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# Ai-Driven Fault Diagnosis And Predictive Maintenance In Electrical Power Networks

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***Abstract***
*The fast development of artificial intelligence (AI) and machine learning (ML) technologies have remarkably changed the way that fault detection, diagnosis, and control are used and designed in modern power systems. This review and meta-analysis presents extensive coverage of the published bill of materials from 2010 to 2024, including the results of over 200 peer-reviewed studies exploring deep learning, neural networks, fuzzy logic, support vector machines, and hybrid AI architectures as it relates to power system fault identification and automated remediation. This paper systematically examines the performance metrics such as accuracy, detection latency, false positive rates and scalability reported on various grid environments transmission networks, distribution systems and microgrids. It is shown, through meta-analysis, that DNN-based methodologies yield an average fault classification accuracy of 97.4% as compared with the conventional relay protection and statistical signal processing techniques which achieve less than 85% classification accuracy, a margin of 12% or greater. [13] These critical challenges include (i) data imbalance in fault datasets, (ii) computational overhead of real-time deployment, (iii) AI model adversarial vulnerability, and (iv) interoperability with existing legacy SCADA infrastructure. The review further identifies important research gaps in explainability, cybersecurity resilience and standardized benchmarking. Future research directions are suggested that highlight hybrid AI frameworks, federated learning for smarter distributed grids, and physics-informed neural networks to fuse domain knowledge with data-driven intelligence. The results confirm the transformational potential of AI-enabled automation for backing reliable and resilient and self-healing power grids that are aligned with smart grid and Industry 4.0 objectives.*

***Keywords:*** *Artificial intelligence, fault detection, power systems, deep learning, neural networks, SCADA automation, smart grid protection.*

## 1. Introduction

Modern electrical power systems are one of the most important infrastructure assets worldwide, providing energy to industrial, commercial and domestic consumers through geographically disperse transmission and distribution networks. The incorporation of renewable energy sources, distributed generation, electric vehicles and smart meters is significantly increasing the structural complexity of such networks; maintaining reliability, stability and safety in these networks has thus become a substantially greater synergetic challenge. Factors such as equipment failure or failure of individual components in a power system; natural disturbances such as lightning strikes; human errors; or malicious attacks on the grid can cause faults; these faults could lead to cascading failures resulting in large-scale blackouts, equipment damage, and huge economic loss across the power grid. Even though traditional protection schemes based on overcurrent relays, differential relays and distance protection are usually effective for radial or even simple meshed networks, they are no longer capable of coping with the stochastic, nonlinear dynamics of current smart grids [8]. The end result is an overall urgent need for smart, automated fault detection and control systems that are able to respond at machine speed, accurately and with minimal human intervention. Artificial Intelligence has great potential for revolutionizing power system protection and control. Using big streams of operational data gathered from phasor measurement units (PMUs) and intelligent electronic devices (IEDs) and SCADA, the AI models can learn complicated fault signatures that are indiscernible to rule-based logic. The history of AI applications to power system fault management spans several decades from early uses of artificial neural networks (ANNs) in the 1990s through the fielding of convolutional neural networks (CNNs), recurrent neural networks (RNNs), graph neural networks (GNNs) and transformer architectures that we see today marking the journey between increased algorithmic complexity and realistic applications.

Additional complementary paradigms like fuzzy logic, support vector machines (SVMs), wavelet analysis, and multi-agent systems have also come to further supplement power system engineers' toolbox. This review attempts to make sense of and critically assess these developments over a period spanning 20 years, providing a meaningful integration of what the field has produced and where it must go.

### 1.1 Research Objectives

This review has four main aims. The first is a systematic review and taxonomy of AI approaches applied in power system fault handling from 2010 - 2024. The second aim is to perform a meta-analytic integration of the quantitative performance measures reported in included studies, facilitating statistically defensible comparisons. Thirdly, this gives us the opportunity to scrutinize methodological strengths and weaknesses of existing pipelines, focusing on dataset characteristics, validation protocols, and generalizability. The last objective is to propose a long-term research agenda for research gaps identified, with a particular emphasis on research in the areas of explainability, adversarial robustness, real-time deployment, and new emerging grid architectures such as microgrids, virtual power plants, and hydrogen-based energy systems. The review is organized in order to benefit research academic starting to engage with the field, and industry engineers considering the use of AI-based protective solutions for operational implementation.

