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Article

State-of-the-art techniques and algorithms for swift and precise fault detection and protection in transmission lines

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ABSTRACT

Transmission lines are crucial for power systems, enabling bulk power transfer from generation sites to load centers. They face challenges such as faults, losses, and delays, necessitating effective management and maintenance strategies. The aim of this paper is to conduct a systematic literature review focusing on techniques and algorithms for swift and precise fault detection and protection in transmission lines. The methodology included a collection of relevant papers, a filtering process, eligibility identification, synthesizing, and trend analysis. This process was facilitated using the Scopus database and VOSviewer software. Results of this survey revealed some key noticeable aspects (among others) across the studies, which included the utilization of diverse signal processing and machine learning techniques to analyze voltage and current signals for identifying faults. This work will contribute by reviewing recent advances in signal processing, analyzing methods to enhance fault detection speed and accuracy, exploring the use of machine learning and neural networks in fault detection models, investigating advanced relay technologies and protection schemes, evaluating statistical techniques for fault isolation, and examines indexing techniques and evolutionary programming tools for precise fault identification, while also proposing future research directions.

1. Introduction

Transmission lines are crucial for power systems, enabling bulk power transfer from generation sites to load centers [1]. They face challenges such as faults, losses, and delays, necessitating effective management and maintenance strategies. Reliability-centered maintenance can prioritize lines based on their condition and importance [2]. Energy harvesting methods for powering wireless sensors are being developed to enhance monitoring capabilities [3]. Fault detection systems are essential for minimizing interruptions and improving reliability [4]. Inspection robots, including climbing, flying, and hybrid types, are emerging technologies for early fault detection [5]. Research trends in transmission lines focus on areas like line inspection, fault location, and artificial intelligence [6]. Delays in transmission projects often stem from right-of-way issues and route changes [7]. Minimizing power losses through techniques like capacitor compensation is crucial for efficient power delivery [8]. Recent research on fault detection in transmission lines focuses on developing swift and precise methods to enhance power system reliability. Various approaches have been proposed, including smart algorithms using phasor measurement units [9], machine learning techniques for simultaneous detection and localization [10], and deep learning models combined with Discrete Wavelet Transform [11]. Wavelet Transform has been widely explored for its effectiveness in fault detection and classification [12,13]. Artificial Neural Networks have shown promise in fault detection, classification, location, and direction discrimination [14]. Some studies have utilized digital signal processing techniques [15] and evolutionary programming tools [16] to improve fault analysis. These advanced methods aim to minimize power losses, reduce downtime, and optimize maintenance efforts in transmission systems, addressing the growing demand for reliable power distribution. Current transmission line analysis and modeling advancements have significantly improved power system management and reliability. State-of-the-art techniques for power flow analysis, such as particle swarm optimization and hybrid algorithms, have shown superior accuracy and efficiency compared to classical methods [17]. Energy harvesting technologies for wireless sensors on transmission lines are evolving rapidly, enabling real-time monitoring and predictive maintenance [18]. Innovative approaches for transmission line simulation using S-parameter data [19] and parameter identification through state estimation [20] have enhanced modeling accuracy. Advanced fault diagnosis and prognosis techniques, including artificial intelligence methods, improve network reliability [21]. Wavelet transform analysis is being applied to identify and classify disturbances on transmission lines [22]. Additionally, metamaterial transmission lines [23] and computational methods for electromagnetic field analysis [24] are expanding the capabilities of microwave and millimeter-wave technologies.

It is evidence that research on fault detection in transmission lines emphasizes the development of swift and precise methods to enhance power system reliability. Various approaches have been proposed, including smart algorithms using phasor measurement units, machine learning techniques for simultaneous detection and localization, and deep learning models combined with Discrete Wavelet Transform. Wavelet Transform has been widely explored for its fault detection and classification effectiveness. Artificial Neural Networks have shown promise in fault detection, classification, location, and direction discrimination. Some studies have utilized digital signal processing techniques and evolutionary programming tools for improved fault analysis. These advanced methods aim to minimize power losses, reduce downtime, and optimize maintenance efforts in transmission systems, addressing the growing demand for reliable power distribution. However, there is a distinguished gap in the literature regarding a comprehensive review of state-of-the-art techniques and algorithms for swift and precise fault detection and protection in transmission lines. Thus, the aim is to conduct a systematic review of these state-of-the-art techniques and algorithms, with contributions focused on:

- Reviewing recent advances in signal processing methods.
- Analysing methods that enhance the speed and accuracy of fault detection and classification.
- Exploring the application of machine learning and artificial neural networks in developing sophisticated models for fault detection.
- Investigating the latest relay technologies and protection schemes that utilize advanced algorithms and smart sensors to improve fault detection and system protection.
- Evaluating specific fault detection methods that employ statistical techniques like the summation of squared currents and moving average methods to identify and isolate faults.
- Examining the development and implementation of indexing techniques and evolutionary programming tools that aid in the precise identification and indexing of faults.

The rest of the paper is arranged as follows: Section II: Developments in fault detection, classification, and location in power systems. Section III: Methodology of how the project was conducted. Section IV: Results and discussion, where all the papers are grouped according to their relevance and the topic being researched. Section V: Literature Review Analysis Observations provides an in-depth examination of the literature review. Section VI: Conclusion and Future Research summarizes the key findings and contributions of the study and offers recommendations for future research recommendations based on the knowledge acquired.

2. Developments in fault detection, classification, and location in power systems

In the past two decades, significant progress has been made in detecting, classifying, and locating faults in power systems. Advancements in signal processing, artificial intelligence, machine learning, GPS technology, and communication systems have allowed researchers to improve and extend traditional fault protection methods. These innovations have also addressed key limitations in online fault diagnosis, enhancing system reliability and performance [25]. As illustrated in Figure 1, the process begins by sampling current and voltage signals, which are fed into a feature extraction module. The extracted features are used by the fault detection, classification, and location modules. The final outputs provided by the system are the fault type and location, determined by the fault classifier and locator, respectively [26]. Figure 2 depicts the structure of the extreme learning machine (ELM) model. The hidden layer comprises 700 nodes, while the output layer includes a single node for fault detection (FD) and 11 nodes for fault classification (FC). Each node is equipped with an activation function, and the ReLU function was used to activate them [27].

