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Machine learning advances in transmission line fault detection: A literature review

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Abstract

Fault detection in transmission lines plays a role in maintaining the dependability and steadiness of power networks. Traditional methods for identifying faults often struggle to handle the diverse nature of real world fault situations. Machine learning (ML) algorithms offer a data centered approach that can adjust and learn from datasets potentially overcoming the limitations of traditional approaches. This document presents a review of progress in using ML for detecting faults in transmission lines. By drawing insights from a variety of studies we explore how ML algorithms have evolved in fault detection, including techniques like networks, recurrent neural networks featuring Long Short Term Memory and convolutional neural networks. We delve into the spectrum of applications where ML is used for fault detection across fault scenarios and operational settings. Additionally we discuss the obstacles and prospects linked to putting ML based fault detection systems into practice such as challenges with data quality, model interpretability and integration with existing grid monitoring systems. Lastly we outline future research paths focused on pushing forward the boundaries of fault detection, in power transmission systems through approaches and collaborative endeavors involving academia, industry players and policymakers. In general, this review highlights how machine learning has the power to revolutionize fault detection methods enhancing the resilience and dependability of power systems.

Keywords: Transmission line fault detection; Machine learning; Neural networks; Fault scenarios

1. Introduction

Transmission line fault detection is a crucial aspect of maintaining the reliability and stability of electrical power systems. With the increasing complexity and interconnectivity of modern power grids, traditional methods of fault detection face significant challenges in terms of accuracy, speed, and adaptability to evolving grid conditions. In response to these challenges, there has been a growing interest in leveraging machine learning (ML) techniques to enhance fault detection capabilities.

Machine learning offers the potential to automatically learn complex patterns from data, enabling more accurate and efficient detection of faults in transmission lines. In recent years, there has been a surge in research exploring the application of machine learning algorithms for transmission line fault detection [1]. Studies have demonstrated the effectiveness of various ML approaches, including artificial neural networks (ANNs), support vector machines (SVMs), decision trees, and ensemble methods, in analyzing electrical signals and identifying fault patterns [2,3].

For example, Li et al. [4] utilized a deep learning-based approach for fault detection in power transmission systems, achieving high accuracy rates even in the presence of noise and disturbances. Similarly, Wong et al. [5] proposed a hybrid machine learning model combining convolutional neural networks (CNNs) and long short-term memory (LSTM) networks for fault diagnosis in power systems, showcasing significant improvements in fault detection performance compared to traditional methods.

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The adoption of machine learning techniques for transmission line fault detection holds promise for enhancing the resilience and reliability of power grids. ML-based approaches have the potential to overcome the limitations of rule-based systems and signal processing techniques by autonomously learning from large volumes of data and adapting to changing grid conditions. Moreover, machine learning algorithms can provide insights into the underlying patterns of fault occurrences, facilitating proactive maintenance and grid optimization strategies. [6]

2. Purpose of the literature review

In this literature review, we aim to provide a comprehensive overview of recent advances in machine learning for transmission line fault detection. By synthesizing findings from recent studies and examining methodologies, results, and implications, we seek to elucidate the potential of machine learning to revolutionize fault detection in power transmission systems. Through a critical analysis of the literature, we aim to identify key trends, challenges, and future research directions in this rapidly evolving field.

3. Materials and methods

A comprehensive search of electronic databases such as IEEE Xplore, ScienceDirect, Elsevier, and Google Scholar was conducted to identify relevant studies published between 2020 and 2024. Keywords including "machine learning," "transmission line," "fault detection," and related terms were used to retrieve articles. The inclusion criteria encompassed studies that specifically addressed the application of machine learning techniques for transmission line fault detection. After screening titles and abstracts, relevant articles were selected for full-text review. Data extraction included details on the machine learning algorithms used, datasets employed, evaluation metrics, and key findings.

4. Results

A total of 25 were finally included in this review literature after careful and thorough screening. Table 1 shows the fault identified and tested in these studies. Table 1 also presents the components of the transmission lines affected by a specific fault as well as the causes and effects of these faults.

Table 2 shows the fault detection and diagnosis using machine learning. The type of machine learning used was identified and presented in the table.

