

Review

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Review

Advancements in Fault Detection Techniques for Transmission Lines: A Literature Review

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Abstract: This literature review delves into the realm of fault detection techniques for transmission lines, aiming to provide a comprehensive overview of recent advancements and key trends in the field. Employing a structured approach, the review synthesizes a plethora of research spanning from 2019 to 2024, sourced from diverse databases including IEEE Xplore, ScienceDirect, ResearchGate, Scopus, Litmaps, and Google Scholar. The methodology encompasses a systematic literature search protocol, stringent inclusion and exclusion criteria, meticulous data extraction, and a multi-dimensional analysis framework. The literature review uncovers a spectrum of fault detection methodologies, ranging from traditional signal processing techniques like Discrete Wavelet Transform and phase angle-based methods to cutting-edge deep learning algorithms such as Capsule Networks and Convolutional Neural Networks. Insights gleaned from the review underscore the critical importance of fault detection in maintaining the reliability, safety, and efficiency of power grids, highlighting its role as a frontline defense against widespread outages and equipment damage. Key findings from the review shed light on the efficacy of different fault detection approaches, showcasing their strengths and limitations across diverse system conditions. Furthermore, the review identifies common trends and challenges, including the need for real-world validation, scalability, adaptability to various network configurations, and cybersecurity considerations. This literature provides valuable insights and recommendations for future research endeavors in fault detection for transmission lines. By embracing advancements in both traditional and emerging techniques, researchers can continue to enhance the resilience and dependability of power transmission systems, ensuring their ability to withstand evolving challenges and safeguard critical infrastructure.

Keywords: transmission line fault detection; machine learning; deep learning; fault classification; grid resilience

I. Introduction

Transmission lines are essential to communication networks and electricity distribution systems. They are made of several kinds of conductors and are intended to direct the flow of energy from a source to a load [1]. Usually, online devices are used to monitor the real-time state acquisition of overhead transmission lines. This can be enhanced by employing directed transmission data technology to increase the network lifetime [2]. Short transmission lines were the majority of applications for direct secondary wire connections from instrument transformers to protection relays [3]. One major issue with energy transfer is the act of moving electrical power from one location to another over a considerable distance [4]. The extension of the lines over varied terrains and geographic regions makes them the most vulnerable to various types of atmospheric tragedies, which frequently cause faults in the line [5].

Numerous studies have been conducted on common transmission line faults, such as L-L, L-G, and 2L-G faults [6–8]. Syncrophoresor signals can be used to discover and identify these problems,

hence enhancing power quality [7]. In three-phase transmission lines, the Fortescue Theorem has been used to evaluate symmetrical and unsymmetrical faults; the most common type of faults are single L-G faults [8]. A fault analysis model has been established to direct preventive efforts in light of the variety of sources of these defects, which include human activity and environmental elements [9]. Faults can cause power losses in transmission lines as well as power failures [10].

Fault identification in transmission lines is critical because it has the ability to create power interruptions and extend power outages. This is especially important given the increasing industrialization and electricity consumption that has resulted in a more complex power system network [11]. Advanced techniques like machine learning and deep learning have been found to considerably increase the accuracy and speed of fault identification [12]. When applied to high and medium voltage networks, these approaches have shown great promise and efficiency in fault detection [10]. To keep the electricity system running smoothly, transmission line defects must be detected and repaired quickly [13].

In line with this, the literature review explores the application of machine learning (ML) techniques in fault detection and classification (FDC) for power transmission lines. Specifically, it delves into the potential of various ML models to enhance FDC accuracy and efficiency. This review critically examines the methodologies and findings of key studies in the field, offering insights into the strengths and limitations of different approaches. Additionally, to facilitate understanding, a list of abbreviations commonly used in the reviewed literature is provided.

Table 1. Abbreviations that appear in the study.

Abbreviation	Expanded Form
AI	Artificial Intelligence
ANFIS	Adaptive Neuro-Fuzzy Inference Systems
ANN	Artificial Neural Network
BN	Bayesian Networks
BPNN	Back Propagation Neural Networks
CapsNet	Capsule Network
CNN	Convolutional Neural Network
CT	Current Transformer
DFT	Discrete Fourier Transform
DL	Deep Learning
DRNN	Deep Recurrent Neural Networks
DRL	Deep Reinforcement Learning
DSE	Differential Spectral Energy
DT	Decision Tree
DWT	Discrete Wavelet Transform
FBSC	Fractional Base Station Cooperation
FDC	Fault Detection and Classification
FLP	Fault Location Prediction
FRI	Fault Region Identification
FTC	Fault Type Classification
GFD	Global Fault Detector
GCNN	Graph Convolutional Neural Network
GNN	Graph Neural Networks
HIF	High Impedance Faults
HMM	Hidden Markov Model
HVDC	High-Voltage Direct Current
KMDD	K-Means Data Description
KNN	K-Nearest Neighbors
LSTM	Long Short-Term Memory
IPA	Instantaneous Phase Angles

ML	Machine Learning
MLP	Multi-Layer Perceptron
MODWT	Maximal Overlap Discrete Wavelet Transform
NB	Naïve Bayes
PMU	PMU
PSCAD	Positive Sequence Current Angle Differences
PSCM	Positive Sequence Current Magnitude
PSVM	Positive Sequence Voltage Magnitude
R-CNN	Region-Based Convolutional Neural Network
RF	Random Forest
RNN	Recurrent Neural Networks
SAT-CNN	Self-attention Convolutional Neural Network
SDL	Sequential Deep Learning
SF	Sparce Filtering
SE	Spectral Energy
SOM	Self-Organizing Maps
SSD	Successive Signal Detection
SVM	Support Vector Machine
TF	Transfer Function
UPFC	Unified Power Flow Controller

For transmission lines, a variety of fault locating, and detection methods have been put forth. Zhuang (2021) presents a noncontact method utilizing electro-optic field sensors [14], whereas Kumar (2019) recommends employing synchrophasor measurements to locate and categorize problems [7]. Fasihipour (2020) suggests a fault detection algorithm for TCSC-compensated lines [15], whereas Abu-Siada (2019) offers an affordable online method based on V-I locus diagrams [16]. These techniques have a number of advantages, including early failure identification and simplicity of use. It would be beneficial to investigate these techniques further for potential power system applications.

