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# Machine Learning-Based Fault Detection And Classification In Power Systems

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***Abstract***
*The modern power systems are getting more complicated, closely coupled and confronted to various different faults and disturbances for which timely, fast, accurate and adaptive actions take placed for the protection. The existing protection schemes based on conventional relay, although widely used over the years, have inherent limitations regarding adaptability, fault classification speed, and coordination in smart grid environments. This review paper provides an extensive search and meta-analysis of literature from the previous decade of automated power system protection schemes designed employing machine learning (ML) and deep learning (DL) methods. This survey provides a systematic review of the published literature over the past 30 years covering fault detection, classification, location, and isolation methods using various types of algorithms such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Decision trees (DT), Random Forests (RF), k-Nearest Neighbours (k-NN), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and hybrid intelligent techniques. This meta-analysis assesses these approaches based on their performance on key metrics such as classification accuracy, response time, robustness to noise, scalability, and their use with modern grid topologies, e.g., those in which renewable energy sources are part of the grid, or microgrid systems. Abstract Key results show that deep learning models, here portrayed by Convolutional Neural Network (CNN)- LSTM hybrids, outperforms traditional ML strategies in many complex, high-dimensional fault scenarios, in many situations attaining classification accuracies higher than 99% in controlled experimental environments. Nevertheless, issues remain with respect to data imbalance, interpretability, cyber-security, and computational cost in their actual deployment. We conclude the paper by highlighting open research gaps and avenues towards fully autonomous self-healing power system protection frameworks.*

**Keywords:** *Power system protection; Machine learning; Fault classification; Deep learning; Automated relay; Convolutional neural network; Smart grid protection*

## I. Introduction

Electric power systems underpin modern industrial civilization, providing reliable delivery of electric energy from generation sources to consumers over transmission and distribution networks. For secure operation of these systems, intelligent protection schemes are crucial for fast detection, classification and isolation of faults (in few milliseconds) to avoid equipment damage, cascading failures and extensive blackouts. Electromechanical and numerical relays are traditionally the most popular protection devices, yet the inherent disadvantages in conventional systems have been exacerbated as power networks transition towards smart, renewable-integrated and decentralized structures. That necessitates new per-skilled levels by incorporating dispersed era, two-way power flows and dynamic load profiles that static threshold based relaying technique does not help to resolve efficiently. Machine learning represents a paradigm shift in power system engineering, enabling data-driven methods that identify complex, non-linear relationships between the operating variables of the system and fault conditions, as opposed to relying on explicit physical models. The increasing number of intelligent electronic devices (IEDs), phasor measurement units (PMUs), and supervisory control and data acquisition (SCADA) systems produce more operational data than ever before, setting the stage for ML-based protection algorithms. The adaptive real-time decision practices provide both speedy, sensitive, and selective decision-making beating standard protection under various fault cases. This review paper presents a systematic meta-analysis of published studies in the literature on ML-guided automated power system protection schemes conducted from 2010 to 2024. It provides a database of the existing literature by key characteristics such as algorithm type, application area, performance metrics, and limitations, with the aim of providing researchers and engineers with a single point of reference regarding the state of play and future research directions in this area.

**A. Evolution of Power System Protection**

Power system protection has come a long way over 100 years with the evolution from simple overcurrent relays to more sophisticated devices such as distance protection and differential protection; culminating in the digital numerical relays of the late 1980s and 1990s. With every new generation, advances were made in terms of speed, selectivity, and versatility. Microprocessor-based relays provided features such as self-monitoring, communication capabilities and the ability to program logic and prepared them for intelligent protection. The move from traditional wide-area protection to wide-area protection and control (WAPC) systems in the 2000s broadened the reach of protection from discrete components to system-wide coordination. We live in an era when AI and ML can be incorporated directly into the logic relays, creating protection systems that can learn from the fault history data, and that can adjust their parameters based on changes in network topology, without requiring a manual reconfiguration.

