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REVIEW ARTICLE

Challenges and solutions of Artificial Intelligence-based fault location methods in power system lines

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ABSTRACT

The accurate and efficient location of faults in power system lines is crucial for ensuring reliable and uninterrupted power supply. In recent years, Artificial Intelligence (AI) has been increasingly used in fault location methods, promising to improve the accuracy and efficiency of fault location. However, AI-based fault location methods also face challenges such as data quality, interpretability, and model robustness. **Review method:** This paper presents a review of the challenges and solutions of AI-based fault location methods in power system lines. The review is based on a comprehensive analysis of existing literature and research studies, focusing on the challenges associated with AI-based fault location methods and the solutions proposed to address these challenges. **Content:** The paper discusses the challenges associated with AI-based fault location methods in power system lines, including data quality, interpretability, and model robustness. The review presents several solutions to address these challenges, including data preprocessing techniques to improve data quality, explainable AI methods to enhance interpretability, and robustness validation techniques to improve model robustness. The accurate and efficient location of faults in power system lines is crucial for ensuring reliable and uninterrupted power supply. AI-based fault location methods have the potential to improve the accuracy and efficiency of fault location. However, these methods also face challenges such as data quality, interpretability, and model robustness. Addressing these challenges through techniques such as data preprocessing, explainable AI, and robustness validation can help to improve the accuracy and reliability of AI-based fault location methods.

Keywords: fault location; power system; Artificial Intelligence; Time Domain Reflectometer

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1. Introduction

The accurate and timely location of faults in power system lines is essential to ensure the reliable and uninterrupted supply of electricity to consumers. Traditional fault location methods rely on manual inspection and require significant time and effort to identify and locate faults. In recent years, Artificial Intelligence (AI) has emerged as a promising solution to improve the accuracy and efficiency of fault location methods. The transmission and distribution lines represent the backbone of electrical power systems[1]. The protection and maintenance efforts of power lines and fault location accuracy for the network are of vital importance in power quality production and outage time reduction[2].

There has been an increasing interest in the use of AI-based fault location methods in power systems. Several studies have been conducted to develop and test various AI-based fault location methods, including deep learning, fuzzy logic, and support vector machines. In general, faults in power systems lines may occur, which is unavoidable for overhead lines due to natural causes of climate, insulation failure, or any other incidents[1,2]. While storms, snowfall, heavy rains, and weather pollutants have no impact on underground cables in transmission and distribution systems. However, it is difficult to know the failure reasons in underground cables when it happens in subsurface lines[3]. The underground cable installations, maintenance, and fault detection are difficult and high cost compared to overhead lines. However, underground cables are higher reliable and have longer service life.

From the other hands, Artificial Intelligence (AI) became the faster and the most accurate method in many of the engineering applications[4–7]. Last thirty years, several nature simulated attitudes have been done to deal with the high complex problems especially power systems[8–10]. Those simulations led to approaching a mathematical description of the movements of many organisms such as Particle Swarm Optimization (PSO), gray wolves, elephant herding optimization, machine learning, and deep learning[11,12]. However, the application of AI-based fault location methods in power system lines also faces challenges such as data quality, interpretability, and model robustness.

This paper provides a comprehensive review of the challenges and solutions of AI-based fault location methods in power system lines. The paper begins by discussing the challenges associated with these methods, including data quality, interpretability, and model robustness. The review then presents several solutions proposed by researchers to address these challenges, such as data preprocessing techniques, explainable AI methods, and model robustness validation techniques. The paper concludes by emphasizing the importance of the integration of AI-based fault location methods into power system operations and the need for collaboration between utilities and researchers to develop more accurate and reliable fault location methods.

2. Conventional fault location technique

The main fault types that may happen in any power system network are balanced and unbalanced faults. Also, faults can also be classified into series and shunt types[13–15]. Both main types are notably affecting the current, voltage, and frequency but in opposite ways. The series fault is one type of unbalanced fault by the sudden change in the series impedance of the power system line, especially in an open circuit. In comparison, the shunt fault occurs if there is a short circuit between the lines or the lines and the neutral[15]. For a three-phase line, shunt faults are categorized as one line-ground, line-line-ground, line-line, and three-phase (symmetrical) faults. 70%, 10%, and 15% are the unsymmetrical occurrence percentage of each line-ground, line-line-ground, and line-line respectively[15]. While the symmetrical fault occurrence percentage is only 5% of the total faults that happened in the power network.