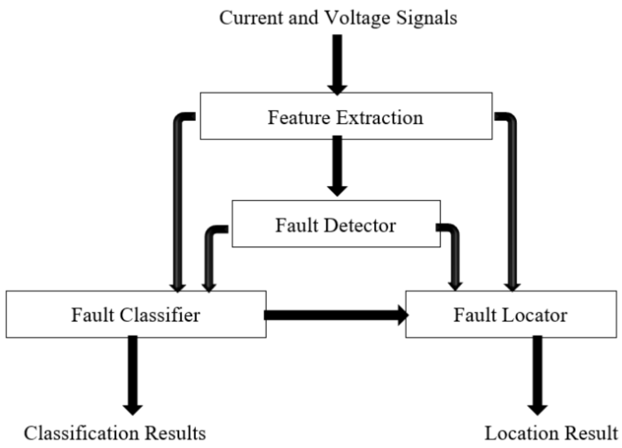

Figure 1. Simplified framework for fault detection, classification, and location

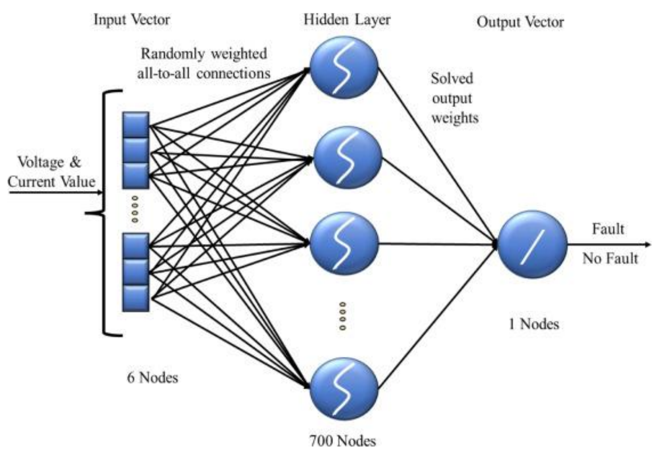

Figure 2. Structure of elm classifier employed

The performance of the models was evaluated using common statistical metrics such as accuracy, precision, recall, and F1-score. The formula for calculating accuracy is provided in Equation 1:

$$Acc = \frac{(PT+TN)}{(PT+TN+FP+FN)} \times 100\ \% \quad (1)$$

In this context, TP represents true positives, indicating correctly detected faults, while TN denotes true negatives, meaning correctly identified non-faulty cases. FP refers to false positives, where non-faulty cases are mistakenly identified as faulty, and FN represents false negatives, where actual faults are missed [28]. Precision (P), as defined in Equation 2, is calculated by dividing the true positives by the total predicted positives. It shows the proportion of correctly detected faults out of all cases predicted as faulty [10]:

$$P = \frac{TP}{(TP+FP)} \quad (2)$$

Recall (R) measures the model's effectiveness in identifying actual faulty cases. It is calculated as the ratio of correctly predicted faults to the total number of actual faults and can be expressed by the following formula:

$$R = \frac{TP}{(TP+FN)} \quad (3)$$

The F1 score is a metric that evaluates a model's overall performance by balancing precision and recall. It is the harmonic mean of precision and recall, with a maximum value of 1.0 indicating perfect precision and recall, while a value of 0 means both are absent. The formula for calculating the F1 score is as follows [29]:

$$F1 - Score = \frac{2(Precision\ x\ Recall)}{(Precision+Recall)} \quad (4)$$

3. Methodology

The methodology involved identifying relevant keywords, conducting a thorough search using the Scopus database, filtering and exporting data, and utilizing VOSviewer software for data analysis. Below is a detailed description of each step taken in the process.

3.1 Topic and keywords

The research topic chosen for this review is the detection of faults in three-phase transmission lines and its societal impact. To gather relevant information, the keywords "Fault Detection," "Transmission Lines," AND "Three Phase" were designed. These keywords were selected to ensure comprehensive coverage of the topic.

3.2 Scopus database

3.2.1 Initial search

The Scopus database was accessed using a University of South Africa student email. In the search settings, "Article title, Abstract, Keywords" was selected. The designed keywords were entered into the search documents box, and the search was executed. This initial search yielded 296 documents. The results were sorted by relevance to prioritize the most pertinent documents.

3.2.2 Filtering by year and subject area

To focus on recent advancements, the publication date range was narrowed to 2019-2023, reducing the number of documents to 137. Next, the subject area was refined to "Engineering," further limiting the results to 102 documents. This step ensured that only engineering-related papers were considered.

3.2.3 Filtering by document type and language

The document type was limited to "Conference paper" and "Article," resulting in 100 documents. The language filter was set to English, further reducing the number to 99 documents. These steps ensured that the selected papers were both relevant and accessible (Table 1).

Table 1. Inclusion and exclusion criteria for fault detection in transmission lines with three-phase systems

Item name	Inclusion criteria	Exclusion criteria
Database	Scopus	Google Scholar
Publication period	2019-2023	2018 and before
Document type	Article and conference paper	Notes, letters, books
Subject area	Engineering	Social, physical, health
Language	English	Spanish, Chinese
File type	CSV	Plain text, RIS, Bibtex, endnote

3.2.4 Exporting data

The 99 documents deemed relevant were selected for export. The CSV file format was chosen, and all relevant information was included in the export. The file was downloaded and saved to a secure location on the computer.

3.2.5 Data processing

The downloaded CSV file was opened, and its content was copied into a new Excel sheet titled "Book 1." This new sheet was used for data processing and analysis. The abstracts were reviewed to ensure relevance, and a new column was added to synthesize the information provided in each paper.

3.2.6 Relevancy assessment

Three additional columns were added to the Excel sheet: Column S for "What was done, "Column T for" Where the problem was solved, and Column U for "Methods, techniques, or procedures used to solve the problem." Irrelevant articles were identified and removed from the dataset, ensuring a focused and relevant literature review.

3.3 VOSviewer software

VOSviewer, a software tool for constructing and visualizing bibliometric networks, was used to analyze the data obtained from the Scopus database. The software was downloaded, installed, and launched. The "Create" option was selected to create a new file. The type of data was set to "Create a map based on bibliographic data," and the data source was set to "Read data from bibliographic database files." The Scopus CSV file was uploaded for analysis.

3.4 Generating and verifying network visualization

The type of analysis was set to "Co-occurrence," the counting method to "Full counting," and the unit of analysis to "All keywords." A threshold of 5 occurrences was set, resulting in 56 keywords meeting the threshold criteria. The network visualization map was generated, displaying all keywords linked in a network. The keywords were verified, and the final network visualization was reviewed for accuracy.

4. Results and discussion

4.1 Signal processing techniques for fault detection in transmission lines

Prasad and Nayak [30] proposed a method utilizing discrete Fourier transform (DFT) to estimate fundamental components of three-phase current phasors, which aids in fault detection. Similarly, Gupta et al. [31] performed MATLAB simulations on a two-terminal transmission line, employing DFT along with a time-frequency approach for fault detection and classification. Patel and Bera [32] leveraged wavelet packet transform (WPT) with the db1 wavelet to isolate high-frequency components from current signals, enabling effective identification of faults in transmission lines.

AsghariGovar et al. [33] further explored WPT in the context of high-impedance fault protection for transmission and distribution systems by extracting high-frequency signal coefficients. Building on wavelet-based techniques, Ashok and Yadav [34] introduced maximal overlap discrete wavelet transform (MODWT) to analyze faulty signals during power swings, employing a fault triangle approach to classify faults. Sailakshmi et al. [35] applied discrete wavelet transform (DWT) in MATLAB to simulate and detect various fault conditions, while Kapoor et al. [36] developed a fault detection framework using Discrete Fast Walsh-Hadamard Transform (DFWHT), evaluating its performance across multiple fault scenarios.