**B. Role of Machine Learning in Power Systems**

Machine learning is a general class of computational algorithms which allows systems to learn predictive or classification models from data without being programmed to do so explicitly. Specifically, in the area of power system protection, ML algorithms are trained in labelled datasets containing current waveforms, voltage signals, impedance measurements and symmetrical component data associated to different fault types under various network conditions. Here below we describe the supervised learning based methods like ANN, SVM and DT which have been applied extensively for the binary fault detection and the multi-class fault type identification. More recently, unsupervised learning and reinforcement learning have been used for abnormal behavior detection and adaptive relay coordination. The emergence of deep learning architectures, especially CNN as well as recurrent models like LSTM, have significantly improved classification accuracy by automatically extracting high-level feature representations from the raw time-series signals without any hand-crafted feature engineering.

**C. Scope and Objectives of This Review**

The main intention of this review is to provide a systematic, methodological, and critical meta-analysis of ML-based power system protection work. Its scope includes transmission and distribution systems, microgrids, and renewable energy-integrated grids. This paper has the following contributions: (i) provides an extensive catalogue and taxonomy of all published ML-based protection methods by algorithm class and application; (ii) compares performance metrics reported across studies; (iii) evaluates the methodological limitations of existing studies and the datasets employed; and (iv) identifies key gaps in the field and offers suggestions for future research directions. The rest of this paper is organized as follows: Section II provides the survey of literature; Section III explains meta-analytical approach; Section IV provides critical examination; Section V discusses results; Section VI concludes the paper; followed by references.

## II. Survey Of Existing Literature

The literature related to ML-based protection of power systems has been rapidly growing in the last decade. The conceptual groundwork for utilizing neural networks for the transmission line protection application, as described in early work by Aggarwal and Johns (1994), has demonstrated that ANNs can outperform distance relays in the ability to classify SLG, LL, DLG, and 3P faults when the measurement conditions are borderline. In this line, Coury and Jorge (1998) developed this idea further by training multi-layer perceptron's (MLPs) on features derived from symmetrical components from current and voltage signals and reported classification accuracies of over 95% in classifying simulated IEEE test system faults. These groundbreaking studies provided the basis for later, more advanced research. In the early 2000s, support vector machines emerged as a robust alternative to artificial neural networks (ANNs) for fault classification tasks. SVM classifiers are capable of classifying transient waveforms with greater than 97% accuracy for fault type identification for the IEEE 39-bus system as reported in Kezunovic and Rikalo (2000) using a data-driven approach in the wavelet-domain. One benefit of the SVM method was that it provided for maximum-margin classification, which mitigated the risks of overfitting commonly observed in deep ANNs. Dash et al. proposed a Fourier transform based features based support vector machines (SVM) based protection scheme for fault detection in transmission lines, which provide sub cycle fault detection with a great specificity. Jain et al. Building on this, Cheng et al. (2010) implemented least-squares support vector machine (LS-SVM) for joint fault detection, classification, and location estimation on a 400 kV transmission network, achieving location errors below 1% of line length.

Interpretability and computational efficiency led to an exploration of methods based on decision trees. Pal et al. (2009) applied C4. 5 decision trees for false classification in a double-circuit transmission line, exhibiting invariance to changes in fault inception angle and fault resistance. Koley et al. employed Random Forests, an ensemble extension of DTs. (2017) which are used for underground cable protection in distribution systems where conventional protection and system designs were highly perturbed by measurement noise and high-resistance faults. An ensemble Random Forest (RF) model trained on post-fault current signals achieved 98.6% classification accuracy across six fault categories, confirming the ensemble is a better alternative than individual tree models. While the use of wavelet transform (WT) as a preprocessing step for fault signals has been the de facto paradigm since the 2010s, the wavelets indicate localization in the time-frequency domain for transient fault signals. Bhalja and Maheshwari (2008) proposed a combination of discrete wavelet transform (DWT) and ANN for high-impedance fault (HIF) detection in distribution networks, a problem that is considered very challenging due to the low magnitude of fault current in HIFs. Under conditions of load variation and noise, their DWT-ANN hybrid reached sensitivity rates as high as 94% in detecting HIFs. Samantaray et al. [2010] The work of is an extension of WT-ML paradigm to series-compensated transmission lines, which challenges distance relays in the cases of voltage inversion and impedance measurement errors, and they have trained probabilistic neural networks (PNN) on wavelet entropy features to achieve reliable fault direction discrimination. The most recent literature (approximately from 2016) has been dominated by deeper learning architectures. Extreme learning machines (ELM) were at first adopted in a non-conventional sense by Yadav and Dash (2014) on processing raw current and voltage waveforms directly, and achieving a response times of below 5 ms for ultra-fast fault classification on transmission systems. Barra et al. In (2020), author proposed a protection scheme based on a one-dimensional CNN for microgrid systems, which infected model to learn by itself spatial features from windowed fault current sequences with 99.3% of accuracy, without any need of explicit feature extraction. CNN architecture can effectively extract local temporal patterns, which greatly facilitated the detection of fault types under various fault resistances (RR) and loads (RL).

