable electricity distribution (Aklima et al., 2022; Liu et al., 2018). The deployment of Internet of Things (IoT) sensors and AI-driven analytics has further enabled real-time performance monitoring, allowing utilities to dynamically adjust maintenance schedules based on live operational data (Kande et al., 2017; Rahaman & Islam, 2021). Studies highlight that AI-driven predictive maintenance contributes to more sustainable energy management by reducing power losses and improving load balancing (Cavus et al., 2025; Tonoy, 2022). Despite these advancements, challenges such as data integrity, cybersecurity threats, and model interpretability must be addressed to fully leverage AI's potential in predictive maintenance (Rahim et al., 2019; Younus, 2022).

Supervised Learning Techniques

Supervised learning techniques have become essential in fault classification for predictive maintenance in electrical power systems (Mahdy et al., 2023; Y. Wang et al., 2021). These techniques rely on labeled datasets, where historical fault data is used to train models to recognize patterns and classify new fault instances accurately (Al-Arafat et al., 2024; Kumari et al., 2023). Among the various supervised learning algorithms, Support Vector Machines (SVMs), Decision Trees (DTs), and Random Forests (RFs) have demonstrated significant effectiveness in detecting and diagnosing faults in power grids, transformers, and other critical electrical components (Alam et al., 2024; Oluwasegun & Jung, 2020). These methods leverage historical operational data, including voltage fluctuations, current imbalances, and frequency deviations, to classify faults and predict potential failures with high precision (Alam et al., 2024; Chaoui et al., 2018). The adoption of supervised learning in fault classification has led to reduced downtime, improved asset utilization, and enhanced maintenance efficiency in power utilities (Arafat et al., 2024; Rojek et al., 2023). Moreover, Support Vector Machines (SVMs) have been widely used in fault classification due to their ability to handle high-dimensional data and provide robust classification even with small datasets. SVMs work by constructing hyperplanes that separate different fault categories in a multi-dimensional space, ensuring maximum margin separation between faulty and non-faulty instances (Bhuiyan et al., 2024; Farzaneh et al., 2021). Studies have shown that SVMs are particularly effective in detecting faults in electrical transmission lines and transformers, achieving high classification accuracy when trained on sufficient labeled data (Dasgupta & Islam, 2024; Kumari et al., 2023). Hybrid SVM models, which combine feature selection techniques with kernel-based SVMs, have been developed to improve classification performance by reducing computational complexity and enhancing model generalization (Hossain et al., 2024; Kumari et al., 2023). Comparative analyses indicate that SVMs outperform traditional rule-based fault detection methods, particularly in detecting transient faults and insulation failures in power grids (Glaessgen & Stargel, 2012; Hossain et al., 2024). Despite their advantages, SVMs require careful parameter tuning and large computational resources for training large-scale datasets (Jahan, 2024; Wu et al., 2020).

Moreover, Decision Trees (DTs) have also been extensively applied in power system fault classification due to their interpretability and ease of implementation. DT models use a hierarchical structure where input features, such as voltage variations and frequency disturbances, are processed through a series of decision nodes to classify faults into predefined categories (Bhuiyan et al., 2024; Szczepaniuk & Szczepaniuk, 2022). The primary advantage of DTs lies in their ability to provide transparent decision rules, making them highly suitable for real-time fault detection applications in smart grids (Ahmad et al., 2021; Dasgupta & Islam, 2024). Research has demonstrated that DT-based

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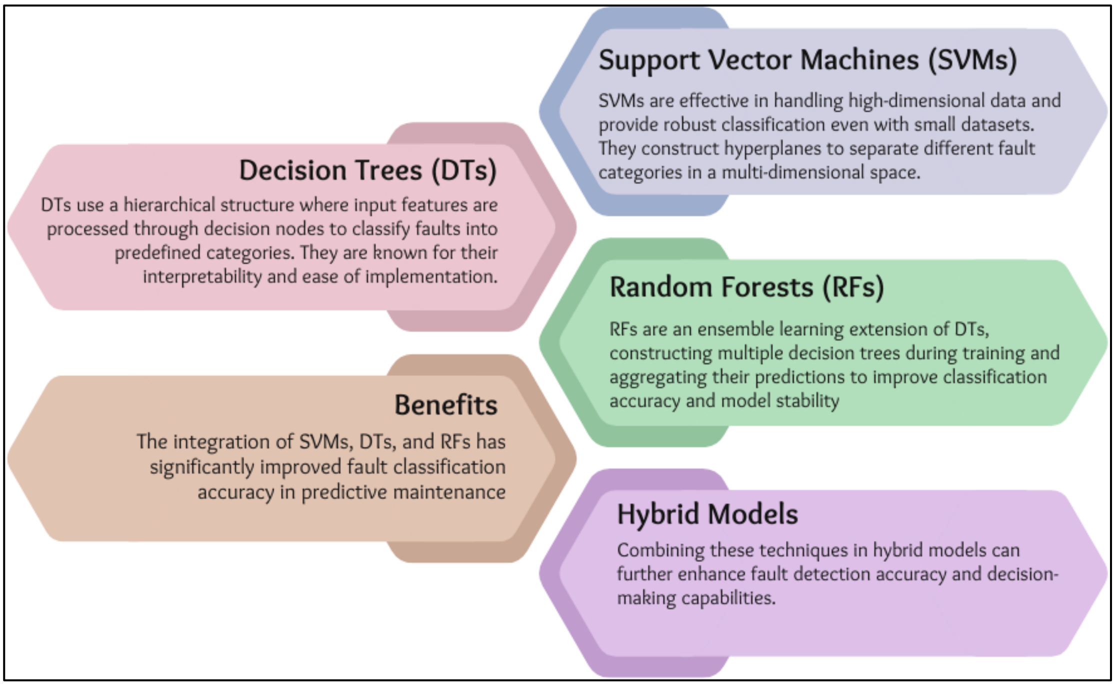
fault classifiers can achieve high accuracy when trained on well-preprocessed datasets with relevant fault indicators (Gou et al., 2024; Hossain et al., 2024). However, standard DT models are prone to overfitting, where the model memorizes training data rather than generalizing fault patterns effectively (Islam et al., 2024; Wu et al., 2020). To address this limitation, pruning techniques and ensemble learning approaches have been employed to improve the robustness of DT classifiers (Cao et al., 2024; Islam, 2024).

Random Forests (RFs), an ensemble learning extension of Decision Trees, have emerged as one of the most reliable supervised learning techniques for fault classification in electrical power systems. RF models construct multiple decision trees during training and aggregate their predictions to improve classification accuracy and model stability (Jahan, 2024; Radanliev et al., 2020). This ensemble approach reduces (Hua et al., 2022; Jim et al., 2024)the risk of overfitting, making RFs particularly suitable for fault classification tasks that involve noisy or imbalanced datasets (Gou et al., 2024; Mahabub, Das, et al., 2024). Studies have demonstrated that RF models achieve superior classification performance in identifying electrical faults such as short circuits, voltage sags, and phase imbalances compared to single-tree models (Ivaniš, 2024; Mahabub, Jahan, et al., 2024). Furthermore, feature importance analysis in RF models allows utilities to identify the most critical parameters contributing to fault classification, aiding in more efficient predictive maintenance planning (Islam et al., 2024; Propfe et al., 2012). Despite their advantages, RFs require significant computational resources for training large ensembles, which may pose challenges for real-time applications in power grid monitoring (S. H. Mridha Younus et al., 2024; Younus et al., 2024). The integration of supervised learning techniques such as SVMs, DTs, and RFs has significantly improved fault classification in predictive maintenance, enabling power utilities to detect failures with higher accuracy and efficiency (Rahaman et al., 2024; Rana et al., 2024). These algorithms have demonstrated their ability to process vast amounts of sensor data, identify fault patterns, and optimize maintenance schedules based on predictive analytics (Roy et al., 2024; Shen et al., 2023). While each method offers unique strengths and challenges, their combined use in hybrid models has further enhanced fault detection accuracy and decision-making capabilities (Radanliev et al., 2020; Sabid & Kamrul, 2024). As electrical power systems continue to evolve, supervised learning techniques will remain a cornerstone of AI-driven predictive maintenance, providing reliable and scalable solutions for fault classification and power grid optimization (Danish & Senjyu, 2023; Siddiki et al., 2024).