4.2 High-speed fault detection and classification in transmission lines

Alizadeh et al. [37] developed a high-speed fault detection technique employing Mathematical Morphology, which uses voltage and current signals to identify faults and distinguish power swings. Das et al. [38] utilized Lissajous patterns of voltage and current signals for fault detection and classification by calculating changes in area to derive fault indices. Anand and Affijulla [39] proposed a method for detecting high-impedance faults using the Hilbert-Huang Transform, where energy was computed from the intrinsic mode functions of voltage and current signals for each phase. In a related study, Das et al. [40] applied Principal Component Analysis to fault detection in overhead transmission lines by analyzing peaks and crests of transient signals at the receiving end.

4.3 Learning algorithms for fault detection and classification in transmission lines

Mukherjee et al. [41] applied a probabilistic neural network to simulate and analyze faults at different locations, generating a fault intensity index based on three-phase fault characteristics. Vyas et al. [42] combined wavelet transform with a Chebyshev neural network to design a fault detection model, verifying its performance using synthetic fault data. Rai et al. [43] and Radhi et al. [44] explored convolutional neural networks (CNNs) for fault detection, focusing on voltage and current signals. While Rai et al. used standard CNN architecture and validated the model through cross-validation, Radhi applied a one-dimensional CNN to a 132 kV transmission system. Mitra et al. [45] built on this by refining the 1D-CNN approach to improve computational efficiency in classifying faults. Ahmed et al. [46] modeled a four-bus power system with three transmission lines for fault detection using a deep neural network. Rathore et al. [47] introduced a hybrid approach involving wavelet analysis and artificial neural networks to detect, classify, and locate faults in a STATCOM-compensated system. Assadi et al. [48] presented an adaptive fault classification method using artificial neural networks. Meanwhile, Huang et al. [49] enhanced fault diagnosis with a method combining variational modal decomposition and support vector machines optimized using a whale algorithm. Coban and Tezcan [50] proposed two separate SVM models to detect and classify faults, simulating various fault scenarios on a 154 kV transmission line.

4.4 Fault detection and protection relay techniques in transmission lines

Biswas and Nayak [51] focused on how transmission lines impact the operation of distance relays by detecting faults through changes in positive-sequence current magnitude. Gupta et al. [52] developed a relay system that identifies and classifies faults by synchronously measuring three-phase currents at two different bus locations. Elmitwally and Ghanem [53] introduced a method based on a reverse synchronous reference frame, which quickly detects and classifies faults using only the three-phase current at the relay site. Abo-Hamad et al. [54] proposed a relay design that initiates fault detection using an impedance index and identifies the fault zone by comparing faulted loop currents with thyristor-controlled series capacitor (TCSC) terminal currents. Alabbawi et al. [55] presented an intelligent relay capable of distinguishing ground faults from non-ground faults by analyzing three-phase currents and zero-current characteristics. Al Kazzaz et al. [56] employed an adaptive neuro-fuzzy inference system (ANFIS) to design a distance relay that detects faults by monitoring phase-wise voltage and current signals.

4.5 Fault detection methods in transmission lines using the summation of squared currents and moving average techniques

Yamuna and Thresia [57,58] as well as Jarrahi et al. [59] presented similar fault detection methods for transmission lines, utilizing the summation of squared three-phase currents (SSC) combined with a moving average approach. These methods rely on specific fault detection criteria (FDC) to identify faults by monitoring current changes and applying a smoothing technique to enhance detection reliability.

4.6 Fault detection and indexing techniques for transmission lines

Jalilian et al. [60] examined how the integration of inverter-based resources (IBRs) influences distance protection by calculating the average zero-sequence current and its superimposed component. Mondal et al. [61] and Kulshrestha et al. [62] developed fault detection methods based on fault indices, with Mondal simulating a 400 kV 9-bus IEEE system in EMTP to capture fault current data at a single line end, while Kulshrestha introduced a classification algorithm for network faults. Mukherjee et al. [63] proposed a technique using entropy analysis to detect faults by observing transient high-frequency current oscillations immediately after the fault. Fahim et al. [64] presented an unsupervised framework for detecting and categorizing faults in transmission systems incorporating superconducting fault current limiters (SFCLs).

4.7 Simulation of a transmission line on matlab/simulink and pscad

Aker et al. [65], Chunguo and Junjie [66], and Naik and Koley [67] worked on fault detection approaches for high-voltage transmission systems using different simulation techniques. Aker et al. modeled a power network in MATLAB/Simulink, introducing faults in various system zones and employing classifiers to determine fault types. Chunguo and Junjie created a fault dataset by simulating a high-voltage power line in MATLAB for diagnostic analysis. Naik and Koley applied the K-nearest neighbor (KNN) algorithm to a 500 kV AC/DC transmission line integrated with a doubly fed induction generator (DFIG) and analyzed multiple fault scenarios through MATLAB simulations. Nale et al. [68] proposed a fault protection method for a 400 kV, 50 Hz system and tested its performance using PSCAD, while Akhikpemelo et al. [69] applied a feed-forward neural network with a backpropagation algorithm for fault identification also utilizing PSCAD for system modeling.

4.8 Other fault detection, classification, and location techniques in transmission lines

Zakri et al. [70] introduced a fault diagnosis approach for wide-area systems using Phasor Measurement Units (PMUs), focusing on detecting three-phase short-circuit faults. Ghaedi et al. [71] further explored fault location accuracy by assessing the influence of measurement errors in PMUs and instrument transformers. Mukherjee et al. [72] utilized Poincaré-based correlation analysis, where fault signals were divided into equal time segments to compute correlation coefficients for identifying transmission line faults. Patel [73] employed Lissajous figures for fault detection and classification during power swings, with a fault index derived from the quarter-cycle moving window sum of the Euclidean norm. Tatar et al. [74] proposed a fault distance detection technique using Field Programmable Gate Arrays (FPGA) and implemented it through Xilinx Vivado Design Suite. Srivastava et al. [75] validated a transmission line protection model using an experimental setup of a scaled-down power system consisting of transmission lines, transformers, and loads. Andanapalli et al. [76] presented a fault detection and classification method for two-terminal long transmission lines using a fundamental phasor-based approach. Fahim et al. [77] designed an unsupervised fault detection and classification framework utilizing an enhanced capsule network with sparse filtering. Mishra et al. [78] developed a cross-differential protection strategy aimed at improving the reliability of parallel transmission lines with thyristor-controlled series capacitors (TCSCs).

4.9 Trends and analysis

4.9.1 Network visualization (gaps)

Network visualization helps to analyze the gaps that are present in the project by comparing the total link strength, the number of links, and the number of occurrences for that certain keyword from cluster to cluster. Table 2 is the representation of clusters obtained from VOSviewer, from these clusters, it is observed that cluster 1 has the highest total link strength of 619 and the highest number of occurrences of 87 on the keyword fault detection, this means that there have been many publications based on this keyword and many authors were more interested in researching about it. Figure 3 illustrates the network visualization obtained from VOSviewer software when all the documents exported to Excel are copied to the software for the analysis of the gaps and trends of the project being reviewed. In this figure, bullets that are much bigger than the others symbolize that the topic or keywords have been researched more, and therefore, there is no need to dwell much on it; only focus more on smaller rounds and fewer links between them.