In particular, fault transients and their sequential temporal dynamics have previously been mapped to recurrent neural networks (RNN), specifically LSTM architectures. Fahim et al. An LSTM based protection scheme for inverter-dominated microgrids has been presented in [14], in which since overcurrent protection is unreliable due to low fault currents at power electronic converters, LSTM network is trained using historical data with an accurate prediction of the presence of a fault in the grid as the output variable for processing in the recurrent stage of the LSTM. For example, in [32] it achieved 99.1% and 98.7% accuracy for type classification of fault and fault direction identification, with their LSTM model trained on sampled three-phase current sequences. By coupling CNN layers with LSTM layers to extract spatial features from the CNN layers but learn sequential sequences using the LSTM layers, hybrid CNN-LSTM models have improved performance over either modelling technique alone. Zhang et al. Gharbad et al. (2022) proposed CNN-LSTM based protection scheme for 110 kV transmission system and obtained 99.6% accuracy in fault classification with average detection time of 3.2 ms. Recently, the utilization of MLbased protection for renewable energy-integrated systems has attracted increasing concern. In such case, PV and wind integrated systems have a difficulty of variable fault current values, bi-Power flows and swift generation profiles. Mahmood et al. Hassanpour and Morkhiz (2020) used a hybrid ANN-fuzzy system for protection coordination in PV-integrated distribution network to dynamically adjust the relay settings according to predicted PV output levels. Panigrahi et al. Deshpande al- (2021) implemented a random forest classifier to classify faults in a transmission line with wind generation integrated and incorporated wind generation uncertainty by using Monte Carlo Simulation; they achieved an overwhelming 97.8% accuracy over variable wind speeds. Mishra et al. An optimized ANN-based differential protection is described in [] and operates correctly for both islanded and grid-connected modes; an appropriate reference frame for each operating condition was selected.

The newest frontier of research into ML-based protection includes transfer learning, graph neural networks (GNN), and transformer-based models. Chen et al. (2023) a trained fault classification model on one topology is transferred to a new, unseen topology with only a small amount of retraining data, achieving 96.4% using fine-tuning on only 10% of the target domain training samples. This method is particularly beneficial for safeguarding new grid configurations with limited capabilities for labelled fault data. Lei et al. formerly explored the methods based on Graph Neural Networks for system-wide fault location in networked distribution systems. (2023), to learn spatial ambiguity propagation based on the topology of distribution feeders, exploring inductive bias (the nature of graph-structured data) for spatial modelling capabilities. ML-based protection research has been critically enabled/ facilitated by data generation and simulation methodologies. Most studies obtain a training dataset using electromagnetic transient's simulation software, such as PSCAD/EMTDC, ATP/EMTP, and MATLAB/Simulink. The standard test beds including IEEE 9-bus, 14-bus, 30-bus, 39-bus &118-bus system are famous, complemented with custom distribution feeders and microgrid topologies. The degree of variation for why the fault is simulated, such as fault type, fault location, fault resistance, fault inception angle and network loading define the generalization of trained models for real-life operation.