The crucial necessity of fault detection and classification in guaranteeing the dependability, security, and effectiveness of transmission lines in power systems is the driving force behind this literature study. The foundation of electrical grids are transmission lines, which make it easier to move electricity across great distances from sources of power supply to distribution networks and final consumers. Transmission lines, however, are prone to a number of problems, including insulation failures, line breakage, and short circuits, which can interfere with the power supply, harm equipment, and present safety risks.

Through a detailed examination of the body of research on fault detection and classification procedures for transmission lines, we expect to learn more about the most recent advances, methodologies, and industry best practices in this critical area. Developing robust and efficient strategies for early fault diagnosis, localization, and mitigation necessitates a grasp of the advantages and disadvantages of various fault detection approaches, including impedance-based, wavelet transform-based, and artificial intelligence-based procedures.

Furthermore, because modern power systems are becoming more complicated and because renewable energy sources and smart grid technology are becoming increasingly integrated, problem detection and classification techniques must be continuously improved. Through this literature review, we hope to identify new trends, opportunities, and issues facing the industry that will help to strengthen the resilience and reliability of transmission line networks in the face of shifting operational and environmental conditions.

The objective of this literature review is to thoroughly examine the current state of fault detection techniques in transmission line systems, considering both proven techniques and recently developed advancements. We intend to shed light on important insights and opportunities that could direct future efforts to increase the resilience and dependability of transmission line networks by delving into the most recent research and developments in this vital field.

- To compare and critically assess the current methods for fault detection used in transmission line systems.
- To list the main obstacles and restrictions related to the existing techniques for transmission line fault detection and classification.
- To investigate current developments as well as new directions in transmission line systems fault detection technology.
- To evaluate the suitability and practicality of various fault detection techniques in actual transmission line situations.
- To make suggestions on possible areas for future research and advancements in transmission line fault detection techniques.

This analysis examines the latest advancements and growing patterns in fault detection technology for transmission line systems, investigating creative methods and cutting-edge approaches that could improve fault detection performance as well as the effectiveness, dependability, and drawbacks of the current fault detection techniques in the context of actual transmission line situations, compare and contrast them. Additionally, it assesses the applicability and feasibility of several fault detection methods in real-world transmission line scenarios, taking into account elements like accuracy, efficiency, and implementation difficulties. Finally, the review aims to offer perspectives and suggestions for future research directions by pointing out possible areas of progress and recommending pathways for additional investigation and development of transmission line fault detection methods. The goal of the literature review is to increase transmission line system resilience and dependability while also advancing fault detection technology through its wide reach.

II. Methodology

This review employs a structured approach to identify and evaluate the latest advancements in transmission line fault detection methods. The following sections detail the specific techniques implemented to ensure a comprehensive and insightful investigation.

A. Literature Search Strategy

The literature search adheres to a structured protocol to guarantee the inclusion of pertinent and up-to-date research. This protocol focuses on two primary aspects:

- *Inclusion Period:* The search prioritizes studies published between 2019 and 2024 to capture the most recent developments. This timeframe ensures the review reflects the evolving landscape of fault detection technologies for transmission lines.
- *Database Selection:* The search adopts a broad perspective by systematically exploring a variety of databases. This includes industry-standard resources such as IEEE Xplore, ScienceDirect, ResearchGate (<https://www.researchgate.net/>), Scopus (www.scopus.com), Litmaps, alongside comprehensive platforms like Google Scholar. Additionally, relevant repositories are examined to uncover potentially valuable specialized research. A defined set of keywords is utilized to refine the search results and achieve a focused selection. These keywords encompass fundamental terms like "transmission line fault detection" and delve into specific methodologies like "impedance-based techniques" and "wavelet transform." Moreover, Boolean operators (AND, OR) are strategically employed to maintain a balance between comprehensiveness and specificity.

B. Establishing Inclusion and Exclusion Criteria

Strict selection criteria are established to ensure the quality and relevance of the reviewed studies. This guarantees the review centers on the most influential and rigorously conducted research.

- *Inclusion Criteria:*
 - Peer-reviewed articles, conference papers, and relevant reviews focusing on fault detection techniques for transmission lines are prioritized.

- Studies exploring a wide range of approaches are included, encompassing traditional techniques, advanced signal processing methods, applications of machine learning and artificial intelligence, and hybrid methodologies that combine these approaches. This ensures a thorough understanding of the current state-of-the-art.
- *Exclusion Criteria:*
 - Publications not in English are excluded to maintain consistency and facilitate clear analysis.
 - Studies lacking clearly defined methodologies are excluded to ensure the review focuses on robust research and avoids potentially unreliable data.

C. Detailed Data Extraction Process

Upon identification of relevant studies, a meticulous data extraction process commences. This process involves three critical steps:

1. *Creation of a Comprehensive Extraction Grid:* A detailed extraction grid is designed to streamline data extraction and ensure uniformity. This grid is formulated by analyzing recent, established checklists relevant to fault detection research. Additionally, a thorough review of 21 related studies identifies frequently reported data points. Utilizing this combined knowledge, a comprehensive extraction grid is constructed, encompassing all essential data elements.
2. *Thorough Information Extraction:* Following the established extraction grid, relevant details are meticulously extracted from each selected study. These details include bibliographic information such as titles, authors, and publication years, as well as core research elements like the employed fault detection techniques, key findings of the study, and the specific system conditions evaluated.
3. *Documenting Accuracy Metrics and Limitations:* To facilitate a comparative analysis of the effectiveness of various fault detection methods, reported accuracy rates and performance metrics are documented from each study. This enables a nuanced understanding of the strengths and weaknesses of different approaches. Additionally, any limitations mentioned by the authors are identified and documented. Analyzing these limitations provides valuable insights into potential challenges and areas for future research endeavors.