Table 2. Clustering of keywords in fault detection, classification, and location for transmission lines

Cluster 1			
Keywords	**Links**	**Total link strength**	**Occurrences**
Distance Protection	22	48	9
Electric fault currents	51	221	27
Electric lines	55	526	66
Fault detection	55	619	87
Fault identifications	30	77	8
Fault inception angles	22	44	6
Matlab	47	219	24
Power swings	14	22	5
Series compensation	23	43	5
Software testing	26	46	6
Three phase faults	30	64	8
Three phase currents	37	110	15
Timing circuit	28	61	8
Transmission line	37	94	11
Transmission system	26	46	6
Wavelet transforms	23	42	5
Cluster 2			
Keywords	**Links**	**Total link strength**	**Occurrences**
discrete wavelet transforms	33	90	11
distance relay	21	25	6
electric load flow	28	61	7
Electric power system protection	52	240	25
Electric power transmission networks	45	184	20
Fault-detection-and classification	43	143	18
overhead transmission lines	25	40	5
power system protection	31	53	6
power transmission lines	38	75	8
protection schemes	26	55	7
relay protection	31	60	7
signal reconstruction	25	56	7
transmission line protection	43	114	14
wavelet transform	23	37	5
Cluster 3			
Keywords	**Links**	**Total link strength**	**Occurrences**
Electric power transmission	55	415	46
Failure analysis	25	46	5
Fault diagnosis	24	45	5
Mean square error	23	43	5
Power	31	66	6
Power system	20	33	6
Power transmission	29	56	5
Support vector machines	30	49	5
transmission	40	100	12
Cluster 4			
keywords	**links**	**Total link strength**	**occurrences**
Artificial neural network	23	54	6
Back propagation	30	76	7
Electric fault location	27	60	7
Fault location	26	54	7
Faults detection	48	194	21

Location	27	64	8
Neural networks	35	105	11
Transmission lines	22	37	8
Transmission-line	47	232	24
Cluster 5			
keywords	**links**	**Total link strength**	**occurrences**
Deep learning	23	34	5
Electric grounding	39	95	13
Fault classification	53	239	30
Learning system	24	51	6
Machine learning	24	57	6
Machine-learning	22	49	5
Signal processing	21	40	5
Transmission line faults	44	129	16

4.9.2 Overlay visualization (trends)

The overlay visualization is the diagram found after using the keywords on VOSviewer. This diagram shows development based on the topic being researched. It will show in years how long the topic has been trending and the most focus areas when the research was conducted.

Figure 4 represents the overlay visualization, based on this project, it is evident that from the year 2020 May up to the year 2021 May, the researchers started to focus more on the issue of fault detection in transmission lines and started to find simpler and efficient ways to do this, but as the time goes on the focus was more on backpropagation and transmission line behavior, this was in the year of 2022. It is clear from the diagram that not much research was conducted on keywords like wavelet transforms and software testing.

5. Literature review analysis observations

The literature covers various methodologies and techniques employed for fault detection and classification in transmission lines. A key noticeable aspect across the studies is the utilization of diverse signal processing and machine learning techniques to analyze voltage and current signals for identifying faults. Methods such as wavelet transforms, Fourier transforms, neural networks, and pattern recognition algorithms are applied to detect faults, classify fault types, and even locate faults within the transmission network. These approaches aim to enhance the reliability and efficiency of protection systems by swiftly identifying and responding to faults, thereby ensuring the stability and integrity of the power grid.

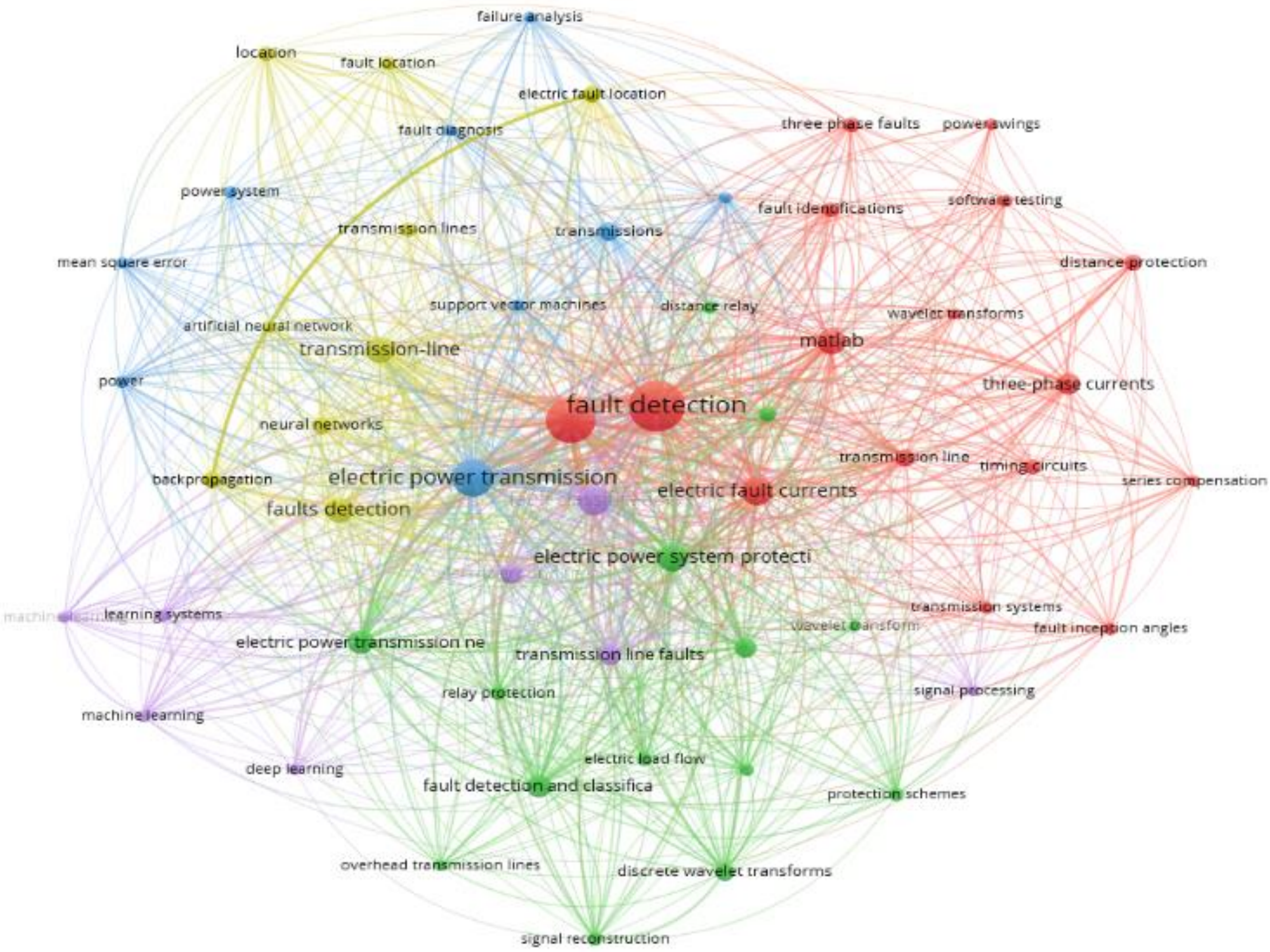

Figure 3. Keyword network visualization for fault detection in three-phase transmission lines