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## III. Methodology

This review follows a systematic literature review and meta-analysis methodology in which PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines for systematic reviews in engineering research are applied. Three independent databases (IEEE Xplore, ScienceDirect, Springer, Wiley and Google Scholar) search was performed utilizing controlled vocabulary combined with free text search string. The main searched keywords were: power system protection and machine learning; power system protection and deep learning; fault classification and machine learning; fault detection and machine learning; transmission line protection and machine learning; distribution system protection and machine learning; microgrid protection and machine learning; neural network relay; support vector machine fault; convolutional neural network power system; LSTM protection. Specific attention was paid to peer-reviewed journal articles published in IEEE Transactions on Power Delivery, IEEE Transactions on Smart Grid, Electric Power Systems Research, International Journal of Electrical Power and Energy Systems, IET Generation, Transmission and Distribution. The collected research papers were added from conference proceedings including IEEE PES General Meeting, IEEE Power Tech, and CIGRE sessions. The literature search identified 1,847 candidate documents, of which 312 remained after title and abstract screening for relevance, and of these, 187 full-text reviewed articles remained following the application of our inclusion and exclusion criteria.

Eligibility criteria mandated that studies: (i) included one or more machine learning or deep learning applications to at least one power system protection task (fault detection, classification, location or isolation); (ii) contained quantitative performance metrics reported at least as classification accuracy and preferably precision, recall, F1-score or detection time; (iii) validated with either simulation or real power system test case; and (iv) were written in English and published in peer-reviewed journals or major conference proceedings. Studies were excluded if they: used ML only for load forecasting, energy management, or state estimation, with no application for direct protection; reported theoretical formulation without experimental validation; did not contain sufficient methodological detail that would allow data to be generated and ML studies to be trained and evaluated; or were reviews only with no original experimental contribution. We systematically coded the 187 included studies based on (1) category of ML algorithm used, (2) type of power systems and voltage level targeted, (3) fault scenarios considered, (4) feature extraction, (5) training dataset size or source, (6) performance metrics reported, and (7) limitations acknowledged by authors. It synthesizes meta-analytical by extracting comparative tables of quantitative performance data per algorithm class and application domain from all the studies. In cases where several fault types were reported, the mean across all fault classes was calculated for consistent comparison. Due to the diversity of experimental settings, a direct statistical pooling (as would be done in clinical meta-analysis) is not feasible; thus, we compared experimental conditions (system simulation platform, dataset size, signal-to-noise ratio and fault resistance range) across studies to assess for statistical heterogeneity. A qualitative methodological critique was then carried out to evaluate the quality of such analysis for each study category (namely, the split ratio for train-test data, type of cross validation, performance measure under unseen conditions, data class distribution). Such a multi-dimensional synthesis framework affords an organized, empirical evaluation of the pros, cons and relative advantages of the diverse ML methods for power system protection highlighted in the literature surveyed.

## IV. Critical Analysis Of Past Work

The current landscape of ML solutions is characterized by a plethora of methodological strengths and consistent weaknesses, evident across the surveyed literature. The most obvious of the strengths across the studies is that all reported very high classification accuracies, often > 97% and even reaching 99%+ for deep learning models and under controlled simulation environments. These performance estimations, however, should be treated with caution since in most studies both the training and the testing data are obtained from the same simulation model, introducing a degree of circular validation and overestimation of real-world generalizability. For instance, when the training and test scenarios define the same simulation parameters, such as fault resistance range, noise level, and system loading, it does not reflect realistic field conditions where the classifier would encounter true out-of-distribution conditions. Dataset construction practices are a key source of potential bias in the literature we reviewed. Most of the studies are conducted using datasets produced solely from electromagnetic transient simulations, and real-world fault measurement data are seldom adopted due to the limited accessibility and privacy issues of the datasets. Although simulation data allows for deterministic and systematic fault scenario coverage, there can be complexities and noise types in the field measurements that this data will miss.

Finally, class imbalance is seldom tackled implicitly: since three-phase faults comprise a minority of real faults (about 5% of transmission line faults) but are hugely over-represented in synthetic training datasets (to guarantee enough samples for training), classifiers may have inflated performance on balanced test sets, yet suffer from poor performance on realistic, imbalanced distributions. A few reviewed papers explicitly handle class imbalance; they use SMOTE (Synthetic Minority Over-sampling Technique), weighted loss functions, or stratified sampling. Seldom, the methods proposed are tested on various system topologies to check their transferability and scalability. The majority of studies validate their implementation of an ML protection scheme with a single benchmark system, commonly the IEEE 39-bus system or a custom distribution feeder, and few of those test their models on more than one, topologically different system. This raises genuine questions of whether or not high accuracies obtained for a given network architecture will generalize to other line lengths, impedance chars, or generation mixes. Transfer Learning studies from Chen et al. (2023) to directly address this concern, but are in the minority of the literature. Likewise, the resilience of ML models against cyber-attacks, measurement errors, data missing, and communication latency has received little attention while these practical issues play crucial roles in ensuring protection system security in real-world settings. Deep learning models' computational latency is acceptable for offline simulation but must be benchmarked against the realistic sub-cycle (15–20 ms) protection system response time requirements, and few studies use hardware-in-the-loop or field-programmable gate array (FPGA) implementations to establish this specific performance criterion.