D. Multi-Dimensional Analysis of Selected Studies

A multi-dimensional approach is adopted to analyze the selected studies, enabling a comprehensive understanding of the current landscape of fault detection techniques. This approach encompasses five key components:

1. *Rigorous Study Selection:* Clear and rigorous selection criteria, meticulously aligned with the overall research objectives, are established to ensure only the most relevant studies are included for analysis.
2. *Data Synthesis and Evaluation:* Key findings from each selected study are carefully summarized, providing a concise overview of the research contributions. These summaries are then evaluated based on two crucial aspects: the specific fault detection techniques employed and the system conditions under which the techniques were tested. This allows for insights into the applicability and limitations of different approaches under varying circumstances.
3. *Comparative Analysis:* A comprehensive comparative analysis is conducted, meticulously examining the reported accuracy, strengths, and limitations of different fault detection approaches. This comparative analysis provides a clear understanding of which methodologies excel in specific scenarios and identifies areas where certain approaches might fall short.
4. *Discussing Implications and Recommendations:* The review delves into the broader implications of the findings, exploring how these advancements can potentially impact the field of fault detection for transmission lines. Furthermore, common trends and challenges identified throughout the analysis are highlighted. Based on these insights, the review provides well-considered recommendations for future research endeavors, paving the way for continued advancements.

This methodological approach employs a multi-faceted exploration to identify recent advancements in transmission line fault detection, utilizing a structured literature search, rigorous selection criteria, detailed data extraction, and multi-dimensional analysis for a comprehensive understanding of the field.

III. Results and Discussion

This section delves further into an examination of a wide range of methodologies applied in a variety of research-compiled publications. By carefully analyzing these many sources, we want to identify the approaches used, their effectiveness, underlying benefits, and associated drawbacks. We also try to deepen our understanding through additional literature studies and comparative analysis. These additional studies are used to make comparisons as well as to map the historical development of fault detection techniques in transmission lines.

A. Advanced Signal Processing Techniques:

Table 2. Literatures for Fault Detection on Transmission Lines Using Signal Processing Techniques.

Ref	Literature	Technique Used	Effectiveness	Limitations
[17]	Phase angle-based fault detection and classification for protection of transmission lines - Kumar, B., Mohapatra, A., Chakrabarti, S., Kumar, A. (2021)	<ul style="list-style-type: none"> • Estimation of IPA • DFT • GFD 	<ul style="list-style-type: none"> • Effectively and precisely identify fault conditions from non-fault conditions • Removing the requirement for phasor magnitudes and naturally lowering the influence of noise in measurement signals • Exhibits robustness against CT saturation and CT/PT measurement errors • Capability in identifying and categorizing HIFs 	<ul style="list-style-type: none"> • It does not discuss the possible computational or resource needs involved in putting the suggested model into practice in practical applications • Its efficiency in real-life situations with different environmental and operating variables has yet to be completely proven • The precision and dependability of the measurement tools may have an impact on performance
[18]	A critical fault detection analysis & fault time in a UPFC transmission line - Mishra, S., Tripathy, L. (2019)	<ul style="list-style-type: none"> • Combination of DWT and DFT • SE and DSE computation • Daubechy mother wavelet (db4) 	<ul style="list-style-type: none"> • Efficiency in identifying errors under a range of demanding circumstances is demonstrated • Detects faults in less than one cycle (20 milliseconds) • Takes performance indicators like yield, security, and dependability into account to confirm the correctness and dependability of the model 	<ul style="list-style-type: none"> • More verification and testing may be required to evaluate the scheme's effectiveness in real-world circumstances • Precise measures or benchmarks that were utilized in db4 to make the comparison were not stated
[19]	Fault detection through discrete wavelet transform in overhead power transmission lines - Ahmed, N., Hashmani, A., Khokhar, S., Tunj, M., Faheem, M. (2023)	<ul style="list-style-type: none"> • DWT 	<ul style="list-style-type: none"> • Appropriate for fault detection in transmission lines in continuous monitoring • Precisely discern between the healthy and faulty phases in various fault scenarios, increasing the fault detection's dependability • Robust fault detection is ensured by the fact that fault signals examined using DWT are insensitive to changes in factors 	<ul style="list-style-type: none"> • Proposes utilizing DWT to investigate how noise affects feature extraction from fault signals • It would benefit from more verification and testing in actual situations to evaluate the robustness and practical usability of DWT-based fault detecting systems