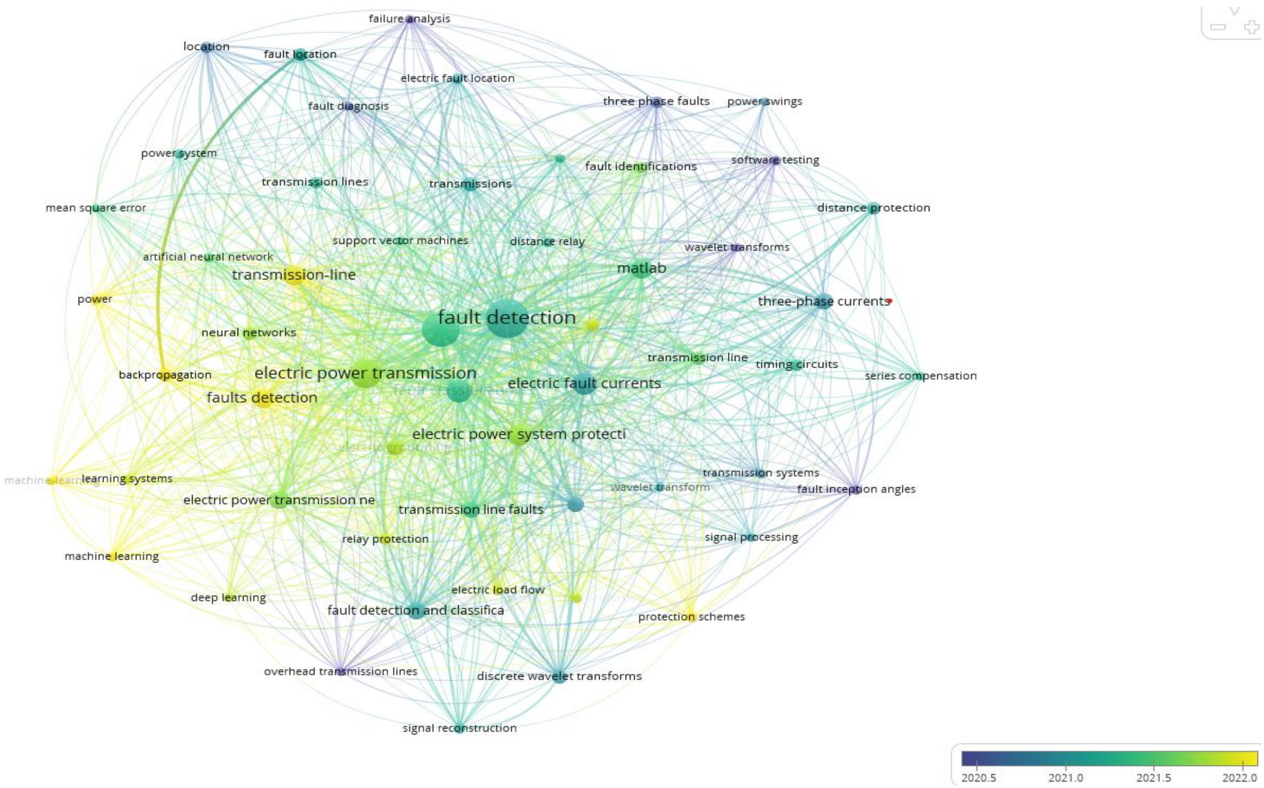

Figure 4. Research trends in fault detection for three-phase transmission lines

6. Conclusion

The aim of this paper was to conduct a systematic literature review focusing on techniques and algorithms for swift and precise fault detection and protection in transmission lines. The methodology included the collection of relevant papers, a filtering process, eligibility identification, synthesis, and trend analysis. This process was facilitated using the Scopus database and VOSviewer software. The results of this survey revealed several key aspects across the studies, including the utilization of diverse signal processing and machine learning techniques to analyze voltage and current signals for identifying faults. This work contributed by reviewing recent advances in signal processing and analysis methods to enhance fault detection speed and accuracy, exploring the use of machine learning and neural networks in fault detection models, investigating advanced relay technologies and protection schemes, evaluating statistical techniques for fault isolation, and examining indexing techniques and evolutionary programming tools for precise fault identification. It also proposed future research directions. Based on the results obtained from the VOSviewer software, it is evident that keywords like, power swing, series compensation, software testing, wavelet transform, overhead transmission lines, distance relay, failure analysis, fault diagnosis, mean square error, power transmission, support vector machines, artificial neural network, deep learning, machine learning and signal processing are the least researched topics. This means that in the future, more research can still be done; this is confirmed by the number of occurrences in each keyword mentioned above. However, considering the increasing adoption of electric vehicles (EVs) and their impact on the power grid, the integration of electric vehicles into transmission line fault detection and classification systems could be a promising future research area. Here are some specific aspects to consider:

- Research could investigate how the presence of electric vehicles, especially during charging or discharging, affects the voltage and current signals on transmission lines.
- Beyond traditional voltage and current measurements, future research could explore integrating data from electric vehicle charging stations or smart charging infrastructure.
- Research could focus on developing fault detection and classification systems that consider the presence and behavior of electric vehicle fleets within the power grid.
- Investigating bidirectional communication between the power grid and electric vehicles could enable advanced fault management strategies.
- Vehicle-to-grid (V2G) technologies enable electric vehicles to provide grid services, including ancillary services during fault events.
- Given the dynamic nature of electric vehicle behavior and their potential impact on grid dynamics during fault events, future research could focus on validating fault detection and classification algorithms under various scenarios involving EV integration.

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Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically with regard to authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The datasets analyzed during the current study are available and can be given upon reasonable request from the corresponding author.

Conflict of interest

The authors declare no potential conflict of interest.

References

[1] Sahu B., “Construction Management of EVH & UVH Transmission Lines A Practical Guide”, International Journal of Innovative Science and Research Technology, vol. 5, 2020, pp. 299-306.

[2] Morteza Abbasghorbani, Yaser Damchi, and Habib Rajabi Mashhadi., “Reliability-Centered Maintenance for Overhead Transmission Lines in Composite Power System”, International Transactions on Electrical Energy Systems, vol. 2022, 2022, pp. 1-11.

[3] Jordi-Roger Riba, Manuel Moreno-Eguilaz and Santiago Bogarra., “Energy Harvesting Methods for Transmission Lines” A Comprehensive Review, vol. 12, 2022, pp. 1-21.