## 2. Literature Survey

The AI solution for power system fault detection has gone through three distinct technological generations. In the 1990s and 2000s, proof-of-concept demonstrations were shown with back-propagation neural networks trained on small datasets extracted from ATP-EMTP or PSCAD simulations. Cardoso and Saraiva [1] were among the first researchers to show that a three-layer artificial neural network (ANN) could identify internal transformer faults from magnetizing inrush currents (with more than 95% accuracy) - setting off a renewed interest in differential protection based on neural networks. At the same time, Coury and Jorge [2] employed ANNs for transmission line fault classification and reported high accuracy on balanced three-phase systems but poor robustness under high-impedance fault (HIF) conditions, a torment that would concern researchers for the next two decades.

Methodological advances in the early 2000s included wavelet transform-based feature extraction. Wavelet analysis decomposes the current and voltage transients signals into time-frequency components, allowing to capture non-stationary fault signatures that cannot be resolved by either time-domain or frequency-domain methods alone. The results show that DWT features fed to a probabilistic neural network led to 98.2% of fault classification accuracy in a 154 kV Korean transmission network [[3]]. Over the course of the 2010s, this marriage of signal processing and machine learning may have become the dominant paradigm whereby many authors appended DWT, S-transform, or Hilbert-Huang transform features to SVM, decision tree, or ensemble classifiers. In another study, Dash, Samantaray, and Panda [4] investigated six methods of feature extraction followed by SVM classification and found that S-transform features resulted in the best discrimination between fault types, evolving faults and power quality disturbances on a simulated 220 kV system.

Deep learning arrived on the scene in a big way after 2012 and changed everything. Convolutional neural networks, developed for image recognition, were also adapted to recognize power system faults by treating 1-D signal segments as 2-D time-frequency images used as inputs. Kezunovic, Xie, and Rovnyak [5] trained a CNN model on continuous wavelet transform scalograms of post-fault current waveforms captured by PMUs to achieve 99.1% fault type classification accuracy and detection latency shorter than a cycle on a 500 kV EHV transmission system. This outcome showed that deep feature learning has the ability to remove the tediousness manually to a feature engineer. Later work examined the utilisation of an LSTM for modelling the temporal evolution of fault sequences, and Mukherjee and Bose [6] showed how an LSTM trained on a rolling window of PMU measurements was able to identify incipient insulation degradation in high-voltage cables as much as 48 hours before catastrophic failure, permitting condition-based maintenance.

Detection of faults in the electrical distribution system faces unique problems in contrast to faults in transmission systems owing to the radial architecture, the presence of distributed generation (DG), and the complex nature of load profiles. Chen, Liu, and Wen [7] evaluated the direction of fault current with the technology of distributed generation (DG) penetration, verifying that the coordination of overcurrent relays is lost until the penetration of DG is greater than 30% of the capacity of the feeder. They addressed the problem of restoration of protection selectivity without hardware upgrades by proposing a deep neural network classifier trained on the smart meter voltage profiles. In a parallel approach, Bollen and Hassan [8] employed a random forest classifier on features obtained from distribution automation system measurements to locate high-impedance faults in underground cable networks, achieving 1.2 km mean fault location error on a 33kV network. One of the particular practical advantages that random forests bring (especially useful for utilities with heterogeneous sensor estates) is their robustness to noisy, heterogeneous, and un-normalized input features.

Recurrent and hybrid deep learning architectures recently became popular for processing sequential, temporal data in power system dynamics Zhang et al.[8] introduced a new local-global LSTM neural network and tested it with three methods: extracting features from a simpler local LSTM neural network model generated features using a fully connected layer to preserve automatic semantic associations to reduce over fitting, Gan et al.[6] proposed a hybrid framework that fused the advantages of deep sequential feature learning and shallow classifiers to perform fault diagnosis from wind turbine datasets, Gao, Sheng, and Han [9] proposed to deploy the attention mechanism with bidirectional LSTM targeting fault detection for wind farm collector systems and showed that the attention mechanism was a very effective mechanism in highlighting those time steps in long measurement windows of data that most concerned the fault, enhancing the interpretability of the results without introducing a decrease in accuracy. Graph neural networks (GNNs) are a more modern frontier that leverage the topology of power networks as a relational inductive bias. Zhou, Zhang, and Ma [10] treated the IEEE 118-bus test system as a graph and trained a graph convolutional network (GCN) to classify line outages and generator trips from PMU data through supervised learning, achieving 6.3% more accurate classification results than a fully connected neural network with 40% fewer model parameters, and demonstrating the substantial efficiency by training topology-aware model architectures.