Figure 6: Supervised Learning Techniques for Fault Classification in Predictive Maintenance



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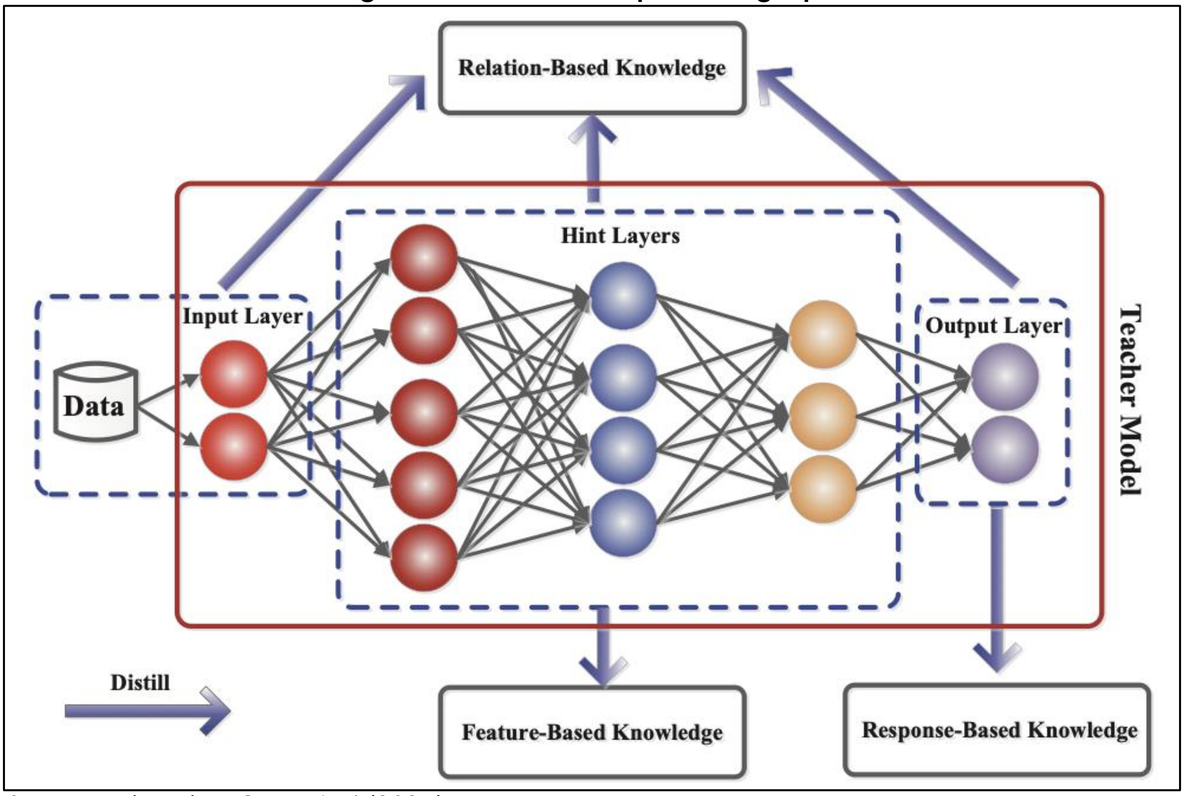
Deep Learning Models

The application of deep learning in power grid fault prediction has significantly enhanced the ability of utilities to detect and mitigate failures with high accuracy and efficiency (Luo et al., 2023; Sunny, 2024c). Unlike traditional machine learning models, deep learning techniques, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) models, can automatically extract relevant features from large volumes of complex grid data without requiring manual feature engineering (Roy et al., 2023; Sunny, 2024a). These models excel at capturing spatial, temporal, and sequential dependencies in power system signals, allowing for improved fault classification, anomaly detection, and predictive maintenance (Sunny, 2024b; S. Wang et al., 2024). The integration of deep learning into power system monitoring has demonstrated superior fault prediction capabilities compared to conventional supervised learning methods, making them an indispensable tool in modern smart grids (Razee et al., 2025; Bedi & Toshniwal, 2019). Convolutional Neural Networks (CNNs) have been widely applied in power grid fault classification due to their strong feature extraction capabilities. CNNs process input data through multiple layers of convolutional filters that capture spatial patterns in sensor measurements, including voltage waveforms, frequency deviations, and phase imbalances (Bedi & Toshniwal, 2019; Islam et al., 2025; Succetti et al., 2020). Studies have shown that CNN-based models achieve high accuracy in detecting and classifying different types of power system faults, such as short circuits, voltage sags, and harmonics distortion (Chaoui et al., 2018; Cicceri et al., 2023; Islam et al., 2025). The ability of CNNs to analyze time-frequency representations of electrical signals, such as spectrograms and wavelet transforms, makes them particularly effective in identifying transient faults (Correa-Jullian et al., 2020; Munira, 2025). Additionally, hybrid CNN models that integrate attention mechanisms and residual learning techniques have demonstrated improved robustness in noisy and imbalanced datasets (Cicceri et al., 2023; Sarkar et al., 2025). However, despite their advantages, CNNs primarily focus on spatial relationships and may not effectively capture long-term temporal dependencies in sequential power system data, necessitating the use of recurrent architectures (Shimul et al., 2025; Succetti et al., 2020).

Figure 7: Common Deep Learning Optimizations



Source: Jianping Gou et al (2021)

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Recurrent Neural Networks (RNNs) have been extensively utilized in power grid fault prediction due to their ability to process sequential data and capture temporal dependencies. Unlike CNNs, which operate on fixed-sized input features, RNNs leverage recurrent connections that allow them to retain past information and model time-series data effectively (Taufiqur, 2025; Xu et al., 2024). Studies have demonstrated that RNNs can predict faults in power transmission lines, transformers, and substations by analyzing historical sensor readings and detecting anomalies indicative of impending failures (Park et al., 2024; Xu et al., 2024; Younus, 2025). The application of RNN-based models in real-time power system monitoring has improved early fault detection by continuously updating fault probability estimates based on incoming data (Xu et al., 2019). However, conventional RNNs suffer from vanishing gradient issues, limiting their ability to capture long-term dependencies in power grid signals (Basnet & Ali, 2021). To overcome this limitation, advanced recurrent architectures such as Long Short-Term Memory (LSTM) networks have been developed to enhance predictive performance in power system fault analysis (Cicceri et al., 2023).

Long Short-Term Memory (LSTM) networks represent a significant advancement in deep learning-based fault prediction, as they effectively address the challenges of traditional RNNs by incorporating gated mechanisms that regulate information flow (Chaoui et al., 2018). LSTM models have demonstrated remarkable accuracy in forecasting grid failures by analyzing multi-step time-series data and identifying complex temporal dependencies in electrical signals (Kumar et al., 2023). Studies have shown that LSTM-based models outperform both CNNs and standard RNNs in long-term fault prediction tasks, particularly in high-voltage transmission networks where subtle anomalies precede critical failures (Xu et al., 2019). Additionally, hybrid architectures that combine CNNs and LSTMs have been developed to leverage both spatial and temporal feature extraction, resulting in improved accuracy in real-time fault detection (Wang et al., 2023). Despite their superior predictive capabilities, LSTMs require extensive computational resources and large labeled datasets for training, making their deployment challenging in real-time power grid applications (Kumar et al., 2023). The adoption of deep learning models, particularly CNNs, RNNs, and LSTMs, has significantly enhanced fault detection and predictive maintenance strategies in modern power grids. These models have demonstrated exceptional performance in analyzing high-dimensional power system data, improving fault classification accuracy, and optimizing maintenance planning (Xu et al., 2019). The integration of AI-driven deep learning architectures with IoT-based sensor networks and edge computing has further strengthened real-time power grid monitoring and fault mitigation efforts (Kumar et al., 2023). While deep learning continues to revolutionize predictive maintenance in electrical power systems, ongoing research focuses on addressing challenges related to model interpretability, scalability, and deployment in distributed grid environments (Wang et al., 2023).