[4] Abhishek Jadhavar, Sandhyarani Gavali, Aashlesha Chavan, and Prof. Sayyad A.P., “TRANSMISSION LINE FAULT DETECTION SYSTEM”, International Journal of Engineering Applied Sciences and Technology, vol. 8, 2023, pp. 289-292.

[5] B. Phanindra Kumar, D. Akhila, K. Manisha, M. Srinivasa Chari, and P. Chandra Prakash., “ELECTRICAL TRANSMISSION LINE INSPECTION ROBOT”, International Journal of Scientific Research in Engineering and Management (IJSREM), vol. 8, 2024, pp. 1-13.

[6] Francisca Alcayde-García, Esther Salmerón-Manzano, Miguel A. Montero, Alfredo Alcayde and Francisco Manzano-Agugliaro., “Power Transmission Lines”, Worldwide Research Trends, vol. 15, 2022, pp. 1-21.

[7] Goutom K. Pall, Adrian J. Bridge, Jason Gray and Martin Skitmore.,“Causes of Delay in Power Transmission Projects: An Empirical Study”, Energies, Australia, 2019, pp. 1-29.

[8] Anyaka Boniface Onyemaechi and Olawoore Olaoluwa Isaac., “Minimization of Power Losses in Transmission Lines”, IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE), vol. 9, 2014, pp. 23-26.

[9] Fady Wadie., “Smart Fault Detection Algorithm for Transmission Networks”, Mechatronics and Robotics Engineering Department, vol. 3, 2024, pp. 791-803.

[10] Dr. Suvarna Pawar, Sahil Gannarpwar, Aman War, Rahul Khandvi and Aditya Talokar., “An Intelligent Approach of Faults Detection and Location Methods for Power Transmission Line”, International Journal of Scientific Research in Engineering and Management (IJSREM), vol. 7, 2023, pp. 1-6

[11] Sazzed Mahamud Khan and Abu Hena MD Shatil., “A Robust Fault Diagnosis Scheme using Deep Learning for High Voltage Transmission Line”, AIUB JOURNAL OF SCIENCE AND ENGINEERING, vol. 21, 2022, pp. 1-8.

[12] Ahmed Sabri Altaie, Ammar Abbas Majeed, Mohamed Abderrahim and Afaneen Alkhazraji., “Fault Detection on Power Transmission Line Based on Wavelet Transform and Scalogram Image Analysis”, Energies, vol. 16, 2023, pp. 1-19.

[13] Nadeem Ahmed, Ashfaq Ahmed Hashmani, Sohail Khokhar, Mohsin Ali Tunio and Muhammad Faheem., “Fault detection through discrete wavelet transform in overhead power transmission lines”, Energy Science Engineering, vol. 11, 2023, pp. 4181–4197.

[14] Anamika Yadav and Yajnaseni Dash., “An Overview of Transmission Line Protection by Artificial Neural Network: Fault Detection, Fault Classification, Fault Location, and Fault Direction Discrimination”, Advances in Artificial Neural Systems, India, 2014, pp. 1-20.

[15] Monali A. Sawale and Dr. Kiran Dongre., “Development of DSP-Based Transmission Line Fault Detection”, International Journal for Research in Applied Science & Engineering Technology (IJRASET), vol. 10, 2022, pp. 687-690.

[16] Abhishek Jadhavar, Sandhyarani Gavali, Aashlesha Chavan, Prof. Sayyad A.P., “TRANSMISSION LINE FAULT DETECTION SYSTEM”, International Journal of Engineering Applied Sciences and Technology, vol. 8, 2023, pp. 289-292.

[17] Aliyu Sabo, Kamaluddeen I. Kanya, Naziru Shu’aibu, Chigozie Onyema, Aliyu Ahmed, Hadiza Tanko, and Sama’ila Kwasau., “A Review of State-of-the-Art Techniques for Power Flow Analysis”, JOURNAL OF SCIENCE, TECHNOLOGY AND ENGINEERING RESEARCH, vol. 4(1), 2023, pp. 36-43.

[18] Jordi-Roger Riba, Manuel Moreno-Eguilaz and Santiago Bogarra., “Energy Harvesting Methods for Transmission Lines: A Comprehensive Review”, Applied Science, vol. 12, 2022, pp. 1-21.

[19] L. Miguel Silveira, Ibrahim M. Elfadel and Jacob K. White., “An efficient approach to transmission line simulation using measured or tabulated s-parameter data”, ACM/IEEE Design Automation Conference, Massachusetts, 1994, pp. 634-639.

[20] Fredy Andrés Olarte Dussán, Carlos Eduardo Borda Zapata and Hernando Díaz Morales., “State Estimation-based Transmission line parameter identification”, engineering investigation, vol. 30, 2010, pp. 56-63.

[21] Marco Bindi , Maria Cristina Piccirilli, Antonio Luchetta and Francesco Grasso., “A Comprehensive Review of Fault Diagnosis and Prognosis Techniques in High Voltage and Medium Voltage Electrical Power Lines”, Energies, vol. 16, 2023, pp. 1-37.

[22] Sitti Amalia, Mardini Hasanah, Yusreni Warmi, Novizon and Abdul Rajab., “Disturbance Modeling on Transmission Lines Using Wavelet Transform Method: A Review”, Andalas Journal of Electrical and Electronic Engineering Technology, vol. 2, 2022, pp. 55-61.

[23] Changjun Liu and Kama Huang., " Metamaterial Transmission Line and its Applications”, Advanced Microwave and Millimeter Wave Technologies Semiconductor Devices Circuits and Systems, China, 2010, pp. 250-274.

[24] Jin Jian Ming., “THEORY AND COMPUTATION OF ELECTROMAGNETIC FIELDS”, library of Congress Cataloging-in-Publication Data, New Jersey, 2010, pp. 3-551.