2.1. Conventional fault location techniques

Fault detection is useful for electrical components to reduce the fault danger before it causes damage to the power system. Any failure in these systems may lead to making a power disturbance or shutdown which is a big issue in today’s life. Form the other hand, the detection of the fault location early and correctly can be avoiding those kinds of problems or reduce the shutdown time. Several types of research on fault studies have been done over the last decades and fault calculation techniques have been proposed to find faults’ location and value in power systems[16–19]. Faults in transmission and distribution systems can be recognized using two main traditional methods which are traveling wave-based, and impedance-based methods.

2.2. The traveling wave (Time Domain Reflectometer)

The traveling wave methods are based on the precept of transmission and reflection of the traveling wave between sending end and the fault position.

Figure 1 shows the traveling wave strategy, where t_1 is the time of the sending wave and t_2 is the time of reflecting wave reaching, and the junction represents the fault point. As shown in Equations (1) and (2).

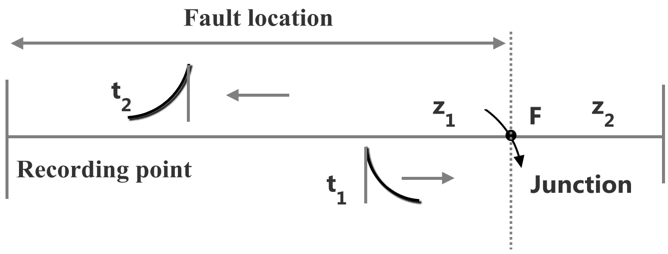

Figure 1. Traveling wave-based method.

$$distance = \frac{v(t_1 - t_2)}{2} \tag{1}$$

Part of the sending surge voltage is reflecting and that depends on the reflection coefficient that calculated according to the surge impedance before and after the junction.

$$Rf = \frac{(z_2 - z_1)}{(z_2 + z_1)} \tag{2}$$

where z_1 is the surge impedance before the junction, and z_2 is the surge impedance after the junction.

Some of the traveling waves examples that have been used in fault detection topic are done in the references[17–19]. Niazy and Sadeh[17] suggested a traveling wave-based method using transients caused by circuit breaker switching instead of fault transients wave. The fault accuracy poison judgment was done by the usage of the polarity wavelet transform to detect the modal component time of the traveling signal. Also, Lee and Mousa[18] used the GPS and lightning signal to estimate the fault position. Bao et al.[19] categorized, studied, and compared traveling waves based on fault detection for OH which were single and two terminal locations.

2.3. Impedance/phasor/time-domain based method

The concept of impedance-based method depends on the injection of a current into the damaged cable and earth termination to detect a ground fault. **Figure 2** shows the basic idea of the impedance method. As shown the injected current passed through the conductor and completes the circuit through the earth stake via the earth from the earth fault site. It is essential to use a highly sensitive voltmeter because a small change in the reading may be caused to expect a wrong fault position. As shown in Equation (3).

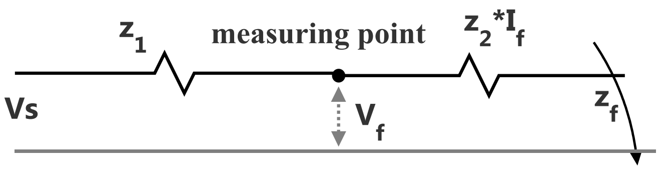

Figure 2. Impedance-based method.

$$distance = \frac{V_f}{(z_2 * I_f)} \tag{3}$$

As a samples of time-domain based method, McKinnon et al.[20] proposed an algorithm used the neutral voltage distortion and negative sequence current present during the unsymmetrical line-ground fault. That development gave the engineering the capability to localize high-impedance faults. McKinnon algorithm was appropriated for high-impedance faults of more than 20 kΩ. Furthermore, Dash et al.[21] utilized the Power Systems Computer Aided Design (PSCAD) Simulink tool to analyze high impedance fault characteristics and developed a detection equation that has been modeled for Micro-Grid application. Chen et al.[22] were consider the system zero-sequence affection. Based on suppressing the impedance affection, their method computes the zero-sequence power factor of the network to analyze the line state using the single-phase instantaneous reactive power theory, and its fourth-order components. The authors used the PSCAD code for verifying the model performance for both high and low impedance. Sun et al.[23] presented a high impedance ground fault feeder to solve the fault location issues. Three steps the authors have suggested started from building a zero-sequence model, passing through analyzing the model current and ending with a calculation correlation coefficient between neutral resistance current and zero-sequence current.

Liu et al.[24] depended on only the estimation of variation of the zero-sequence voltage and zero-sequence admittance to guess the real fault location to get the advantage of zero effect for the asymmetry of the non-direct ground power system.