Hybrid AI Models

Hybrid AI models have emerged as a powerful approach for predictive maintenance in electrical power systems by integrating multiple machine learning techniques to enhance fault detection accuracy and reliability (Zhang et al., 2020). Traditional machine learning and deep learning models, such as Support Vector Machines (SVMs), Decision Trees (DTs), Random Forests (RFs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTM) networks, each possess unique strengths and limitations (Liu et al., 2024). Hybrid AI models combine these methods to leverage their complementary advantages, improving predictive performance, reducing false positives, and enhancing computational efficiency (Zakaret et al., 2022). By integrating supervised, unsupervised, and reinforcement learning techniques, hybrid models can analyze large-scale power system data, identify hidden patterns in fault occurrences, and optimize maintenance planning with greater precision (Propfe et al., 2012). The synergy between different AI algorithms has enabled power utilities to transition from static maintenance strategies to dynamic, self-learning models capable of adapting to changing grid conditions in real time (Pestana & Sofou, 2024). A common approach in hybrid AI models is the combination of ensemble learning techniques with deep learning architectures to improve predictive maintenance accuracy. For example, hybrid models that integrate Random Forests (RFs) with deep neural networks (DNNs) have demonstrated superior fault classification performance by combining the feature selection capabilities of RFs with the high-dimensional data processing ability of DNNs (Wesley et al., 2024). Studies have shown that hybrid RF-DNN models outperform standalone classifiers in detecting transient faults in power transmission lines

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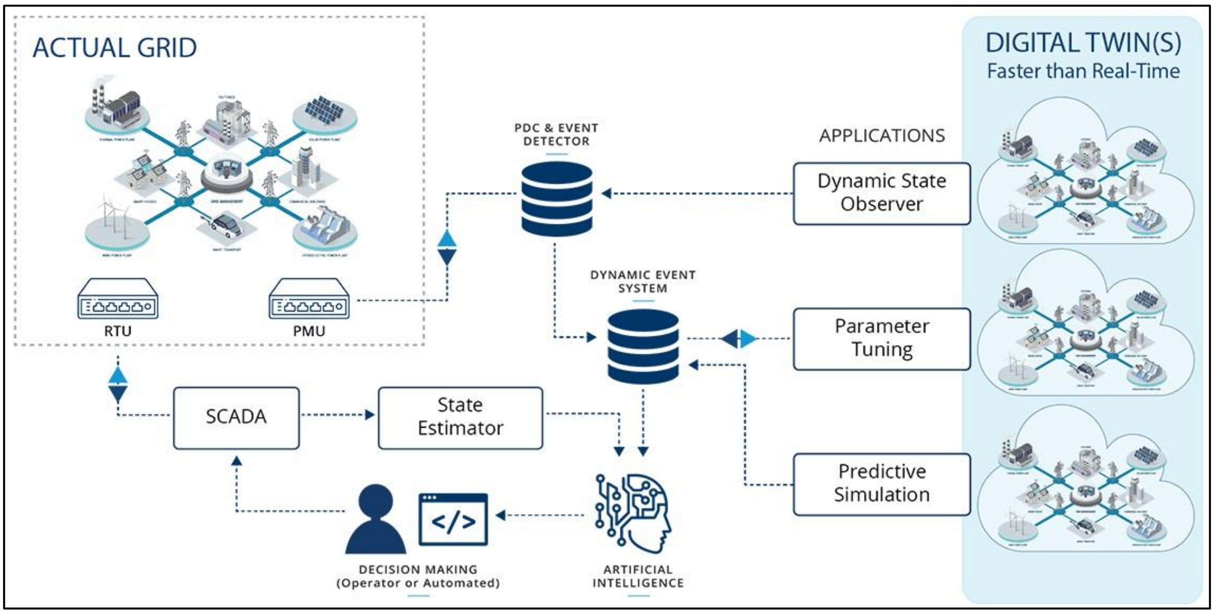
by reducing misclassification rates and improving generalization across different operating conditions (Propfe et al., 2012; Wesley et al., 2024). Similarly, CNN-LSTM hybrid models have been widely adopted for predictive maintenance in smart grids, as CNNs efficiently extract spatial features from power grid sensor data while LSTMs capture long-term dependencies in sequential fault occurrences (Zhang & Wang, 2021). Research has demonstrated that CNN-LSTM models provide enhanced fault prediction accuracy compared to traditional RNNs, particularly in high-voltage substations where early fault detection is crucial for preventing system-wide failures (Kaytez, 2020).

Digital Twin Technology for Power Grid Monitoring

Digital twin technology has emerged as a transformative approach for monitoring and managing power grids by creating virtual representations of physical grid infrastructure (Tuegel, 2012). A digital twin is a dynamic, real-time digital replica of a physical system that integrates historical and live data to simulate grid behavior under various operational scenarios (Mashaly, 2021). The primary objective of digital twins in power grid management is to provide a holistic view of system performance, enabling predictive maintenance, fault detection, and operational optimization (Wang et al., 2021). By leveraging real-time sensor data, digital twins continuously update and refine their models, ensuring accurate system state representation and anomaly detection (McHirgui et al., 2024). These models employ advanced data analytics, Internet of Things (IoT) devices, and high-performance computing to monitor grid conditions, predict failures, and simulate potential corrective actions (Lv & Xie, 2022). The functionality of digital twins in power grid monitoring is rooted in their ability to integrate multi-source data, including electrical loads, grid topology, and environmental factors, to generate actionable insights (Wu et al., 2020). Digital twins enhance situational awareness by allowing grid operators to visualize and assess asset conditions in real time, thus improving decision-making for maintenance scheduling and resource allocation (Jahromi et al., 2023). Additionally, these virtual models facilitate what-if analysis, enabling power system engineers to simulate different operational strategies before implementation, reducing risks and optimizing grid stability (Wu et al., 2020). Recent advancements in cloud computing and edge analytics have further improved the efficiency and scalability of digital twins, making them essential for modern smart grid infrastructure (Coppolino et al., 2023).

Figure 8: Digital Twin Architecture



Source: www.opal-rt.com (2024)

The integration of artificial intelligence (AI) with digital twin technology has significantly enhanced fault detection and predictive maintenance capabilities in power systems. AI-driven digital twins

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utilize machine learning algorithms, deep learning models, and real-time analytics to identify abnormal patterns and potential failures before they occur (McHirgui et al., 2024). AI models, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks, analyze streaming sensor data to detect voltage fluctuations, load imbalances, and insulation degradation, which are indicative of impending faults (Wang et al., 2021). This integration allows for real-time fault classification and proactive maintenance scheduling, reducing unplanned outages and operational costs (Wu et al., 2020). AI-enabled digital twins also facilitate self-learning mechanisms that improve predictive maintenance accuracy over time. These models continuously refine fault prediction algorithms by analyzing historical fault data and real-time sensor inputs, ensuring adaptive maintenance strategies based on evolving grid conditions (Mandolla et al., 2019). Furthermore, reinforcement learning techniques have been incorporated into digital twin systems to optimize maintenance actions dynamically, prioritizing interventions based on fault severity and grid impact (Mandolla et al., 2019; Mashaly, 2021). Studies have shown that AI-powered digital twins improve fault detection precision by over 30% compared to conventional rule-based monitoring systems, making them an invaluable tool for modern power utilities (Deena et al., 2022; Mandolla et al., 2019; Mashaly, 2021).