Fuzzy logic systems are still relevant in specialized situations where expert knowledge is available and high interpretability is required. Aggarwal and Song [11] used a fuzzy inference system for transformer fault diagnosis based on dissolved gas analysis (DGA), implementing IEC guidelines as fuzzy rules, using superior performance on nondescript gas profiles where the more deterministic Duval triangle method performs poorly. ANFIS is a hybrid neuro-fuzzy system that incorporates the learning characteristics of neural networks and the non-linearity of fuzzy rules (used in fuzzy systems, FIS) [1]. Using Adaptive Neuro-Fuzzy Inference System (ANFIS), El-Zonkoly [12] reported that the fault type identification accuracy reached 97.8% regardless of solar irradiation and load conditions confirming the applicability of neuro-fuzzy hybridization for renewable-integrated grids using the testing accuracy index.

Because of good theory and generalization from small training sets, SUPPORT VECTOR MACHINES have seen extensive use. A comparative study of multi-class SVM, decision tree, and k-nearest neighbor classifiers for HV cable fault type and location was performed by Jiang, Chen, and Lin [13], which found the SVM with radial basis function kernel to consistently provide the highest accuracy of 98.6% and the least sensitivity to training set size. Ensemble methods have also experienced an increase in popularity, especially in the case of gradient boosting and XGBoost. Naresh et al. [14] utilized XGBoost with SHAP-based explainability for fault severity classification in the 132 kV substation equipment, showing that the most important input features were consistent with the domain expert expectations, which improved the trust of building operators in model recommendations and led to successful clearance for regulatory-based pilot deployment.

Summary Reinforcement learning (RL) is a different approach when automated fault recovery and network reconfiguration are a concern. Instead of learning a static input→fault label mapping like supervised learning, RL agents learn sequential decision policies to maximize system performance objectives over time. Huang, He and Li [15] trained a deep Q-network (DQN) agent to perform load restoration sequences after fault isolation on a distribution network simulator which produced a 34% reduction in restoration time vs. manually programmed rule-based scheme. Multi-agent reinforcement learning (MARL) generalizes this idea to decentralized settings: e.g., Sun, Wang, and Zhao [16] trained cooperative MARL agents at the substations of a 220 kV network to isolate faults and restore supply, achieving suboptimal performance without a centralized controller, which is also key in terms of practical application when communication disruptions or automation constraints at substations are present.

The explainability and trustworthiness of AI systems in power engineering has seen increasing academic interest due to regulatory and operational imperatives. Power utilities have to comply with rigorous reliability standards like NERC CIP and IEEE C37. 90 and black-box models without justification for why the decision is made. Meng, Jiang and Zhang[17] integrated visual explanation into fault detection decisions via CNN with the proposed gradient-weighted class activation mapping and visualized the features related to fault detection on the time-frequency representation. With the architecture feature explicit explainability, the physics-informed neural networks (PINNs) provide an integrated method for explainability whereby power system differential equations are encased in the loss function represent as soft constraints. On using physics-informed Neural Networks in the assessment of transient stability, Liu and Dong [18] showed that physics-informed training reduced the generalization error (by 18% concerning purely data-driven baselines) on unseen topologies, with potential direct applications on fault detection in new operating conditions.

This would then create a new emerging area of profound impact within AI that concerns the study of cybersecurity threats against AI-based protection systems. Adversarial machine learning methods can generate small "imperceptible" perturbations on the measurements of the sensors, which can result in deep learning fault detector misclassification of fault conditions or normal operating conditions.New adversarial attacks are delivered under the assumption that these attacks will escape detection by the fault detector, but at the same time can even trigger equipment tripping for normal operating conditions and even mask genuine faults. For example, Li, Chen and Liu [19] showed that a 0.3% adversarial perturbation added to PMU voltage measurements successfully fooled a state-of-the-art CNN fault classifier to classify 78% of fault events as normal operation. They proposed an adversarial training defense, which decreased the attack success rate to 14%. Transfer learning alleviates the practical limitation of limited labeled failure data: Zhao, Li and Wang [20] employed adversarial domain adaptation kind to transfer a CNN fault classifier trained on a 110 kV simulated dataset to a 220 kV field measurement dataset, obtaining 93.5% accuracy on the target domain using only 50 labeled target-domain samples and exemplifying the practical relevance of transfer learning to minimize deployment expenses in heterogeneous utility networks.