[25] Kezunovic M.: "Smart fault location for smart grids", IEEE Trans. Smart Grid, vol. 2, 2011, pp. 11–22.
[26] De La Ree J., Centeno V., and Thorp J.S., "Synchronized phasor measurement applications in power systems", IEEE Trans. Smart Grid, vol.1, 2010, pp. 20–27.
[27] Nahiduzzaman, Md., Goni, Md.O.F., Anower, Md.S., Islam, Md.R., Ahsan, M., Haider, J., Gurusamy, S., Hassan, R., Islam, Md.R., "A novel method for multivariant pneumonia classification based on hybrid CNN-PCA based feature extraction using extreme learning machine with CXR images", IEEE Access, vol.9, 2021, pp. 147512-147526.
[28] David M. W. Powers., "Evaluation: from precision, recall and F-measure to ROC, informedness, markedness and correlation", International Journal of Machine Learning Technology, vol.1, 2011, pp. 37-63.
[29] Y. Sasaki, R. Fellow., "SNP analysis of the LAMA1 gene in Japanese patients with high myopia", Department of Ophthalmology and Visual Science, Yokohama City University, Graduate School of Medicine, vol.58, 2007, pp. 25-31.
[30] Prasad, Ch.D; and Nayak, Paresh Kumar., "A DFT-ED based approach for detection and classification of faults in electric power transmission networks", Ain Shams Engineering Journal, vol.10, 2019, pp.171-178.
[31] Gupta, Abhishek; Pachar, Ramesh Kumar; Khan, Baseem; Mahela, Om Prakash; and Padmanaban, Sanjeevikumar).,"A multivariable transmission line protection scheme using signal processing techniques", IET Generation, Transmission and Distribution, vol. 15, 2021, pp. 3115-3137.
[32] Patel, Bikash; Bera, Parthasarathi, "Fast fault detection during power swing on a hybrid transmission line using WPT" , IET Generation, Transmission and Distribution, vol. 13, 2019, pp. 1811-1820.
[33] AsghariGovar, Saeed; Pourghasem, Pouya; and Seyedi, Heresh., "High impeance fault protection scheme for smart grids based on WPT and ELM considering evolving and cross-country faults", International Journal of Electrical Power and Energy Systems, vol. 107,2019, pp. 412-421.
[34] Ashok, Valabhoju; and Yadav, Anamika, "A real-time fault detection and classification algorithm for transmission line faults based on MODWT during power swing", International Transactions on Electrical Energy Systems, vol. 30, 2020.
[35] Sailakshmi; Navyasri, Goteti Sai; Deepa, K.; Sailaja, V; Manitha, V.P, "Fault Analysis in Three Phase Transmission Lines using Wavelet Method", 2022 6th International Conference on Trends in Electronics and Informatics, ICOEI 2022 – Proceedings, Bengaluru, India, 2022, pp. 248-254.
[36] Kapoor, Gaurav; Mishra, Anuprita; Shaw, Rabindra Nath and Ajmera, Siddharth, "Complex faults categorization technique for series-compensated transmission lines connected with wind-turbines based on DFWHT", 2020 IEEE International Conference on Computing, Power and Communication Technologies, GUCON 2020, India, 2020, pp. 703-708.
[37] Alizadeh, Behzad Asle Mohammad; Khederzadeh, Mojtaba; Razzaghi, Reza, "Fault detection during power swing in thyristor-controlled series capacitor-compensated transmission lines", Electric Power Systems Research, vol. 187, 2020.
[38] Das, Sayan; Mondal, Arkadeep; and Patel, Bikash., "Detection and classification of faults on the transmission line using lissajous figure", Lecture Notes in Electrical Engineering, vol. 575, 2020, pp. 81-88.
[39] Anand, Abhisekh and Affijulla, Shaik, "Hilbert-Huang transform based fault identification and classification technique for AC power transmission line protection", International Transactions on Electrical Energy Systems, vol. 30, 2020.
[40] Mukherjee, Alok; Kundu, Palash K.; and Das, Arabinda., "A supervised principal component analysis-based approach of fault localization in transmission lines for single line to ground faults", Electrical Engineering, vol. 103, 2021, pp. 2113-2126.
[41] Mukherjee, Alok; Chatterjee, Kingshuk; Kundu, Palash Kumar; and Das, Arabinda. "Probabilistic Neural Network-Aided Fast Classification of Transmission Line Faults Using Differencing of Current Signal", Journal of The Institution of Engineers (India): Series B, vol. 102, 2021, pp. 1019-1032.
[42] Vyas, Bhargav Y; Maheshwari, R.P; and Das, Biswarup., "Versatile relaying algorithm for detection and classification of fault on transmission line", Electric Power Systems Research, vol. 192, 2021.
[43] Rai, Praveen; Londhe, Narendra D; Raj, Ritesh., "Fault classification in power system distribution network integrated with distributed generators using CNN" , Electric Power Systems Research, vol. 192, 2021.
[44] Radhi, Ahmed Thamer; Zayer, Wael Hussein; Dakhil, Adel Manaa (40761201500)., "Classification and direction discrimination of faults in transmission lines using 1d convolutional neural networks", International Journal of Power Electronics and Drive Systems, vol. 12, 2021, pp. 1928-1939.
[45] Mitra, Subhrajit; Mukhopadhyay, Rajarshi; Chattopadhyay, Paramita, "PSO driven designing of robust and computation efficient 1D-CNN architecture for transmission line fault detection", Expert Systems with Applications, vol. 210, 2022.
[46] Ahmed, Sheikh Iftekhar; Rahman, M. Fahmin; Kundu, Shomen; Chowdhury, Raihan Mahmud; Hussain, Auronno Ovid; Ferdoushi, Munia, "Deep Neural Network Based Fault Classification and Location Detection in Power Transmission Line", 12th International Conference on Electrical and Computer Engineering, ICECE 2022, Dhaka, Bangladesh, 2022, pp. 252-255.
[47] Rathore, Bhuvnesh; Mahela, Om Prakash; Khan, Baseem; Alhelou, Hassan Haes; Siano, Pierluigi, "Wavelet-Alienation-Neural-Based Protection Scheme for STATCOM Compensated Transmission Line", IEEE Transactions on Industrial Informatics, vol.17, 2021, pp. 2557-2565.
[48] Assadi, Khaoula; Slimane, Jihane Ben; Chalandi, Hanene; Salhi, Salah, "Shunt faults detection and classification in electrical power transmission line systems based on artificial neural networks", COMPEL - The International Journal for Computation and

Mathematics in Electrical and Electronic Engineering, vol.42, 2023, pp. 1518-1530.

[49] Huang, Ruiling; Wang, Hongbin; He, He; Chen, Li, “Fault Diagnosis of Short Circuit in Transmission Line Based on Variational Modal Decomposition and Whale Algorithm”, 2021 3rd Asia Energy and Electrical Engineering Symposium, AEEES 2021, Chongqing, China, 2021, 130-135.

[50] Coban, Melih; and Tezcan, Suleyman S, “Detection and classification of short-circuit faults on a transmission line using current signal”, Bulletin of the Polish Academy of Sciences: Technical Sciences, vol. 69, 2021.

[51] Biswas, Sauvik; and Nayak, Paresh Kumar, “A Fault Detection and Classification Scheme for Unified Power Flow Controller Compensated Transmission Lines Connecting Wind Farms”, IEEE Systems Journal, vol.15, 2021, pp. 297-306.

[52] Gupta, Ruchika; Ali, Shoyab; Kapoor, Gaurav., “A Novel Current Differential Relaying Scheme for Transmission Line Protection”, 2020 IEEE 17th India Council International Conference, INDICON 2020, Bundi, India, 2020.

[53] Elmitwally, Akram; and Ghanem, Abdelhady, “Local current-based method for fault identification and location on series capacitor-compensated transmission line with different configurations”, International Journal of Electrical Power and Energy Systems, vol. 133, 2021.

[54] Abo-Hamad, Ghada M; Ibrahim, Doaa Khalil; Aboul Zahab, Essam; Zobaa, Ahmed F., “Adaptive mho distance protection for interconnected transmission lines compensated with thyristor controlled series capacitor”, Energies, vol. 14, 2021.