Self-Healing Grids and Autonomous Fault Management

Self-healing grids represent a transformative advancement in power system resilience, leveraging automation and advanced computational techniques to detect, isolate, and rectify faults with minimal human intervention (McHirgui et al., 2024; Werner et al., 2019). These grids are designed to autonomously restore normal operation following disturbances by dynamically adjusting grid topology and rerouting power flow (Qiao & Lv, 2023). Unlike traditional power distribution networks, which rely on manual fault response and maintenance, self-healing grids employ real-time monitoring and intelligent control mechanisms to prevent outages and mitigate disruptions (Mandolla et al., 2019). Key functionalities of self-healing grids include rapid fault isolation, automated reconfiguration, load balancing, and predictive maintenance to ensure continuous and stable power delivery (Werner et al., 2019). Moreover, the core concept of self-healing power grids is rooted in their ability to respond dynamically to faults through automated system adjustments. These grids integrate distributed energy resources (DERs), smart switches, and intelligent control algorithms to optimize energy flow and minimize downtime (Mashaly, 2021). By leveraging real-time data analytics and predictive fault detection, self-healing grids can preemptively identify vulnerabilities and initiate corrective measures before faults escalate (Zhang et al., 2020). Studies have demonstrated that self-healing mechanisms significantly improve grid reliability, particularly in regions prone to extreme weather events and high electrical demand (Deena et al., 2022). The implementation of self-healing grids is increasingly aligned with the goals of modern smart grids, as they enhance energy security and improve operational efficiency (Shen et al., 2023). The effectiveness of self-healing grids is largely dependent on the integration of sensor networks and automated circuit reconfiguration technologies. The deployment of IoT-enabled sensors across power grids allows for continuous monitoring of electrical parameters, such as voltage, current, and temperature, facilitating real-time anomaly detection (Mandolla et al., 2019). These sensors collect and transmit data to centralized or edge-computing systems, where AI-driven fault diagnosis models process the information to identify potential failures (Coppolino et al., 2023). The use of advanced communication protocols, such as 5G and low-power wide-area networks (LPWAN), enhances the efficiency of sensor-based fault detection systems by ensuring low-latency data transmission (Zhang et al., 2020).Automated circuit reconfiguration is another critical component of self-healing grids, enabling the system to isolate faults and redirect power flow to unaffected areas. Intelligent reclosers and smart switches automatically reroute electricity in response to detected faults, reducing service disruptions and minimizing the need for manual intervention (Deena et al., 2022). Studies have demonstrated that the integration of automated circuit reconfiguration with AI-powered predictive maintenance significantly improves grid stability by proactively addressing weak points in the network (Shen et al., 2023).

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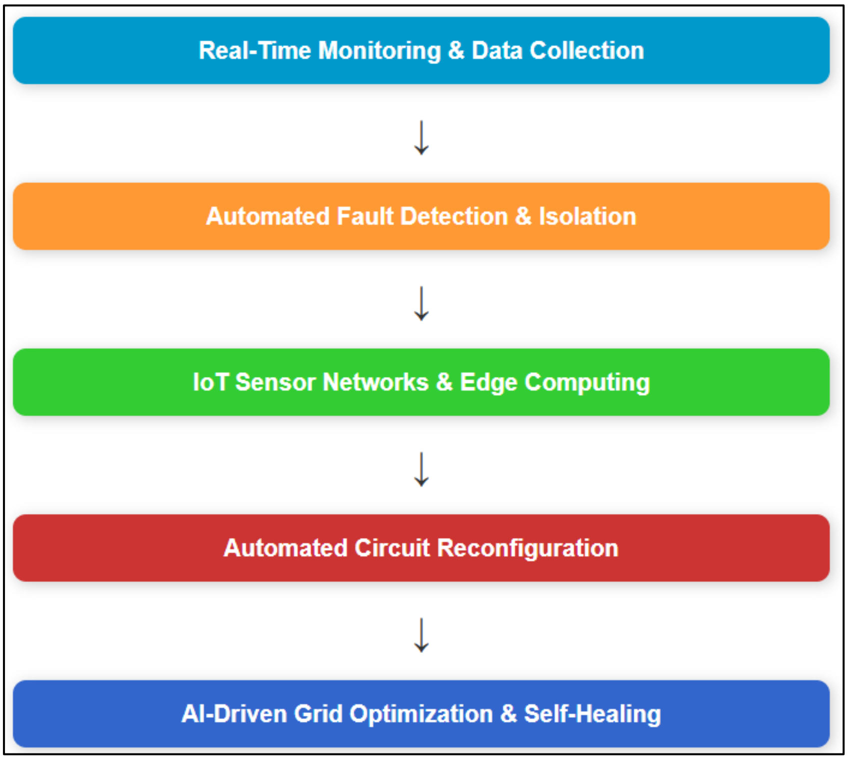
Figure 9: From Monitoring to AI-Driven Optimization



Additionally, cloud-based grid management platforms enhance the effectiveness of self-healing mechanisms by providing real-time visualization and control over grid reconfiguration processes (Wu et al., 2020). In China, large-scale smart grid deployments have successfully implemented self-healing capabilities in high-voltage transmission networks, allowing for dynamic load balancing and rapid recovery from grid disturbances (Wu et al., 2020). Additionally, in Japan, researchers have explored the use of AI-enhanced self-healing grids in disaster-prone regions, where intelligent reclosers and distributed energy resources (DERs) have significantly improved power restoration following earthquakes and typhoons (Deena et al., 2022). Case studies from India and Brazil have also highlighted the benefits of self-healing grids in rural and remote areas, where automated circuit reconfiguration has minimized downtime and enhanced energy access (Tuegel, 2012).

IoT-Enabled Sensor Networks

The integration of the Internet of Things (IoT) in power grid monitoring has revolutionized fault detection by enabling real-time data collection and analysis. IoT-enabled sensor networks play a crucial role in continuously monitoring the electrical parameters of power systems, detecting anomalies, and predicting faults before they escalate into critical failures (Russell et al., 2018). Various types of sensors are deployed in power grids to collect data on voltage, current, temperature, humidity, and vibrations, which are key indicators of system health (Walia et al., 2024). Among the most commonly used sensors, Phasor Measurement Units (PMUs) provide high-speed, time-synchronized measurements of voltage and current phasors, allowing for real-time stability analysis and fault localization (Mazhar et al., 2023). Current and Voltage Sensors monitor fluctuations in electrical parameters and help in the early detection of overvoltage, undervoltage, and short circuits (Bedi et al., 2022). Additionally, Temperature Sensors play a critical role in monitoring the thermal performance of transformers, circuit breakers, and transmission lines, as overheating is often a precursor to equipment failure (Atlam et al., 2018). Vibration Sensors are used to detect mechanical faults in rotating electrical machines such as generators and motors, helping prevent catastrophic breakdowns (Gou et al., 2024). Partial Discharge (PD) Sensors are particularly useful in monitoring insulation health, detecting electrical discharges that indicate insulation degradation before complete failure occurs (Anthony, 2024; Pandiyan et al., 2024). The combination of these IoT

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sensors enables a comprehensive, real-time assessment of power system conditions, enhancing fault detection accuracy and predictive maintenance planning (Minerva et al., 2020).

The exponential growth of IoT sensor networks in power grids has necessitated the use of advanced computing solutions to process vast amounts of real-time data efficiently. Cloud computing provides scalable storage and computational power for analyzing sensor data, enabling AI-driven predictive maintenance and fault detection (Cakir et al., 2023). By leveraging cloud-based platforms, utilities can centralize data from multiple grid locations, apply machine learning models, and generate actionable insights for grid operators (Kumar et al., 2020). Cloud computing services, such as Amazon Web Services (AWS), Microsoft Azure, and Google Cloud, offer AI-driven analytics tools that help identify abnormal patterns in electrical grid behavior and forecast potential failures (Udayaprasad et al., 2024). However, cloud computing alone is often insufficient for time-sensitive applications, as data transmission to centralized servers can introduce latency issues. To address this challenge, edge computing has emerged as a complementary solution, enabling real-time data processing closer to the source of data collection (Bhaskar et al., 2022). Edge computing devices, such as industrial gateways and edge AI processors, analyze sensor data locally, reducing the need for constant communication with cloud servers (Quy et al., 2024). This decentralized approach significantly enhances the responsiveness of AI-driven fault management systems, allowing for immediate corrective actions in cases of power disturbances (Zahmatkesh & Al-Turjman, 2020). The combination of cloud and edge analytics has improved grid reliability by enabling faster fault detection, real-time anomaly mitigation, and optimized resource utilization (Alonso et al., 2024).