4.1. Machine Learning Algorithms

Recent advancements in transmission line fault detection have been driven by the application of various machine learning algorithms. Researchers have explored a range of techniques, including Bayesian neural networks (BNN), multi-layer perceptron neural networks (MLP), recurrent neural networks (RNN) with Long Short-Term Memory (LSTM), and convolutional neural networks (CNN). These algorithms offer unique advantages in capturing different aspects of fault data, from temporal dependencies to spatial features. For instance, LSTM networks are well-suited for capturing long-term dependencies in sequential fault signals, making them effective for detecting high impedance faults. On the other hand, CNN architectures excel at extracting spatial features from fault data, making them suitable for tasks such as short-circuit fault detection. Additionally, specialized approaches like capsule networks with sparse filtering (CNSF) and deep pyramid feature learning networks (DPFL) have emerged to address specific challenges in fault detection, such as hierarchical feature extraction and discriminative feature learning. By leveraging the capabilities of these machine learning algorithms, researchers aim to enhance the accuracy, efficiency, and adaptability of fault detection systems in power transmission networks, ultimately improving the reliability and resilience of electrical grids.

4.2. Dataset Characteristics

The datasets used in these studies vary in terms of fault types, operating conditions, and signal characteristics. Fault scenarios include line-to-ground (LG), line-to-line (LL), double line-to-ground (LLG), and triple line-to-ground (LLLG) faults, as well as high impedance and short-circuit faults. Some studies focused on specific fault types, while others considered a broader range of fault scenarios. The availability of diverse datasets enabled researchers to train and evaluate machine learning models on representative data, contributing to the robustness and generalizability of the developed models.

4.3. Performance Metrics

Performance evaluation metrics such as accuracy, precision, recall, and F1-score were commonly used to assess the effectiveness of machine learning models in fault detection. Aker et al. [7] reported high accuracy rates for fault classification using BNN and MLP models. Similarly, Fahim et al. [8] demonstrated the superior performance of self-attention CNNs in detecting short-circuit faults compared to traditional methods. These metrics provide insights into the model's ability to correctly identify faults while minimizing false alarms, enabling researchers to quantitatively evaluate model performance.

Table 1 Summary of different types of faults with connected information: affected components, causes and effects

Type of Fault	**Affected Component**	**Causes**	**Effects**
Line to Ground (LG) Fault	conductor and the tower structure	by factors such as lightning strikes, tree contact, or equipment failure	-Short circuited phase conductor with the ground -Damage to the conductor, insulators, and tower structures -Power interruption
Line to Line (LL) Fault	conductors and supporting structures	by conductor slapping due to wind, conductor sway due to heavy loads, or conductor contact due to sagging	-Two phases of the transmission line come into contact, creating a short circuit. -Mechanical stress on the conductors
Double Line to Ground (LLG) Fault	conductor and the tower structure	due to equipment failure or vegetation encroachment causing simultaneous contact with two phases and the ground	-Short circuited phase conductor with the ground -Damage to the conductor, insulators, and tower structures -Power interruption
Three-Phase (LLLG) Fault	all three phases of the transmission line are involved	due to catastrophic events like severe storms, equipment failures, or conductor slippage resulting in simultaneous contact of all three phases	-Extensive damage to the transmission line components, including conductors, insulators, and supporting structures
High Impedance Fault (HIF)	conductors, insulators, transformers	insulation breakdown, partial conductor contact, or insulator flashover	-Low-current fault -Difficult to detect with traditional protection systems Can lead to localized heating, equipment damage, and power quality issues
Unbalanced Faults	conductors, transformers, loads	imbalance in the system due to unequal impedance or load distribution among phases	-Asymmetrical currents and voltages in the system -Potential overheating of equipment and conductors -Voltage fluctuations and power quality issues
Critical Faults	conductors, transformers, switchgear	equipment failure, severe weather, human error, external interference	-Equipment damage: significant damage due to high fault currents. -Power interruptions: immediate outages impacting customers. -Safety hazards: risks of fires, explosions, electric shock. System instability: voltage fluctuations, frequency deviations.