[55] Alabbawi, Ali Abbawi Mohammed; Alnaib, Ibrahim Ismael; Al-Yozbaky, Omar Sharaf Al-Deen Yehya; Mohammed, Karam Khairullah., “Faults detection, location, and classification of the elements in the power system using intelligent algorithm” , Bulletin of Electrical Engineering and Informatics, vol. 12, 2023, pp. 597-607.

[56] Al Kazzaz, Sa’Ad Ahmed S; Ismael, Ibrahim; Mohammed, Karam Kairullah, “Fault detection and location of power transmission lines using intelligent distance relay”, International Journal of Power Electronics and Drive Systems, vol.11, 2020, pp. 726-734.

[57] Yamuna, U; Thresia, M.M, “Fault Detection In Transmission Lines using Summation of Squared Three-Phase Currents”, International Conference on Futuristic Technologies in Control Systems and Renewable Energy, ICFCR 2022, Kerala, Kannur, India, 2022.

[58] Yamuna, U; and Thresia, M.M., “Summation of Squared Three-Phase Current-Based Fault Detection in Transmission Lines”, Lecture Notes in Electrical Engineering, vol. 1022 LNEE, 2023, pp. 225-237.

[59] Jarrahi, Mohammad Amin; Samet, Haidar; Ghanbari, Teymoor., “Fast Current-Only Based Fault Detection Method in Transmission Line”, IEEE Systems Journal, vol. 13, 2019, pp. 1725-1736.

[60] Jalilian, Amin; Muttaqi, Kashem Sutanto, Danny; Robinson, and Duane., “Distance Protection of Transmission Lines in Presence of Inverter-Based Resources: A New Earth Fault Detection Scheme during Asymmetrical Power Swings”, IEEE Transactions on Industry Applications, vol. 58, 2022, pp. 1899-1909.

[61] Mondal, Arkadeep); Das, Sayan; and Patel, Bikash., “Fault detection during power swing using fast discrete S-transform”, Lecture Notes in Electrical Engineering, vol. 575, 2020, pp. 73-79.

[62] Kulshrestha, Atul; Mahela, Om Prakash; Gupta, Mukesh Kumar; Khan, Baseem; Alhelou, Hassan Haes; Siano, Pierluigi, “Hybridization of the stockwell transform and wigner distribution function to design a transmission line protection scheme”, Applied Sciences (Switzerland), vol. 10, 2020, pp. 1-15.

[63] Mukherjee, Alok; Kundu, Palash Kumar; Das, Arabinda, “Classification and Fast Detection of Transmission Line Faults Using Signal Entropy”, Journal of The Institution of Engineers (India): Series B, vol. 102, 2021, pp. 655-670.

[64] Fahim, Shahriar; Sarker, Subrata; Das, Sajal; Islam, Md. Rabiul; Kouzani, Abbas; Mahmud, M. A. Parvez., “A Probabilistic Generative Model for Fault Analysis of a Transmission Line with SFCL”, IEEE Transactions on Applied Superconductivity, vol. 31, 2021.

[65] Aker, Elhadi; Othman, Mohammad Lutfi; Veerasamy, Veerapandiyan; Bin Aris, Ishak; Wahab, Noor Izzri Abdul; and Hizam, Hashim, “Fault detection and classification of shunt compensated transmission line using discrete wavelet transform and naive bayes classifier”, Energies, vol. 13, 2020.

[66] Chunguo Fei; and Junjie Qin, “Fault Location after Fault Classification in Transmission Line Using Voltage Amplitudes and Support Vector Machine”, Russian Electrical Engineering, vol. 92, 2021, pp. 112-121.

[67] Naik, Supriya; and Koley, Ebha., “Fault Detection and Classification scheme using KNN for AC/HVDC Transmission Lines”, Proceedings of the 4th International Conference on Communication and Electronics Systems, ICCES 2019, India, 2019, pp. 1131-1135.

[68] Nale, Ruchita; Verma, Hari; Biswal, Monalisa, “An Enhanced Fuzzy Rule Based Protection Scheme for TCSC Compensated Double Circuit Transmission System”, International Journal of Modelling and Simulation, vol. 41, 2021, pp. 120-130.

[69] Akhikpemelo, Abraham; Evbogbai, Ma-Riekpen J. E; Okundamiya, Michael S, “Fault detection on a 132kV transmission line using artificial neural network” , International Review of Electrical Engineering, vol. 14, 2019, pp. 220-225.

[70] Zakri, Azriyenni Azhari; Mustafa, Mohd Wazir; Syaibi, Herman; Sofimieari, Ibim., “Monitoring Fault Diagnosis Based on Phasor Measurement Unit at Wide Area Systems”, CENCON 2019 - 2019 IEEE Conference on Energy Conversion, Royal Ambarrukmo HotelYogyakarta; Indonesia, 2019, pp. 245-249.

[71] Ghaedi, Alireza; Hamedani Golshan, Mohammad Esmail; Sanaye-Pasand, Majid, “Transmission line fault

location based on three-phase state estimation framework considering measurement chain error model", Electric Power Systems Research, vol. 178, 2020.
[72] Mukherjee, Alok; Chatterjee, Kingshuk; Kundu, Palash Kumar; and Das, Arabinda., "Application of Poincaré analogous time-split signal-based statistical correlation for transmission line fault classification", Electrical Engineering, vol. 104, 2022, pp. 1057-1075.
[73] Patel, Bikash., "A new technique for detection and classification of faults during power swing", Electric Power Systems Research, vol. 175, 2019.
[74] Tatar, Guner; Kilic, Osman; Bayar, Salih., "FPGA Based Fault Distance Detection and Positioning of Underground Energy Cable by Using GSM/GPRS" , 2019 International Symposium on Advanced Electrical and Communication Technologies, ISAECT 2019, Rome; Italy, 2019.
[75] Srivastava, Ankur; Tuan, Le Anh; Steen, David; Carlson, Ola; Mansour, Omar; Bijwaard, Dennis, "Transmission Line Protection Using Dynamic State Estimation and Advanced Sensors: Experimental Validation", IEEE Transactions on Power Delivery, vol. 38, 2023, pp. 162-176.
[76] Andanapalli, Kumarraja; Shaik, Nazeer; Vudumudi, Srinivas; Yenugu, Bhanu Chandar)., "Fault etection, classification and location on transmission lines using fundamental phasor based approach", International Journal of Recent Technology and Engineering, vol.8, 2019, pp. 288-293.
[77] Fahim, Shahriar Rahman; Sarker, Subrata K.; Muyeen, S.M.; Das, Sajal K.; Kamwa, Innocent, "A deep learning based intelligent approach in detection and classification of transmission line faults", International Journal of Electrical Power and Energy Systems, vol.133, 2021.
[78] Mishra, Praveen Kumar; Yadav, Anamika; Pazoki, Mohammad, "Resilience-oriented protection scheme for TCSC-compensated line", International Journal of Electrical Power and Energy Systems, vol.121, 2020.