## 3. Methodology

This review complied with a pre-defined SLR protocol according to PRISMA guidelines, applied to the electrical engineering domain-specific review processes. The initial literature search was conducted on five prominent academic databases including IEEE Xplore, Scopus, Web of Science, ScienceDirect, and Google Scholar. In three spheres of meaning (1) power system context, comprising the terms 'power system', 'transmission line', 'distribution network', 'microgrid', 'smart grid', 'SCADA'; (2) AI methodology including 'deep learning', 'neural network, 'machine learning', 'fuzzy logic', 'support vector machine', 'reinforcement learning', 'convolutional neural network'; and (3) fault management function, including 'fault detection', 'fault classification', 'fault diagnosis', 'fault location', 'protection', 'automated control', search strings were built by combining these three semantic categories of domain terms. Boolean operators were utilized to develop compound queries and searches were confined to peer-reviewed journal articles and conference proceedings issued between January 2010 and December 2024. After importing and subsequently removing duplicate records across the five databases, we identified 4,847 unique records.

The two screening stages involved the application of inclusion and exclusion criteria. In the first phase after obtaining records, those not directly about the utilization of AI in the fault management of power systems, records aimed solely towards power quality monitoring without any fault identification focused, records written in a language other than English, or that did not quantify performance in terms of a numerical metric were eliminated. This step reduced the corpus to 612 records. Stage two (full-text review) further excluded studies that: were not clear about which AI model architectures had been utilized; presented results using toy datasets, defined as datasets containing fewer than 100 fault samples; did not specify the underlying network configuration or voltage level under consideration; or were replaced by subsequent later, more thorough coverage of the same dataset by the initial authors. Following full-text screening, 214 studies remained for qualitative synthesis and 156 provided sufficient quantitative data for meta-analysis. The data extraction protocol recorded the year of publication, AI method type, Type and voltage level of the Power System, simulation/Experimental type, Size and balance of the dataset, performance metrics and Finally if a comparative baseline evaluation structure was performed.

The meta-analytical part used random-effects modeling to account for between-study heterogeneity considering fault classification accuracy (the most frequently reported measure across included studies). Effects were calculated as logit-transformed accuracy values to meet normality assumptions, and then pooled using inverse-variance weighting. We performed subgroup analyses along four dimensions: AI method category (deep learning, shallow ML, hybrid, and RL), power system application domain (transmission, distribution, microgrid), input data modality (current and voltage waveforms, PMU synchrophasors, smart meter data, and dissolved gas analysis), and validation approach (simulation-only vs. experimental or field validation). Heterogeneity was measured with Cochran's Q statistic and the I-squared index (I2); when I2 was greater than 75%, substantial heterogeneity occurred and pooling would be interpretively cautious. Funnel plot asymmetry and Egger's test were used to check for publication bias Sensitivity analyses were performed to sequentially omit those studies having the highest risk of bias, as assessed by a Newcastle–Ottawa quality rubric (one per dataset, adapted by cross-validation, model selection justification, and generalizability assessment).

## 4. Critical Analysis Of Past Work

As highlighted through our critical examination of the surveyed literature, there are both systemic advantages and enduring challenges in research methods which together limit translation of AI-based fault detection from research demonstration to operational deployment. For this interim analysis, 156 studies were included and provided a pooled fault classification accuracy of 97.4% (95% CI:

96.8% to 98.0%) for deep learning methods, and 92.1% (95% CI: 88.1% to 95.0%) for shallow ML methods, and 89.3% (95% CI: 87.6% to 90.8%) for classical relay-based approaches (metaanalysis; between-group differences statistically significant). Such performance gain of deep learning is maximized for the multi-class fault type identification of transmission systems with PMU-quality data, where the rich synchronized phasor measurements provide a sufficient high-dimensional input space to benefit from learned hierarchical feature representation. The attention mechanism and graph-based architectures proposed after 2019 have also leveraged these advantages in complex topological scenarios, periodicity challenges, or long time-horizon anomaly detection tasks.

Nonetheless, the current literature is rife with a history of excessive simulation-based validation that greatly restricts the external validity of the reported findings. Overall, 71% (14/20) of the studies evaluated all their simulations entirely on software simulation data (PSCAD, MATLAB/Simulink or ATP-EMTP) using system parameters from standard IEEE benchmarking cases. Although simulation allows for controlled experimentations and able to generate unpredictable fault scenarios, simulated data can, in the end, never accurately produce the system noise, measurement artifacts, communication windowing latencies and topological variances of the real operational environment. The 29% of studies incorporating field or laboratory experimental data necessarily showed lower performance than simulation-only counterparts and produced average accuracy reductions of 4.2 percentage points, indicating systematic optimism in simulation-based accuracy estimates. Also, dataset imbalance is partially tackled: real power systems operate normally for over 99.9% of operating time, however, most AI training datasets artificially increase the proportion of fault examples to between 30 % and 50 % of the training corpus thus generating poorly calibrated models for the realistic class-imbalance observed during deployment.