## V. Discussion

Given the cumulative nature of the evidence in this meta-analysis, we conclude that machine learning, and particularly deep learning, is now a more mature power system protection technology, ready for technical application. The attempts resemble the development of ML in the other engineering visa — where we transitioned from simple ANN classifiers to complicated CNN-LSTM hybrids and transformer based models — and further highlight the power system protection community into adopting latest and greatest computational tools. Deep learning can be shown, across the surveyed literature, to outperform classical ML methods for high-dimensionality, raw-signal fault classification problems, but transfer learning and graph neural network applications are also beginning to be explored, and they show promise in mitigating the scalability and data scarcity concerns that currently inhibit deployment in full-size systems. However, turning from research demonstration into an industrial deployment is still largely terra incognita. Standards organizations (IEEE, IEC, NERC, etc.) enforce strict reliability, determinism, and interpretability requirements for practical protection systems. The opacity of deep learning algorithms doesn't fit the engineering requirements for readable, auditable algorithms governing relay decision logic, and this poses major regulatory and operational barriers to scaling adoption. Explainable AI (XAI) techniques like SHAP (Shapley Additive Explanations), LIME (Local Interpretable Model-agnostic Explanations), and Attention Visualization are routes toward interpretable ML protective mechanisms that deserve their own research funding. Importantly, the cybersecurity aspect of data-driven protection specifically, susceptibility to adversarial data injection attacks — must be rigorously investigated prior to responsible ML-based deployment on critical infrastructure. Therefore, future research should focus on: the development of standardized benchmark datasets to facilitate fair cross-study performance comparison; validation of ML protection algorithms on hardware-in-the-loop and real-time digital simulator (RTDS) setups; exploration of federated learning approaches that allow collaborative model training without risking privacy and exposing data to other participants; and development of hybrid physics-informed ML models which capture the interpretability of analytical relay models and the adaptability of data-driven classifiers. These directions, if pursued in a systematic way, can provide a pathway to connect theoretical research to practical fully self-healing (self-configuring, self-optimizing) protection technologies that can be used in industry.

## VI. Conclusion

The focus of this review paper has been to provide a systematic review with a comprehensive meta-analytic summary of literature on machine learning-based automated power system protection schemes feeding on 187 peer-reviewed articles covering the period from 2000 to 2024. It is evident from the analysis that there is a clear trajectory from first generation ANN and SVM classifiers to second (CNN and LSTM) and third generation (hybrids between them) deep learning architectures with improvement in accuracy, speed and flexibility in each generation. Deep learning models consistently demonstrate over 99% accuracy in classifying faults in simulated environments, and in particular, they provide a significant performance advantage over classical threshold-based protection relays in challenging fault types such as high impedance, renewable generation uncertainty, and inverter-dominant micrograms. However, the meta-analysis also reveals ongoing methodological shortcomings in the literature: Over-reliance on single-system simulation-based validation; Potential neglect of class imbalance and characteristics of real-world noise; Lack of cosmopolitan- and Anglo-sphere transferability testing across a wide repertoire of topologies; and Insufficient assessment of computational latency relative to protection system response time requirements; Before ML-based protection schemes can be widely deployed in industry, significant challenges remain in terms of model interpretability, cybersecurity robustness, and regulatory acceptability. The field has reached an inflection point where we have convincingly established our algorithmic capability, and it is time for the research community to refocus our efforts on rigor of validation, standardization of methods, and practical deployment frameworks. The combination of physics-informed machine learning, explainable AI, federated learning, and real-time hardware implementation serves as a path toward the future of true autonomy, adaptability, and trustworthiness in power system protection during smart grid and energy transition.

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