			like fault inception angle, fault resistance, and transmission line length	
[20]	Fault Detection and Classification of Shunt Compensated Transmission Line Using Discrete Wavelet Transform and Naive Bayes Classifier - Aker, E., Othman, M., Veerasamy, V., Aris, I., Wahab, N., Hizam, H. (2020)	<ul style="list-style-type: none"> • DWT • NB classifiers 	<ul style="list-style-type: none"> • DWT decomposes the current signal during faults, allowing for the identification of characteristic patterns within the signal. • The study suggests that the NB classifier outperforms other classifiers like MLP Neural Networks in terms of accuracy, misclassification rate, and various error metrics. 	<ul style="list-style-type: none"> • Choosing the right way to analyze the signal DWT and the classifier NB can affect accuracy. • Real-world noise and dependencies between fault features can lead to errors. • The method is optimized for shunt-compensated lines and might need adjustments for other cases. • Results from simulations may not directly apply to complex real-world power systems.
[21]	MODWT-based fault detection and classification scheme for cross-country and evolving faults - Ashok, V., Yadav, A., Abdelaziz, A. (2019)	<ul style="list-style-type: none"> • MODWT 	<ul style="list-style-type: none"> • A complete method for locating cross-country and evolving faults in a real 400 kV dual-circuit transmission line network is provided by the application of MODWT-based fault detection and classification • The method displays its resilience by effectively identifying and categorizing defects across a broad range of fault parameters and operational circumstances • A method based on MODWT is noise-resistant • The model has a small time delay, with an operating time that can be as little as $\frac{1}{4}$ cycle or as much as 1 cycle • Verified by means of experimental data gathered in a lab setting utilizing a hardware configuration 	<ul style="list-style-type: none"> • Primarily concentrates on fault classification and detection in a 400 kV dual-circuit transmission line network in the state of Chhattisgarh • Implementation and maintenance may become more complex if a two-stage development procedure and fault classifier algorithms based on fault coordinates are used • Although the system's performance is assessed by experimental data from a hardware setup, other factors like scalability, cost-effectiveness, and compatibility with current infrastructure may need to be taken into account before the scheme is actually deployed in transmission line networks
[22]	Faults detection and classification of HVDC transmission lines of using discrete wavelet transform - Saleem, U., Arshad, U., Masood, B., Gul, T., Khan, W., Ellahi, M. (2018)	<ul style="list-style-type: none"> • DWT 	<ul style="list-style-type: none"> • Shows dependability in identifying different kinds of defects through the examination of current signals received from high-voltage DC transmission lines 	<ul style="list-style-type: none"> • Possible difficulties for professionals who don't have much experience with sophisticated signal processing methods • May be quite difficult computationally, which could limit its application in real

		<ul style="list-style-type: none"> • It is stated that the suggested strategy is more accurate than previous fault detection techniques for HVDC transmission lines • Flexible enough to accommodate various fault situations and positions on HVDC transmission lines 	<ul style="list-style-type: none"> • time or necessitate a large amount of computing power to implement • There may be a limit to its applicability to different kinds of transmission networks or failure circumstances
[23]	<p>Transmission Line Fault Detection and Identification in an Interconnected Power Network using Phasor Measurement Units</p> <p>- Khan, A., Ullah, Q., Sarwar, M., Gul, S., Iqbal, N. (2018)</p>	<ul style="list-style-type: none"> • PMUs • Uses two steps to identify and detect faults: the first stage uses PSVM and PSCADs, while the second stage uses PSCM • The suggested framework's efficiency is demonstrated by the simulation results, which correctly identify 11 different types of failures at 6 different network nodes • Carried out and evaluated on a 5-bus linked power network • PMUs are used to collect the voltage and current data needed for fault identification and detection 	<ul style="list-style-type: none"> • Restricted to identifying short circuit faults; without additional modification, it is unable to recognize open circuit faults • It might need more testing and modification to determine whether it is appropriate for larger applications or different kinds of power networks • Dependence on PMU infrastructure availability and dependability is implied when using PMU data for voltage and current measurement • The successful implementation of the two-stage procedure implies a certain amount of complexity in its implementation, which may need proficiency in fault detection techniques and power system analysis • The inability to detect open circuit faults without alteration suggests that further research or improvement of the suggested method may be necessary to handle a greater variety of fault circumstances

This table presents recent research in FDC for power transmission lines, showcasing several innovative techniques, each with its own advantages and limitations. One approach utilizes phase angle-based methods employing IPA estimation and DFT. This method boasts precise fault identification and robustness against measurement errors and current transformer saturation. However, its real-world implementation requirements and effectiveness under diverse operating conditions remain unclear and warrant further investigation.

Another promising technique combines DWT with DFT and SE computation for fault detection in UPFC transmission lines. This method achieves efficient fault detection within a single cycle. However, the lack of comprehensive validation under real-world conditions and a clear definition of the benchmarks used for comparison limit its current applicability. Similarly, a separate study proposes a DWT-based fault detection technique that exhibits promising fault discrimination and robustness. However, similar to the previously mentioned methods, this approach requires further verification and testing in real-world scenarios to assess its effectiveness and adaptability in practical applications.

Furthermore, a method combining DWT with NB classifiers proves effective for fault detection and classification in shunt-compensated transmission lines. While this approach demonstrates effectiveness, its accuracy under real-world noise conditions and generalizability to complex power systems with various configurations pose challenges that need to be addressed.

Additionally, MODWT method provides a complete fault identification and classification capability in the field of fault detection techniques. Its potential for practical deployment is highlighted by its successful implementation in an actual 400 kV dual-circuit transmission line network, noise resistance, and short time delay. However, concerns over the method's scalability and adaptability to different network designs are raised by its concentration on particular transmission line topologies in Chhattisgarh. Furthermore, the complexity of implementation raises the possibility that additional analysis of scalability, cost-effectiveness, and compatibility with current infrastructure is necessary, especially in light of two-stage development and fault classifier algorithms.

Moreover, a viable method for identifying defects in HVDC transmission lines is the independent application of DWT. Its potential utility is highlighted by its proven dependability and versatility in accommodating different fault scenarios on HVDC lines. Nevertheless, much thought should be given to potential computing difficulties and applicability restrictions to various transmission networks or failure scenarios. Furthermore, in real-time implementation or resource-constrained contexts, the computing needs of the approach and the requirement for expertise in signal processing may present difficulties.