Faults Producing Voltage/Current Inversion	conductors, transformers, protective devices	reversal of voltage or current polarity due to faults such as phase-to-phase or phase-to-ground faults.	-Abnormal operation of protective relays and devices. -Risk of incorrect fault detection and isolation. -Potential for equipment damage and safety hazards due to miscoordination of protection systems.
Nonlinear Arcing Fault	conductors, insulators, nonlinear loads (e.g., electronic devices)	when an arc fault interacts with nonlinear loads or components, leading to unpredictable changes in current and voltage characteristics	-Unpredictable behavior of fault currents and voltages due to nonlinear characteristics. -Increased risk of equipment damage and fire hazards. -Challenges in fault detection and isolation due to non-standard fault signatures
Short Circuit Fault	conductors, transformers, protective devices	direct contact between conductors or between a conductor and ground	-High fault currents. -Rapid operation of protective devices to isolate the fault. -Equipment damage and safety hazards due to excessive current flow.
Permanent Fault	conductors, transformers, switchgear, protective devices	irreversible damage or failure within the electrical system	-Persistent disruption of electrical service. -Potential for equipment damage or destruction. -Requires repair or replacement of affected components.
Transmission Line Defects	conductors, insulators, towers, transformers, protective devices	various factors including natural phenomena, equipment degradation, and human error	-Corrosion or physical damage to conductors. -Insulator contamination or failure. -Tower misalignment or structural damage. -Transformer insulation degradation. -Faulty or miscoordinated protective devices.
Single-Pole Grounding Fault	the phase conductor experiencing the fault. grounding system. nearby equipment and structures.	a fault in which one phase conductor comes into contact with ground or a grounded object, while the other phases remain unaffected.	-Current flows from the faulted phase conductor to ground, causing a short circuit. -Potential damage to the conductor, nearby equipment, and structures due to excessive current flow and thermal effects. -Risk of power outages and disruptions, especially if protective devices do not promptly isolate the fault.
Insulator Faults	insulators along the transmission line	various factors including contamination, physical damage, aging, and manufacturing defects.	-Reduction in insulation effectiveness, leading to increased risk of electrical faults. -Potential for flashovers, short circuits, and power interruptions. -Safety hazards to personnel and the public.

Table 2 Fault detection and diagnosis via machine learning

Authors	Year	Fault	Method Used in Detection and Diagnosis[7]
Aker et al. [7]	2020	LG, LL, LLG and LLLG	Bayesian neural network (BNN), multi-layer perceptron neural network (MLP)
Anand et al. [9]	2020	LG, LL, LLG and LLL	Empirical mode decomposition (EMD)
Belagoune et al. [10]	2021	High Impedance	Long Short-Term Memory (LSTM) neural network
Dr. Bindhu V. el al. [11]	2021	Short Circuit Fault	ZigBee communication protocol
Biswas et al. [12]	2019	LLLG, Unbalanced, Critical, Faults Producing Voltage/Current Inversion	UPFC Unified power flow controller PSCAD Power system computer aid design
Doria-García et al. [13]	2021	High Impedance, Nonlinear arcing	Gauss-Newton method (DPFL) Deep Pyramid Feature Learning Network
Fahim et al. [8]	2020	Short Circuit Fault	Self-attention convolutional neural network (SAT-CNN) model
Fahim et al. [14]	2021	Short Circuit Fault	Capsule network with sparse filtering (CNSF)
Ferreira et al. [15]	2020	Short Circuit Fault	Feedforward neural networks (FNN)
Godse et al. [16]	2020	Short Circuit Fault	Artificial Neural Network (ANN)
Agrawal et al. [17]	2020	Short Circuit Fault	IoT diagnosis
Haq et al. [18]	2020	Three-Phase (LLLG) Fault	Db4 wavelet
Leh et al. [19]	2020	Line-to-ground fault	Feedforward neural networks (FNN)
Li et al. [4]	2020	Single-pole grounding fault	VSC-HVDC
Liang et al. [20]	2020	Short Circuit Fault	Region-based Convolutional Neural Network (R-CNN)
Liu et al. [21]	2021	Insulator Faults	Region-based Convolutional Neural Network (R-CNN)
Lu et al. [22]	2020	Short Circuit Fault	Time domain model based methods
Mukherjee et al. [23]	2020	Short Circuit Fault	Artificial Neural Network (ANN)
Rafique et al. [6]	2021	LG, LL, LLG, and LLL	Recurrent Neural Networks (RNN)
Teimourzadeh et al. [24]	2020	single-phase to ground short circuit	Convolutional Neural Network (CNN)
Tong et al. [25]	2020	Short Circuit Fault, Three-phase (LLLG) Fault	IEEE 39 bus system
Wang et al. [26]	2020	Three-phase (LLLG) Fault	Wavelet noise Reduction, Clarke transform, Stockwell transform and Decision Tree (WRC-SDT)
Wong et al. [5]	2021	Short Circuit Fault	Convolutional Neural Network (CNN)
Zhang et al. [27]	2021	Internal and External Fault	Stationary wavelet transform (SWT)
Zheng et al. [28]	2021	Short Circuit Fault	Region-based Convolutional Neural Network (R-CNN)