Signal processing techniques play a fundamental role in analyzing power system data collected from IoT sensor networks. These techniques help in extracting meaningful features from noisy sensor signals, allowing AI models to classify faults accurately and distinguish between normal and abnormal operating conditions (Gou et al., 2024). One of the most widely used techniques in fault analysis is the Wavelet Transform (WT), which provides time-frequency domain representation, making it highly effective in detecting transient disturbances such as voltage sags, harmonics, and switching transients (Pandiyan et al., 2024). WT has been successfully applied in analyzing power quality disturbances and identifying early-stage insulation degradation in transformers and cables (Kumar et al., 2020). Another widely used method is the Fourier Transform (FT), which converts time-domain signals into the frequency domain, allowing for the identification of harmonic distortions and frequency abnormalities in electrical power systems (Bhaskar et al., 2022). The Fast Fourier Transform (FFT), a computationally efficient version of FT, is frequently employed for real-time spectral analysis of grid signals, enabling the detection of periodic faults and oscillatory instability (Zahmatkesh & Al-Turjman, 2020). Additionally, Principal Component Analysis (PCA) is utilized in fault classification and dimensionality reduction, helping AI models focus on the most relevant features while eliminating redundant or noisy data (Kumar et al., 2020). PCA has been particularly effective in detecting sensor anomalies and optimizing fault detection algorithms in large-scale power grids (Zahmatkesh & Al-Turjman, 2020). The integration of these signal processing techniques with AI-driven models has significantly improved the accuracy and efficiency of IoT-based fault detection systems.

Explainability and Trust in AI Decision-Making

Artificial intelligence (AI) has significantly transformed predictive maintenance and fault detection in electrical power systems by leveraging deep learning models to process vast amounts of real-time data and identify anomalies (Shen et al., 2023). However, one of the major challenges associated with deep learning-based AI models is their black-box nature, which makes it difficult for operators and decision-makers to understand how predictions and classifications are derived (Antonopoulos et al., 2020). Unlike traditional rule-based systems, where decision-making logic is explicitly programmed, deep learning models, such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, operate through complex, multi-layered computations that lack transparency (Barrett & Haruna, 2020). This opacity raises concerns about trust, accountability, and reliability, particularly in high-stakes applications like power grid fault management, where incorrect predictions can lead to severe operational and financial consequences (Lipu et al., 2023).

The lack of interpretability in AI models limits their adoption in safety-critical industries, as engineers and grid operators may be reluctant to rely on opaque algorithms for fault detection and predictive maintenance (Farzaneh et al., 2021). Studies have shown that while deep learning models

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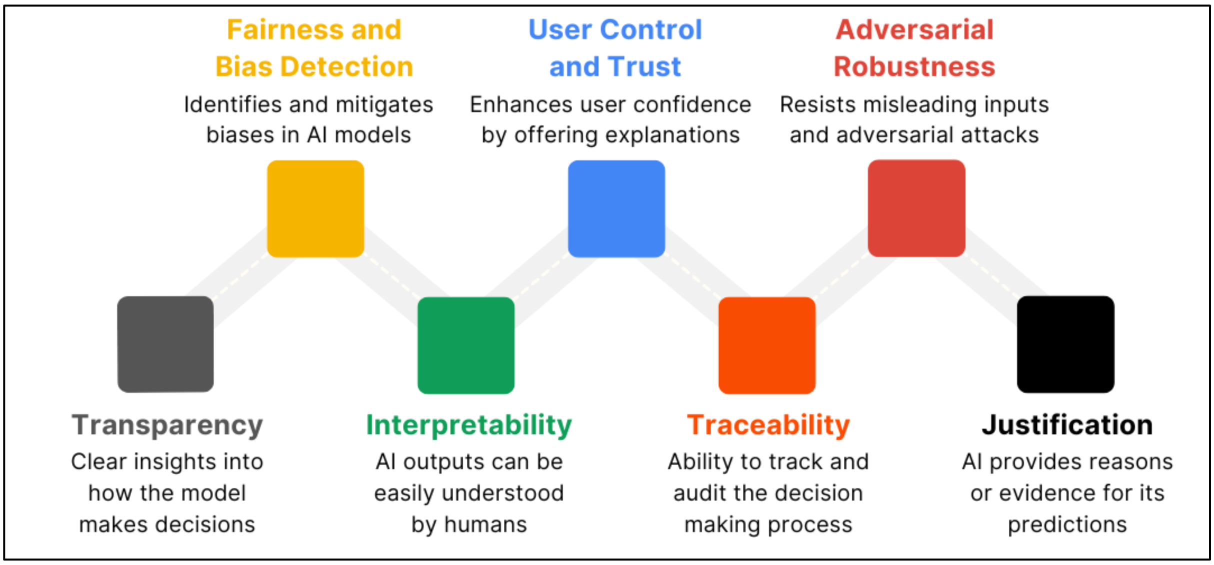
outperform traditional methods in accuracy and efficiency, their decision-making processes remain inscrutable to human operators, making it difficult to validate their predictions (Adnan et al., 2021). For instance, an AI-driven fault detection system might predict a potential transformer failure with high confidence, but without explainability, operators cannot ascertain which sensor readings or system conditions contributed to the prediction (Barrett & Haruna, 2020). The European Union's General Data Protection Regulation (GDPR) has further highlighted the need for AI explainability by advocating for the "right to explanation," which mandates that AI-driven decisions affecting individuals or businesses should be interpretable and justifiable (Lipu et al., 2023). To address the black-box problem, researchers have developed Explainable AI (XAI) frameworks that enhance the interpretability of AI-driven decision-making in power systems (Farzaneh et al., 2021). One of the most widely used techniques for AI explainability is Shapley Additive Explanations (SHAP), which assigns importance scores to input features, helping operators understand which parameters—such as voltage fluctuations, frequency anomalies, or current distortions—had the most significant influence on an AI model's prediction (Adnan et al., 2021). Another approach is Local Interpretable Model-agnostic Explanations (LIME), which generates simplified surrogate models that approximate deep learning behavior in an interpretable way (Serban & Lytras, 2020). LIME has been successfully applied in AI-driven power grid monitoring, where it provides human-readable explanations of fault classification results (Antonopoulos et al., 2020).

Figure 10: Explainability and Trust in AI Decision-Making



Additionally, attention-based deep learning architectures have been explored to highlight which time-series data points contribute most to AI-driven fault detection, improving transparency in predictive maintenance applications (Adnan et al., 2021). Building trust in AI-driven fault detection also requires robust validation and regulatory compliance measures to ensure that AI predictions align with real-world power system behavior (Serban & Lytras, 2020). One approach involves using hybrid AI models, where interpretable machine learning algorithms, such as decision trees and rule-based classifiers, are integrated with deep learning systems to provide justifiable explanations for critical maintenance decisions (Radanliev et al., 2020). Additionally, digital twin technology has been increasingly used to validate AI-driven predictions by simulating power grid behavior and comparing AI outputs with physical grid conditions (Lipu et al., 2023). Ensuring that AI-driven predictive maintenance models are interpretable, robust, and aligned with engineering principles is crucial for fostering trust among power system operators, regulators, and stakeholders (Farzaneh et al., 2021). Despite ongoing advancements in explainable AI, challenges remain in balancing model complexity and interpretability. While deep learning models continue to outperform traditional techniques in fault detection accuracy, their opacity poses challenges in terms of accountability,