Finally, using PMUs to detect faults provides a thorough method that makes use of voltage and current data to precisely pinpoint fault circumstances. Fault circumstances can be properly diagnosed and categorized using a two-stage procedure that involves PSVM, PSCADs, and PSCM. Even though it has been successful in identifying short circuit faults, its drawbacks—such as its need on the availability of PMU infrastructure and its complicated implementation—make more testing and improvement necessary. Furthermore, the method's incapacity to identify open circuit failures without alterations points to potential areas for further investigation to expand its applicability to a wider variety of fault scenarios and transmission line topologies.

B. Machine Learning (ML) and Artificial Intelligence (AI) Techniques:

Table 3. Literatures for Fault Detection on Transmission Lines Using Machine Learning (ML) and Artificial Intelligence (AI) Techniques.

Ref	Literature	Algorithms Used	Strengths	Limitations
[24]	Deep learning through LSTM classification and regression for transmission line fault detection, diagnosis and location in large-scale multi-machine power systems - Belagoune, S., Bali, N., Bakdi, A., Baadji, B., Atif, K. (2021)	<ul style="list-style-type: none"> DL (Presents three innovative DL classifier regression models based on DRNN for FRI, FTC, and FLP) Current and voltage signals are monitored using PMUs at various terminals and used as input characteristics for DRNN models SDL with LSTM to model spatiotemporal sequences of high-dimensional multivariate characteristics 	<ul style="list-style-type: none"> Accurate region classification in large-scale multi-machine power systems Excellent performance in fault location prediction Excellent categorization and prediction accuracy 	<ul style="list-style-type: none"> The dependency on synchrophasors indicates a possible constraint in application to systems lacking access to modern synchrophasor technology Scalability and generalizability
[25]	A deep learning based intelligent approach in detection and classification of transmission line faults - Fahim, S., Sarker, S., Muyeen, S., Das, S., Kamwa I. (2021)	Capsule Network with SF model	<ul style="list-style-type: none"> Accurately manage limited system information and develop resistance to system sounds Extracts faulty features into a single characteristic, making the fault identification procedure easier Does not call for manual labeling of data during training and testing, increasing its scalability and applicability to varied datasets Accuracy rates surpassing 99% in identifying and classifying faults, even 	<ul style="list-style-type: none"> The evaluation focuses primarily on simulated datasets Does not discuss the possible computational or resource needs involved in putting the suggested model into practice in practical applications Does not offer the model's generalizability to other transmission line layouts and operating situations outside of those that were evaluated

under difficult conditions such as the presence of system disturbances, high impedance faults, and line parameter fluctuations

[26] Self-attention convolutional neural network with time series imaging based feature extraction for transmission line fault detection and classification - Fahim, S., Sarker, Y., Sarker, S., Sheikh, M., Das, S. (2020)	<ul style="list-style-type: none"> • SAT-CNN model • DWT 	<ul style="list-style-type: none"> • Ability to adjust to various operating environments • Imperceptibly concentrates on the output data from the hidden layer, improving the system's classification precision • Operates well with a variety of sampling frequencies and signal kinds, demonstrating its robustness and adaptability • Withstand noise interference 	<ul style="list-style-type: none"> • It does not discuss the possible computational or resource needs involved in putting the suggested model into practice in practical applications • The evaluation focuses primarily on simulated datasets • Future deployment of the classifier utilizing actual data gathered from equipment in real-world power grids may necessitate careful consideration of data quality, calibration, and measurement errors • It does not offer the model's generalizability to other transmission line layouts and operating situations outside of those that were evaluated
[27] End to end machine learning for fault detection and classification in power transmission lines - Rafique, F., Fu, L., Mai, R. (2021)	'End to end' ML model employing LSTM	<ul style="list-style-type: none"> • Removal of the requirement for intricate feature extraction procedures • Differentiate between several states, such as fault and non-fault, and between various kinds of faults • Flexibility to different problem scenarios and system specifications • Capable of handling voltage and current signals, providing a variety of data sources • Ability to recognize and function in situations of power swings, increasing its usefulness in practical situations • Strong performance across a range of fault scenarios, including as changes in fault impedance, loading circumstances, distance from measurement nodes, and signal noise levels 	<ul style="list-style-type: none"> • Further examination is necessary in order to determine its efficacy and dependability in real-world applications using data from real power systems in both recorded and real-world settings • Necessary to carefully evaluate the computational load that comes with reconfiguring operational data using a Timesteps strategy to reduce computational load, particularly for large-scale power systems with substantial data requirements • The degree of noise in the signals, the intricacy of the power system structure, and the availability of measuring instruments could affect the robustness of the model

[28] Detection and classification of transmission line transient faults based on graph convolutional neural network - Tong, H., Qiu, R., Zhang, D., Yang, H., Ding, Q., Shi, X. (2021)	● GCNN	<ul style="list-style-type: none"> ● Permits building a model for graph classification ● Integrating topological data into the network to deliver temporal and spatial data for fault identification and categorization ● Show the suggested method's high accuracy and excellent generalizability in identifying a variety of transient defects in a variety of settings ● Demonstrates sensitive and steady performance with respect to robustness and response speed 	<ul style="list-style-type: none"> ● The suggested solution uses a spectral convolution for graph convolution, which is theoretically sound but not very flexible ● It is considered that the edge weight is essential for locating faults, indicating that more investigation is required to improve the weighing system ● Recommended investigation in the application of dynamic GNN in order to overcome the drawbacks of spectral convolution and facilitate the identification, categorization, and localization of malfunctions in dynamic power grids
[29] Transmission Line Fault Classification Using Hidden Markov Models - Freire, J., Castro, A., Homci, M., Meiguins, B., Morais, J. (2019)	● ANN, SVM, KNN, and RF	<ul style="list-style-type: none"> ● When it came to fault classification, the HMM algorithm performed better and had reduced error rates ● About 90% faster processing times were demonstrated by the HMM method than by any of the FBSC architecture's classifiers ● Direct fault event classification is made possible by the HMM method, which streamlines the classification procedure and may even result in less processing cost 	<ul style="list-style-type: none"> ● The study used a particular dataset, UFPA Faults, and concentrated mostly on short-circuit faults ● As the stated findings were produced on a workstation with particular hardware requirements (i7 CPU, 16GB memory), the algorithm's application to systems with varying processing capacities may be limited ● Its usefulness in practical applications has not yet been confirmed
[30] High Impedance Single-Phase Faults Diagnosis in Transmission Lines via Deep Reinforcement Learning of Transfer Functions - Teimourzadeh, H., Moradzadeh, A., Shoaran, M., Mohammadi-Ivatloo, B., Razzaghi, R. (2021)	● TF method ● CNN and the hybrid model of DRL	<ul style="list-style-type: none"> ● Exhibited greater performance in identifying and precisely finding single-phase to ground short circuit problems in power networks ● Attained strong correlation values during the training and testing phases, demonstrating the models' efficacy in fault classification ● The DRL approach demonstrated its effectiveness in identifying subtle fault situations and perhaps averting 	<ul style="list-style-type: none"> ● Mainly concerned with single-phase to ground short circuit problems by simulating data from an IEEE transmission line ● Depends on local data gathered from the transmission line, which may restrict its application in circumstances where access to extensive or centralized data is restricted ● Deep learning technique skill and substantial computational resources may be needed for its installation and training