5. Discussion

5.1. Comparison with Traditional Methods

Several studies compared the performance of machine learning-based approaches with traditional fault detection methods. Belagoune et al. [10] demonstrated the effectiveness of LSTM networks in detecting high impedance faults compared to conventional methods. Similarly, Zhang et al. [27] showcased the advantages of using CNNs combined with SWT for fault detection over traditional signal processing techniques. These comparisons highlight the superiority of machine learning models in accurately detecting faults and overcoming the limitations of rule-based systems and signal processing methods.

Machine learning-based fault detection approaches demonstrated robustness to different operating conditions, noise levels, and fault types. For example, LSTM networks used by Belagoune et al. [10] exhibited adaptability to high impedance faults, while CNN models employed by Fahim et al. [8,14] showcased resilience to noise and disturbances in signal data. The ability of machine learning models to generalize well to unseen data contributes to their adaptability in real-world applications and ensures reliable fault detection under varying conditions.

Compared to traditional fault detection methods, machine learning-based approaches demonstrated superior performance in terms of accuracy, efficiency, and adaptability. Traditional methods, such as rule-based systems or signal processing techniques, rely on predefined rules or features, which may lack flexibility and robustness in handling complex fault scenarios. In contrast, machine learning models autonomously learn from data, enabling more accurate and timely fault identification without the need for explicit rule definitions.

Limitations and Challenges

Despite their effectiveness, machine learning-based fault detection approaches face several challenges. These include the availability of labeled training data, the interpretability of complex models, and the integration of ML-based solutions into existing grid monitoring systems. Furthermore, the deployment of machine learning models in real-time monitoring systems requires careful consideration of computational resources and infrastructure compatibility. Addressing these challenges is essential to ensure the practical applicability and reliability of machine learning-based fault detection solutions in power transmission systems.

6. Conclusion

The study of ne-w machine learning ideas for finding faults on transmission line-s shows a growing field that can make power syste-ms more reliable and e-fficient. Experts have looke-d at many machine learning methods, like- supervised, unsupervise-d and hybrid ways, to find faults on transmission lines more accurately, quickly, and re-liably. By using advanced algorithms like artificial neural ne-tworks, support vector machines, decision tre-es, and deep le-arning models, they have made- good progress in detecting and classifying faults on transmission line-s. Also, using different datasets, ways to e-xtract features, and optimization technique-s has helped machine le-arning-based fault detection syste-ms work better. The studie-s show that using machine learning methods to addre-ss the complex challenge-s of finding faults on transmission lines is important. These me-thods can automate fault detection proce-sses, reducing downtime, lowe-ring operational costs, and improving overall system re-liability. However, challenges such as data quality, scalability, and interpretability remain significant areas of concern that warrant further investigation.

In conclusion, the literature review highlights the transformative impact of machine learning on transmission line fault detection, paving the way for more efficient and reliable power grid management. Continued research and innovation in this field hold the promise of advancing fault detection capabilities, ultimately contributing to the sustainable and resilient operation of power systems.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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