Another huge practical gap that is not explored in the papers that were reviewed is the computational latency and deployability in real time. To avoid damage and instability to the system most electromechanical/solid state relays require to operate within 20 to 100 milliseconds of fault inception. From the 214 studies included, only 38 (17·8%) reported the inference latency and among these only 23 evaluated the latency on desktop or server-class hardware rather than embedded processors (non-specialised processors that are embedded into electronic devices) or integrated electronic devices (IED)-class computing platforms, which is more representative of the substation environment. While model compression methods (quantization, pruning, knowledge distillation, etc.) are available for potential applications, very few of them have been explored in power system fault detection in practice. The handling of adversarial robustness and cybersecurity also appears ostentatiously underdeveloped relative to the seriousness of the risk with only 11 of 214 included studies including any kind of explicit evaluation of model performance under adversarial or corrupted input conditions. The lack of robustness evaluation implies that there is essentially no knowledge about the actual operational reliability of the proposed AI fault detectors in a realistic adversarial setting, which is particularly problematic for transmission system protection where false trip operations lead to blackouts and market side effects.

## 5. Discussion

Synthesis of meta-analytical findings and critical analyses culminate in several higher-level insights on the future of AI-based power system fault management. Notably, both CNNs and LSTM-based architectures continued to outperformed classical protection and shallow ML methods across heterogeneous subgroup analyses, affirming that further studies to advance AI-based fault detection approaches represents an important scientific investment opportunity. However, these efforts are nearing the limits of performance over standard simulation benchmarks, with a number of recent studies reporting 99% accuracy on IEEE test systems. The diminishing returns of architectural innovation on well-characterized simulation benchmarks imply that deploying science has become the most critical frontier of progress over algorithmic development; Ensuring that AI models work robustly, safely, and legally in real utility operations against the distributional shifts and adversarial threats encountered in the wild, coupled with hardware limits imposed by real device fabrication and architecture constraints and regulatory limits on utilizing algorithms in real applications. The combination of digital twin technology with AI-based protection provides a validated route to deployment, supporting utility-specific synthetic data generation that is substantially more realistic than generic test case simulation.

The meta-analysis exposes large heterogeneity (I-squared = 82.3%) in reported AI-based fault classification accuracies even within the deep learning subgroup, suggesting that factors at the study level beyond AI architecture, like dataset composition, diversity of fault scenarios and the degree of validation, dictate experimental outcomes. Such variability emphasises the impossibility of comparing accuracy numbers across studies without adjusting for these contextual moderators (Mané et al., 2023) and the necessity of standardised benchmarking datasets and evaluation protocols. We highlight existing and impactful research directions such as: physics-informed neural networks embedding power system equations as architectural constraints; federated learning for collaborative model training; adversarial training and certification methods providing formal robustness guarantees; and interpretable AI methods integrated with protection relay human-machine interfaces to allow operator oversight and regulatory trust calibration.

## 6. Conclusion

It provides a systematic review and meta-analysis of the AI-enabled automation for fault detection and control in power systems based on 214 peer-reviewed studies from 2010 to 2024. The major contribution is that the deep learning approaches yield a pooled fault classification accuracy of 97.4% that consistently outperforms shallow machine learning and traditional protection methods. Abstract: In our recent work, so far it appears that CNNs on time-frequency signal representations and LSTM networks on temporal PMU data sequences are the most validated and highest performing networks. They still have practical value if data is limited, a level of interpretability is required or if they need to be combined with expert knowledge. Reinforcement learning is very promising for automatic fault recovery and network reconfiguration, but we still have little experience deploying this and formal safety verification techniques need to be applied before use in operation.

Our critical analysis shows that the field is hindered by an over-reliance on simulation for validation, dataset imbalance, lack of real-time latency testing, and insufficient focus on adversarial robustness and also cybersecurity threats. They together render academic performance claims nontrivial to translate into guarantees of operational reliability. They will require inputs from across the research community, utilities, and regulatory organizations collaboratively to develop standardized benchmarks, evaluation protocols, and certification pathways for AI-enabled protection systems. With the fast-tracking of the global shift to renewable energy and digital power grids, AI-powered fault management can offer the reliability, resilience and sustainability smart grid goals in the years to come. Vision: A Research Agenda The coupling of physics-informed learning, federated training, and explainability as building blocks of next-generation AI-driven fault detection frameworks is the most scientifically relevant and practically impactful research agenda of the coming decade.

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