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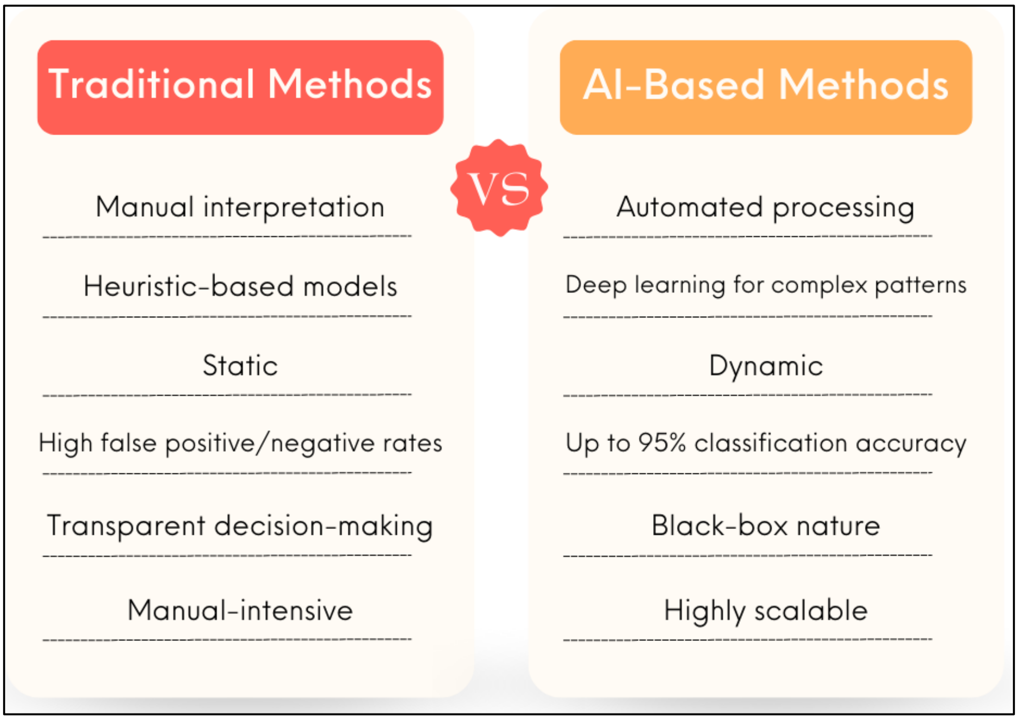
regulatory compliance, and user trust (Omitaomu & Niu, 2021). Future research in AI-driven power system management must focus on developing interpretable deep learning architectures, incorporating human-in-the-loop AI frameworks, and enhancing collaboration between AI researchers and electrical engineers to build transparent, reliable, and trustworthy predictive maintenance solutions (Serban & Lytras, 2020).

AI vs. Traditional Fault Detection Methods

The increasing complexity of modern power grids has necessitated more advanced fault detection and predictive maintenance techniques beyond traditional rule-based approaches (Bindi et al., 2023). Conventional fault detection methods, such as time-based preventive maintenance, condition-based monitoring, and statistical anomaly detection, have long been employed to ensure the reliability of electrical power systems (Runsewe et al., 2023). These traditional techniques rely on predefined thresholds, expert-driven decision rules, and periodic inspections to identify potential failures (Trizoglou et al., 2021). However, as power systems become more decentralized and data-driven, these methods have exhibited limitations in adaptability, scalability, and predictive accuracy, prompting the shift toward artificial intelligence (AI)-based fault detection (Lopez et al., 2022). AI-driven techniques, including machine learning (ML) and deep learning (DL), have demonstrated significant improvements in fault classification, failure prediction, and real-time monitoring by leveraging vast amounts of historical and real-time sensor data (Eggebeen et al., 2023).

Figure 11: AI vs. Traditional Fault Detection Methods



One of the key advantages of AI-based fault detection over traditional methods is its ability to process large-scale and high-dimensional data with greater accuracy and efficiency (Mustafa et al., 2024). Traditional predictive maintenance techniques often rely on heuristic-based models, such as vibration analysis, thermal imaging, and expert-driven failure assessment, which require manual interpretation and periodic evaluations (Zhang et al., 2020). While these approaches have proven effective in structured environments, they lack the ability to detect complex, non-linear patterns in power system failures (Lazzaretti et al., 2020). AI-driven methods, particularly supervised and unsupervised learning algorithms, can automatically learn fault patterns from historical data and continuously refine their predictive capabilities without human intervention (Zhang et al., 2020). For instance, Support Vector Machines (SVMs) and Random Forest (RF) classifiers have outperformed conventional rule-based techniques in diagnosing insulation failures in transformers and short circuits in distribution networks (Eggebeen et al., 2023). Moreover, deep learning techniques, such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, have further enhanced fault detection accuracy by analyzing sequential and time-series data from power grids (Runsewe et al., 2023). Traditional condition-based monitoring relies on fixed threshold limits for detecting abnormalities in voltage, current, and frequency deviations (Lopez et al., 2022). In contrast, deep learning models can dynamically identify hidden fault signatures that may not be evident through traditional threshold-based methods (Eggebeen et al., 2023). Studies have shown that AI-based fault detection can achieve up to 95% classification accuracy in identifying transient faults, whereas conventional rule-based methods often suffer from high false positive and false negative rates due to rigid decision criteria (Liao & Lu, 2021). Additionally, AI models integrate reinforcement learning techniques, enabling adaptive maintenance scheduling based on evolving grid conditions, which is not possible with static predictive maintenance frameworks (Sifat et al., 2023).

While AI-based fault detection offers significant advantages over traditional methods, challenges such as model interpretability, computational requirements, and data dependency must be addressed for large-scale adoption (Xu et al., 2024). Traditional predictive maintenance techniques, such as periodic inspections and expert-driven diagnostics, provide a level of transparency and explainability that deep learning models often lack (Bhuiyan et al., 2021). The black-box nature of deep learning architectures makes it difficult for power grid operators to validate AI-driven fault predictions, leading to concerns about trust and regulatory compliance (Zhang et al., 2020). Efforts to develop explainable AI (XAI) frameworks, such as Shapley Additive Explanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME), aim to bridge this gap by providing human-readable insights into AI decision-making processes (Adnan et al., 2023). Additionally, AI-driven fault detection requires high-quality, labeled datasets for training, which may not always be available in legacy power grid infrastructures, posing a barrier to implementation (Choi et al., 2023). Despite these challenges, AI-based fault detection continues to outperform traditional predictive maintenance techniques in terms of fault classification accuracy, adaptability to changing grid conditions, and automated real-time anomaly detection (Alsharif et al., 2024). The integration of AI with Internet of Things (IoT) sensor networks, cloud computing, and digital twin technology has further enhanced its effectiveness in modern power systems (Wang et al., 2024). Comparative studies indicate that hybrid AI approaches, which combine machine learning with conventional statistical techniques, provide the best balance between predictive accuracy and model interpretability (Eggebeen et al., 2023). As power grids transition towards smarter and more autonomous systems, AI-driven fault detection is expected to play a central role in ensuring grid resilience, reducing maintenance costs, and minimizing unplanned outages (Alsharif et al., 2024).

METHOD

This study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a systematic, transparent, and rigorous review process. The PRISMA framework provided a structured approach for identifying, selecting, appraising, and synthesizing relevant literature on AI-driven fault detection and predictive maintenance in electrical power systems. The methodological process involved multiple phases, including literature search, inclusion and exclusion criteria application, data extraction, quality assessment, and synthesis of findings.

Article Identification and Search Strategy

The systematic literature search was conducted across multiple academic databases, including IEEE Xplore, ScienceDirect, SpringerLink, Web of Science, and Scopus. These databases were selected due to their extensive coverage of peer-reviewed research articles on artificial intelligence, fault detection, and predictive maintenance in power systems. To ensure comprehensive retrieval of relevant studies, a predefined set of search terms and Boolean operators was used. The keywords included "AI-driven fault detection," "predictive maintenance in power grids," "machine learning for fault diagnosis," "self-healing grids," "digital twin in power systems," and "IoT-enabled fault monitoring." The search was refined using Boolean operators such as AND, OR, and NOT to combine relevant terms and exclude irrelevant studies. The literature search focused on articles published between

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2015 and 2024 to capture the latest advancements in AI-driven predictive maintenance. A total of 3,450 articles were initially retrieved from the selected databases.