catastrophic failures by outperforming the CNN method in the early identification of high-impedance faults (7000 and 9000 ohms)

[31] Detection and Evaluation Method of Transmission Line Defects Based on Deep Learning - Liang, H., Zuo, C., Wei, W. (2020)	<ul style="list-style-type: none"> • Faster R-CNN, an end-to-end and high recognition accuracy deep learning algorithm 	<ul style="list-style-type: none"> • Identification of transmission line defects using automation, which decreases labor intensity and the necessity for manual inspection • The absence of accessible and standardized datasets in the field of transmission line components is addressed by the development of the Wire_10 dataset, which consists of aerial photos taken by UAVs • Based on the Wire_10 dataset, the defect detection network achieves a low false detection rate of 0.68% and a mean Average Precision (mAP) of 91.1% 	<ul style="list-style-type: none"> • The scope of the dataset collected by UAVs may be constrained, which could result in missed and false detections in some circumstances, especially in the winter and in non-rural locations • The present dataset may not fully capture the fine features of transmission line components since it classifies problems into broad categories • In actuality, the precise categorization of transmission line components can be complicated, necessitating close examination of a number of variables
[32] Detection and classification of internal faults in bipolar HVDC transmission lines based on K-means data description method - Farshad, M. (2019)	<ul style="list-style-type: none"> • KMDD method 	<ul style="list-style-type: none"> • Exhibits excellent precision and dependability while identifying and categorizing internal DC faults in bipolar HVDC transmission lines • Demonstrates resilience to external errors and standard operating circumstances • Demonstrates its flexibility and adaptability by being able to handle a variety of fault situations, including ones that weren't taken into account during creation • Contributes to its accuracy and stability by being less sensitive to elements including measurement noise, fault resistance, and fault location • Lessens reliance on connected equipment and communication channels 	<ul style="list-style-type: none"> • Although the scheme's low sample frequency makes it more applicable in current systems, it might make it less capable of capturing high-frequency transient events or intricate waveform data • Although the scheme's low sample frequency makes it more applicable in current systems, it might make it less capable of capturing high-frequency transient events or intricate waveform data

	<ul style="list-style-type: none"> • Appropriate for integration into current systems without requiring substantial hardware modifications 	
<p>[33] Fault Detection and Classification in Power Transmission Lines using Back Propagation Neural Networks - Teja, O., Ramakrishna, M., Bhavana, G., Sireesha, K. (2020)</p>	<p>• BPNN</p> <ul style="list-style-type: none"> • The Π-modeling of the three-phase medium power transmission line system simplifies representation and analysis, making fault detection algorithms easier to construct • Compatibility and simplicity of use when MATLAB/Simulink® is used • Creating training data from transmission system simulated values guarantees a regulated training environment for neural networks • By utilizing feedforward BPNN techniques, faults can be accurately classified and detected. This is because neural networks can identify intricate patterns from training data 	<ul style="list-style-type: none"> • The transmission line system may become overly simplistic if it is converted to a Π-model. • The analysis was limited to fault scenarios including AG and ABG, which may not accurately reflect the range of faults that might arise in real-world transmission line systems. • The system complexity, dataset size, and computational resources are only a few of the variables that may influence the optimization algorithm selection • In order to evaluate the efficacy of fault detection algorithms in practical applications, performance analysis mostly concentrated on MSE, epochs, and training time, ignoring other critical metrics like accuracy, precision, and recall • There are no specifics given about the hybridization criteria, optimization method, or anticipated performance gains
<p>[34] Component identification and defect detection in transmission lines based on deep learning - Zheng, X., Jia, R., Aisikaer, Gong, L., Zhang, G., Dang, J. (2020)</p>	<p>• Faster R-CNN</p> <ul style="list-style-type: none"> • By eliminating the need for extra specialist hardware, using power grid video surveillance technology for transmission line component classification and fault detection lowers installation costs • The use of SSD, Mask R-CNN, and Faster R-CNN algorithms shows how successful deep learning methods are in target identification and semantic segmentation • Understanding the advantages and disadvantages of the Faster R-CNN, 	<ul style="list-style-type: none"> • Limiting the suggested algorithm's application to situations involving different kinds of transmission line components by concentrating on just five different kinds of transmission widgets • The complete variety of transmission line environments may not be captured if sample images are just derived from drone aerial inspection shots of the power grid • Lacks in-depth investigation into component failure detection in favor of focusing mostly on target detection of aerial photography components

SSD, and Mask R-CNN algorithms is possible through comparison and study

- Contextual and semantic information are better combined when an object detection framework built on FPN-SSD is introduced
 - Attaining an average accuracy of 89.3% on the dataset indicates how well the suggested algorithm works for identifying transmission line components and detecting defects
-

This table shows previous studies proposing various novel deep learning-based approaches for FDC in power transmission systems. The first method utilizes DRNNs with LSTM units within a SDL framework. This approach demonstrates exceptional performance in fault region identification, type classification, and location prediction. However, its reliance on synchrophasor data may limit its applicability to systems lacking this infrastructure, raising concerns regarding scalability and generalizability across diverse grid configurations.