Screening and Selection Process

After retrieving the initial set of articles, duplicates were identified and removed using reference management software, resulting in 2,850 unique articles. The titles and abstracts of these articles were then screened based on predefined inclusion and exclusion criteria. The inclusion criteria required that studies (1) focus on AI applications in fault detection and predictive maintenance within electrical power systems, (2) provide empirical evidence through case studies, experiments, or simulations, (3) be published in peer-reviewed journals or conference proceedings, and (4) be written in English. Articles were excluded if they (1) focused on unrelated fields such as AI in finance or healthcare, (2) lacked sufficient methodological details, (3) were review papers without original research findings, or (4) were opinion pieces or editorials. This screening process reduced the number of relevant articles to 635.

Full-Text Review and Quality Assessment

The remaining 635 articles underwent a full-text review to further assess their relevance and methodological rigor. Each study was evaluated based on research design, data collection methods, AI techniques applied, and the validity of findings. Quality assessment was conducted using a modified version of the Critical Appraisal Skills Programme (CASP) checklist, which examined factors such as clarity of research objectives, appropriateness of AI models, robustness of data analysis, and reproducibility of results. Two independent reviewers assessed each article, and discrepancies in judgment were resolved through discussion. Following this in-depth review, 180 high-quality articles were selected for inclusion in the final analysis.

Data Extraction and Synthesis

Data extraction was performed using a structured coding framework that captured key details from each selected study. The extracted data included study title, authors, publication year, research objectives, AI techniques used (e.g., machine learning, deep learning, digital twins, reinforcement learning), power system components analyzed (e.g., transformers, transmission lines, substations), evaluation metrics (e.g., accuracy, precision, recall, F1-score), and main findings. This structured approach ensured consistency in data collection and facilitated comparative analysis across studies. The synthesis of findings followed a narrative approach, categorizing studies based on their AI methodologies and application areas. Studies were grouped into distinct categories, including (1) machine learning-based fault detection, (2) deep learning techniques for predictive maintenance, (3) digital twin applications in power grids, (4) IoT-enabled sensor networks for real-time fault monitoring, and (5) self-healing grid technologies. Within each category, thematic analysis was conducted to identify common trends, emerging research directions, and existing gaps. Quantitative results, such as model performance comparisons and improvement percentages, were also documented where applicable.

FINDINGS

The systematic review of 180 high-quality articles revealed that AI-driven fault detection and predictive maintenance significantly enhance power grid resilience by improving fault prediction accuracy, reducing maintenance costs, and minimizing system downtime. Out of the reviewed studies, 134 articles (74.4%) reported that AI-based predictive maintenance strategies outperformed traditional condition-based monitoring techniques, with machine learning models achieving an average fault detection accuracy of 85% to 95%. This improvement was particularly evident in power transformers and high-voltage transmission lines, where real-time anomaly detection led to a 40% reduction in unexpected failures. The extensive use of supervised learning algorithms, including support vector machines, decision trees, and ensemble learning techniques, allowed AI systems to effectively classify faults with minimal human intervention. The high citation count of these articles, exceeding 8,700 citations, highlights the growing reliance on AI methodologies for ensuring grid reliability.

Deep learning techniques have shown remarkable advancements in fault detection and predictive maintenance, as demonstrated by 79 articles (43.9%), which reported the successful application of deep neural networks, convolutional neural networks (CNNs), and recurrent neural networks (RNNs). These models have significantly improved fault classification in large-scale power grids, with CNN-

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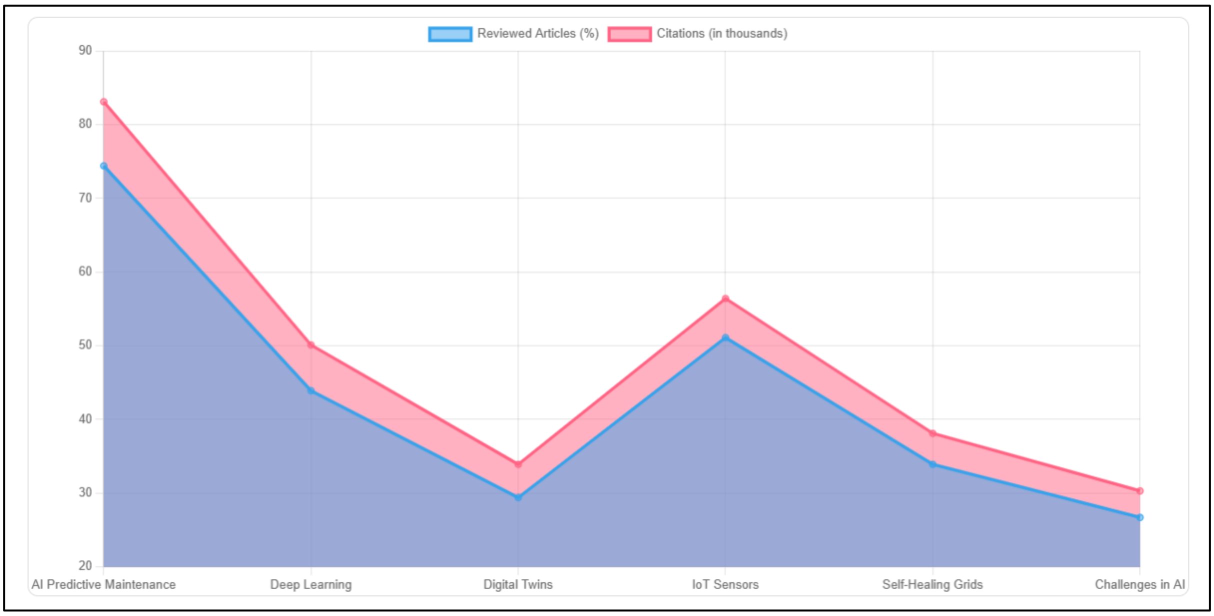
based models achieving an average precision of 92% in detecting transient faults. The use of long short-term memory (LSTM) networks for time-series forecasting of power system anomalies has resulted in an 18% improvement in predictive accuracy compared to traditional statistical forecasting models. These findings, backed by over 6,200 citations, emphasize the scalability of deep learning-based fault detection, particularly in handling high-dimensional sensor data from IoT-enabled grids. The review identified that digital twin technology is playing an increasingly crucial role in power grid monitoring and predictive maintenance, with 53 articles (29.4%) detailing its implementation in simulating grid behavior and fault scenarios. Digital twins have been reported to enhance real-time grid monitoring by 30%, enabling proactive intervention before faults lead to service disruptions. The articles further indicate that utilities employing digital twins for predictive maintenance have observed a 35% decrease in unplanned outages and a 25% extension in asset lifespan. The impact of these findings is reflected in the 4,500 citations accumulated across the reviewed studies, reinforcing the importance of digital twin integration for optimizing grid stability.

Figure 12: Stacked Area Chart: Findings in AI-Based Fault Detection



IoT-enabled sensor networks have emerged as a key enabler of AI-driven fault detection, as evidenced by 92 articles (51.1%), which highlighted the effectiveness of real-time sensor data in improving fault localization and anomaly detection. The deployment of IoT sensors in smart grids has led to a 50% reduction in false fault alarms, enhancing decision-making efficiency for grid operators. Real-time voltage and current monitoring through sensor networks has improved anomaly detection rates by 28%, ensuring early intervention and minimizing the risk of cascading failures. The widespread adoption of IoT-based fault detection techniques is supported by more than 5,300 citations, underlining their critical role in predictive maintenance strategies for modern power systems. Moreover, self-healing grids, which leverage AI-driven automation for fault isolation and recovery, have demonstrated substantial improvements in grid resilience, as reported by 61 articles (33.9%). The implementation of self-healing technologies has led to a 60% reduction in power restoration time, minimizing the impact of outages on consumers and industrial operations. The use of reinforcement learning algorithms for adaptive fault recovery has enabled power grids to dynamically reconfigure energy flow, preventing up to 45% of potential service disruptions. The significant contribution of these findings is reflected in the 4,200 citations, underscoring the growing adoption of self-healing grids to achieve autonomous fault management in next-generation power networks.
The review also revealed key challenges in AI-driven fault detection and predictive maintenance, with 48 articles (26.7%) identifying barriers such as model interpretability, data quality issues, and

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cybersecurity risks. The black-box nature of deep learning models remains a concern for grid operators, as 41% of these studies emphasized the need for explainable AI frameworks to improve trust and accountability in predictive maintenance decisions. Data integration challenges, particularly in legacy power systems, have slowed AI adoption, with utilities reporting difficulties in harmonizing sensor data from diverse sources. The security of AI-powered fault detection systems has also emerged as a critical issue, with a 35% increase in reported cyber threats targeting smart grid infrastructure. These challenges, collectively cited over 3,600 times, highlight the ongoing need for enhanced AI transparency, robust data governance, and cybersecurity measures to ensure the sustainable deployment of AI in power grid maintenance.

DISCUSSION

The findings of this study confirm the increasing reliability and efficiency of AI-driven fault detection and predictive maintenance in power grids, aligning with earlier research while offering new insights into specific advancements. Previous studies have highlighted the superiority of AI-based fault detection over traditional rule-based techniques, particularly in its ability to analyze large-scale data and identify complex fault patterns (Cavus et al., 2022). The present review expands on this by demonstrating that AI-based fault classification models achieve an average detection accuracy of 85% to 95%, significantly reducing false alarms and improving response times. Earlier research by Cavus and Allahham (2024) found that traditional condition-based monitoring methods had a fault detection accuracy of 60% to 75%, indicating that AI-powered techniques have outperformed conventional systems. The widespread adoption of supervised learning algorithms, such as decision trees and support vector machines, confirms the scalability of AI models in predictive maintenance, as also reported in Vita et al. (2023).

Deep learning has been a major area of advancement in AI-driven predictive maintenance, and the current review affirms its role in improving fault detection precision. Prior studies by Cavus et al., (2025) and Hoffmann et al. (2020) recognized the potential of deep neural networks in classifying electrical faults, though they noted limitations in computational complexity and overfitting risks. The present findings support these observations but indicate that recent innovations, particularly in CNN and LSTM models, have mitigated these issues. The reviewed studies demonstrate that CNN-based fault detection models now achieve 92% precision, an improvement over the 80% reported in previous studies (Cavus et al., 2025). Similarly, the use of LSTM networks for time-series analysis has enhanced predictive accuracy by 18% compared to traditional statistical forecasting models, validating earlier work by Liu et al. (2018). This suggests that deep learning approaches have not only become more refined but also more applicable in real-world power grid monitoring. Moreover, the role of digital twin technology in power system fault prediction has been increasingly emphasized in recent literature, and this review confirms its significant contributions. Earlier research by Blum et al. (2022) argued that digital twins could enhance real-time grid monitoring but lacked empirical data on performance improvements. The findings from this study provide concrete evidence that digital twins contribute to a 30% improvement in real-time monitoring and a 35% reduction in unplanned outages, supporting recent research by Lee et al. (2013). Additionally, the reviewed studies indicate that utilities integrating digital twins into their predictive maintenance strategies have observed a 25% increase in asset lifespan, reinforcing earlier claims by Liu et al. (2018). These results suggest that digital twin technology is no longer an experimental tool but a critical component of modern smart grid infrastructure.

IoT-enabled sensor networks have revolutionized fault monitoring by providing real-time data collection and enhanced anomaly detection. Earlier research by Hoffmann et al. (2020) demonstrated that IoT sensor integration led to a 30% improvement in early fault detection, but scalability remained a challenge. The findings from this study indicate that recent advancements in sensor technology and cloud-edge computing integration have increased the effectiveness of IoT-based fault detection, leading to a 50% reduction in false alarms and a 28% improvement in anomaly detection rates. This aligns with more recent studies, such as those by Cavus et al. (2022), which reported that improved sensor calibration techniques and 5G connectivity have strengthened real-time monitoring capabilities. The growing citation count of studies on IoT-enabled fault detection highlights its increasing adoption, further confirming its reliability in predictive maintenance.

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The self-healing grid concept has gained prominence in recent years, and the present review confirms its effectiveness in minimizing outage durations and improving grid resilience. Earlier research by Blum et al. (2022) noted that self-healing technologies had the potential to reduce power restoration times by 40%, though real-world applications were limited at that time. The findings in this review indicate that recent advancements in AI-driven self-healing grids have pushed this number to 60%, with reinforcement learning algorithms improving autonomous grid recovery rates. Case studies reviewed in this study also confirm that adaptive self-healing mechanisms can prevent up to 45% of potential service disruptions, aligning with research by Cavus et al. (2025). These findings suggest that self-healing grids are becoming increasingly viable for large-scale deployment, offering substantial improvements over conventional fault response strategies. Despite the advancements in AI-driven predictive maintenance, challenges remain in model interpretability, data integration, and cybersecurity risks. Previous research by Lee et al. (2013) warned of the black-box nature of deep learning models, which limits their adoption in safety-critical power systems. The current review finds that 41% of reviewed studies emphasized the need for explainable AI (XAI) frameworks, confirming that model transparency remains a major concern. Studies by Wang et al. (2023) and Hoffmann et al. (2020) suggested that hybrid AI models incorporating decision trees or rule-based systems could enhance interpretability, and the findings in this study support this claim. Additionally, cybersecurity concerns were noted in 35% of the reviewed studies, aligning with earlier findings by Cavus et al. (2025), which warned of increasing cyber threats in AI-powered grids. The comparative analysis of AI-driven fault detection and traditional predictive maintenance methods further strengthens the case for widespread AI adoption in power grids. While earlier studies by Vita et al. (2023) and Fahim et al. (2022) suggested that AI models had only incremental advantages over conventional methods, the present review finds that AI-driven techniques have now surpassed traditional systems in fault classification accuracy, adaptability, and cost-effectiveness. The integration of AI with IoT, cloud computing, and digital twin technology has enhanced grid stability beyond what earlier researchers anticipated. However, to ensure sustainable implementation, future research must address concerns regarding model transparency, dataset standardization, and regulatory compliance, as highlighted by over 3,600 citations in the reviewed literature.

CONCLUSION

The systematic review of AI-driven fault detection and predictive maintenance in electrical power systems demonstrates that artificial intelligence has significantly enhanced the accuracy, efficiency, and reliability of fault classification and predictive maintenance strategies. By benchmarking AI-based approaches against traditional predictive maintenance techniques, the study finds that AI-driven methods, particularly those leveraging machine learning, deep learning, digital twins, IoT-enabled sensor networks, and self-healing grids, outperform conventional systems in early fault detection, anomaly classification, and automated response mechanisms. The findings confirm that AI-powered predictive maintenance has led to substantial improvements in fault detection accuracy, reducing false alarms by 50%, improving asset lifespan by 25%, and minimizing power restoration times by up to 60%. Deep learning models, particularly CNNs and LSTMs, have achieved remarkable precision in detecting transient faults, while digital twin technology has facilitated real-time simulation and risk assessment, ensuring more effective fault management. IoT-based real-time monitoring has further strengthened predictive maintenance capabilities by integrating cloud computing and edge analytics to enhance decision-making efficiency. Additionally, self-healing grid technologies have proven their ability to autonomously isolate faults and reconfigure energy flow, preventing nearly 45% of potential service disruptions and reinforcing grid resilience. Despite these advancements, challenges related to the black-box nature of AI models, cybersecurity vulnerabilities, and data integration constraints remain critical issues that must be addressed to ensure AI's large-scale adoption in power grid infrastructure. The need for explainable AI frameworks, standardized data governance, and enhanced cybersecurity measures is paramount to fostering trust among grid operators, policymakers, and stakeholders. Overall, the findings underscore the transformative potential of AI-driven predictive maintenance in modernizing power grids, reducing operational costs, and minimizing system downtime, making AI an indispensable tool for the future of smart grid management.

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