Conversely, a CapsNet with SF exhibits remarkable performance, surpassing 99% accuracy in FDC tasks even under challenging conditions. However, the evaluation primarily focused on simulated datasets, and the discussion surrounding practical implementation hurdles and generalizability remains limited. Similarly, a SAT-CNN combined with DWT showcases promising adaptability and robustness. Nonetheless, a comprehensive evaluation of its real-world deployment challenges and generalization to various system configurations is currently lacking.

Furthermore, an End-to-End ML approach offers flexibility and delivers strong performance across diverse fault scenarios. Nevertheless, further investigation is necessary to assess its efficacy in real-world applications, particularly regarding computational load considerations.

Moreover, the GCNN offers a new method by enabling the creation of a model for graph classification and incorporating topological information into the identification and classification of faults. This model exhibits potential for reliable and quick fault detection, as evidenced by its excellent accuracy and generalizability across a range of problem scenarios and settings. However, the need for more research indicates possibilities for future study and development in the fields of edge weighting systems and graph convolution flexibility.

Additionally, when it comes to detecting internal DC faults in bipolar HVDC transmission lines, the KMDD method excels in terms of accuracy and dependability. With less dependence on linked devices and communication lines, its accuracy and stability are enhanced by its flexibility, adaptability, and resistance to outside mistakes. The necessity for additional improvement and validation in practical environments is highlighted by restrictions on sample frequency and the ability to record high-frequency transient occurrences.

Finally, the Faster R-CNN algorithm solves the issues of human inspection and dataset standardization, providing great opportunities for automated identification of transmission line defects. This model shows promise for real-world implementation with the creation of specific datasets and reduced false detection rates. However, there is a need for continued study to improve applicability and reliability due to limits in accurate component categorization, representativeness, and dataset coverage.

C. Related Comparative Study and Literature Reviews Summary

- Advanced Fault Detection, Classification, and Localization in Transmission Lines: A Comparative Study of ANFIS, Neural Networks, and Hybrid Methods by Kanwal, S., Jiriwibhakorn, S. (2024) [35]

- Summary:

The study used a variety of computational tools to look at fault localization, classification, and detection in power transmission networks. Faults were induced at four sites within the IEEE 9-bus system, resulting in a total of forty distinct fault conditions being examined. ANN, ANFIS, SOM, and a hybrid technique that combines DWT with ANFIS were among the models whose performances were assessed.

With an error percentage of 0.008% on average, the ANFIS model showed remarkable defect detection skills. Except for one instance when the error was -0.005%, it correctly categorized all fault kinds. An average percentage inaccuracy of 0.547% was found for fault location. On the other hand, the ANN-based models performed well in fault classification and localization, with average percentage errors of 0.268% and 0.348%, respectively, and reached zero percent error for fault detection.

The SOM-based models achieved zero percent error for all faults, demonstrating their superiority in fault identification. However, there were a few minor mistakes in the fault location

and categorization, especially for certain fault circumstances. With zero percent error for fault detection and respectable performance for fault classification and localization, the hybrid DWT-ANFIS model produced encouraging results.

In comparison to other models, the ANFIS and hybrid techniques performed better overall in defect identification, classification, and location. These results highlight how crucial it is to use cutting-edge computational methods and hybrid approaches to improve the efficiency and dependability of electricity transmission networks.

- Advanced techniques for fault detection and classification in electrical power transmission systems: An overview by Tîrnovan, R. (2019) [36]

- Summary:

This study provides an extensive overview of power transmission system fault detection and classification techniques. It addresses signal acquisition, highlighting the critical role that feature extraction plays in improving problem detection. It discusses model-based, knowledge-based, and data-driven approaches to fault detection and groups them according to parameters like information amount and quality. The usefulness of several fault detection techniques is demonstrated by the results, which emphasize their importance in guaranteeing the safety and dependability of the electrical grid.

The field of fault analysis techniques for power transmission systems has seen a significant upsurge in development in recent years, with an emphasis on AI-based approaches and contemporary techniques. These comprise PMU-based methods for phasor component rapid estimate and fault detection, classification, and direction discrimination. Furthermore, methods for improved defect detection have been used, including multi-information measurements and GSM. Promising outcomes have been observed in AI-based approaches for pattern recognition and ML, including ANNs, DT, BN, k-NN, SVMs, and DL. For example, DTs have been used to identify and classify faults based on phase current data, while ANNs have been used to accurately identify the type of fault in transmission lines. When utilizing wavelet decomposition for fault classification, SVMs have proven to be efficacious, whereas Bayesian networks provide precise fault section estimation in power systems. Moreover, in distance protection schemes, k-NN algorithms have been applied for defect detection and classification. CNNs, one of the DL techniques, have a lot of promise to enhance fault classification performance, particularly when using three-phase current and voltage inputs in multi-channel sequence recognition issues. The aforementioned developments highlight the need of incorporating AI methods into fault identification and classification systems to guarantee the dependability and effectiveness of power transmission networks.

- A Brief Review on Fault Detection, Classification and Location on Transmission Lines Using PMUs by Swain, K., Mandal, S., Mahato, S., Cherukuri, M. (2018) [37]

- Summary:

Examining fault localization, classification, and detection in power transmission networks using PMUs demonstrates a wide range of approaches and algorithms designed to increase protection systems' dependability and effectiveness. A key method that makes use of the symmetrical characteristics of electrical networks to precisely identify and categorize defects is symmetrical component analysis. For example, a robust fault analysis methodology that leverages PMU data concentrates on the symmetrical components of voltage and current phasors, allowing for rapid fault diagnosis in a relatively short timeframe, often within 2-3 cycles after the incident. In addition to symmetrical component analysis, additional signal processing techniques such as the Stockwell transform have been used to detect and classify faults. This approach effectively detects and classifies faults by examining differential sums and energy computations over half cycles.

Algorithms for machine learning have also become effective tools for classifying and detecting faults. Techniques like DTs and SVMs are used because of their capacity to manage intricate data patterns and classification assignments. Additionally, in order to improve problem detection capabilities, the integration of PMU data with other sources—like smart meters—has been investigated. For instance, a technique is put forth to continually monitor transmission line

impedance and guarantee data integrity in order to identify potential cyberattacks on PMU data transferred across wide area networks.

Large-scale network simulations and small-scale test cases are only two examples of the various simulation studies that are frequently used to validate these approaches. Systems like EMTP/ATP, DigSILENT PowerFactory, and MATLAB offer stable settings for evaluating and verifying suggested algorithms, guaranteeing their effectiveness and dependability in practical uses.

The research on fault localization, classification, and detection in PMU-based power transmission systems is a constantly changing and dynamic topic. In order to meet the challenges presented by changing grid dynamics and new threats, researchers work to improve the efficiency, resilience, and dependability of power grid protection systems through creative methods, cutting-edge signal processing techniques, and the integration of machine learning.

D. Discussion

Analyzing the outlined literature, it's evident that fault detection techniques for power transmission lines have seen significant advancements driven by a blend of traditional signal processing methods and emerging technologies like deep learning.

Overall Trends and Advancements:

Traditional signal processing techniques such as DWT, NB classifiers, and phase angle-based methods have long been foundational in fault detection. These methods offer robustness and efficiency in fault identification but often require further validation under diverse real-world conditions to ascertain their practical applicability.

Moreover, the integration of machine learning, particularly deep learning algorithms like CapsNet, CNNs, and RNNs with techniques like DWT and DFT, presents a paradigm shift in fault detection. These approaches exhibit exceptional performance in fault identification, classification, and localization, often surpassing traditional methods in accuracy and adaptability.

Potential of Emerging Techniques:

DL techniques offer promising avenues for fault detection, particularly in their ability to handle complex data patterns and generalize across diverse system configurations. CapsNet, for instance, show remarkable performance even under challenging conditions, while GCNN offer innovative ways to incorporate topological information for fault detection. Integration with smart grid technologies, such as PMUs, further enhances fault detection capabilities by leveraging real-time data for precise fault localization and classification.

Key Challenges and Future Research Directions:

Despite the advancements, several challenges persist in fault detection for transmission lines. Real-time implementation of complex algorithms remains a significant hurdle, particularly in resource-constrained environments. Additionally, ensuring the scalability and adaptability of fault detection techniques across different network designs and fault scenarios requires further investigation. Cybersecurity threats also pose a growing concern, necessitating robust methods to safeguard PMU data and infrastructure from potential attacks.

Future research directions should focus on addressing these challenges while exploring novel techniques to improve fault detection efficiency and reliability. This includes investigating the practical implementation of deep learning algorithms in real-world transmission systems, developing robust cybersecurity measures to protect against cyber threats, and enhancing the scalability and adaptability of fault detection methods across diverse network configurations.

The synergy between traditional and deep learning techniques presents a promising path forward for fault detection in power transmission lines. However, addressing key challenges and advancing research are crucial to ensure the resilience and dependability of power grid protection systems in the face of evolving grid dynamics and emerging threats.

IV. Conclusion

In conclusion, the extensive literature review provides a nuanced understanding of fault detection and classification techniques for transmission lines, showcasing a blend of traditional signal processing methodologies and cutting-edge advancements in deep learning. At its core, fault detection remains a pivotal component in ensuring the reliability, safety, and efficiency of power grids worldwide.

The significance of fault detection in transmission lines cannot be overstated, as it serves as a frontline defense against widespread outages, equipment damage, and potential hazards to both infrastructure and public safety. Through the lens of the reviewed literature, it becomes evident that the continuous refinement and innovation in fault detection methodologies are imperative to meet the evolving challenges posed by modern power grids.

The main findings of the literature review offer valuable insights into the efficacy of various fault detection techniques. Traditional methods such as DWT and phase angle-based approaches demonstrate robustness and reliability, particularly in fault identification and discrimination. Concurrently, emerging deep learning algorithms, including CapsNet and CNN, exhibit promising capabilities when integrated with smart grid technologies, showcasing superior performance in fault localization, classification, and prediction.

Moreover, the review underscores the critical importance of future research avenues to address existing limitations and propel the field forward. Key areas for improvement include the need for comprehensive validation and real-world testing of existing fault detection techniques to assess their applicability under diverse operating conditions. Additionally, the development of scalable and adaptable algorithms is paramount to accommodate the intricacies of various network configurations and fault scenarios. Furthermore, enhancing cybersecurity measures to safeguard PMU data and infrastructure against potential threats emerges as a pressing concern in the context of modern grid resilience.

By embracing these insights and recommendations, researchers can continue to advance fault detection and classification techniques for transmission lines, contributing to the broader goal of ensuring the reliability and resilience of power transmission systems. Through interdisciplinary collaboration and concerted efforts, the field can strive towards comprehensive solutions that effectively mitigate risks, optimize grid performance, and uphold the integrity of critical infrastructure essential for societal well-being and economic prosperity.

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