3. Artificial Intelligence (AI) techniques

According to the successful applications of the AI in the high complex of power system problems, AI applied in the various uncertainty parameters that are difficult to figure out using traditional methods[25,26]. One of the most important applications is the fault location detection. Generally, those methods require specific information such as feeder measurements, substations, and feeder switchgear status data. Those data have been analyzed using AI methods. In this paper, the AI methods that have been employed in fault locations is categorized into three methods.

3.1. Basic methods

Each AI method that the scientist developed for the first time could be categorized as a basic method such as PSO, Genetic Algorithm (GA), firefly algorithm, neural network, Garra rufa optimization (GRO), or super vector machine[27–30].

Verma et al.[28] used the ARDUINO controller based on machine learning prototype to detect the length of the fault from the cable source. Wang and Xu[29] used a chaotic neural network and MATLAB/Simulink for both terminals traveling wave locations to identify fault location.

GA was one of the methods that were widely used in fault topic. Jin and Ju divided power system network of complex details and single power source into main and subsidiary lines. GA was designed for finding the fault in the main lines, while the fault in the subsidiary lines was founded by the fault current[30]. Also, GA used actual fault enrolled data for the south grid of China to locate the fault transmission lines by analyzing the line parameters for both sides[31].

Fuzzy membership was also applied to identify the fault type and distance from the source in a double power line circuit system[32]. The balance currents and the positive and negative components were the base of the fuzzy membership data and classification.

Gururajapathy et al.[33] selected the Malaysian distribution system and Support Vector Machine (SVM) method as a database for expecting the fault position according to the Euclidean distance approach. The PSCAD software was used to simulate and validate the model.

3.2. Modified methods

The methods that have an improvement in their equations or the main loops to be suitable for some applications could be categorized as modified methods. Modified FA, Continuous Genetic Algorithm (CGA), Deep Belief Network (DBN), Segmentation PSO (Se-PSO), are examples of the modified methods[34–37].

Bedekar et al.[36] modified the Genetic Algorithm by adding Hebb's rule and continues loop until reached an acceptable error of the fault section identification. A comparison between basic GA and CGA results via damaged section identification and execution time. Qin et al.[37] simulated an enhanced deep learning AI by creating DBN model. This enhancement was applied with the other three types of conventional shallow neural networks and compared to validate the ability to find the cable fault.

3.3. AI hybrid methods

The combination of two or more AI methods represents the AI hybrid methods. AI hybrid methods could be applied one algorithm after one (serial), all of the algorithms at the same time (parallel), or using an algorithm to select the other parameters (embedding)[38–40].

Nakho and Hamam[38] hybrid the discrete wavelet transform and k-Nearest neighbor machine learning AI methods to recognize the line to ground fault and its class. The validation of the hybridization was done using two other methods which are SVM and Naive Bayes.

The wavelet transform and SVM were used together as locator approach for transmission lines[39,40]. The wavelet transform, SVM, and support vector regression were used serially for extracting frequency components, fault type identifying then fault distance identification[39]. In the previous method, there was no phase damage consideration in the system. To overcome this issue, Deng et al.[40] selected the eigenvalues of the zero-sequence current by the wavelet transform method and then identify the fault distance by SVM.

In another work, Ray and Mishra[41] used SVM, Particle Swarm Optimization method, and wavelet packet transform as a hybrid to calculate the fault type and the fault position along the transmission line.

4. Discussion

In this paper, the previously presented works are a collection of fault identification that were done in the last twenty years. Those methods are classified in a new style to make the fault location topic smoother for reading. **Figure 3** provides a general description of the proposed classification.

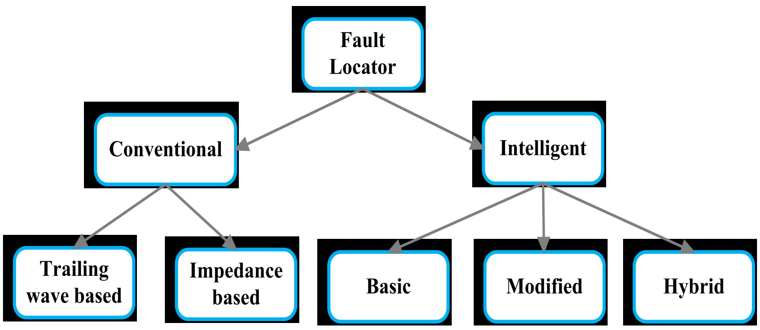

Figure 3. Fault classifications.

Based on the performance of different each fault identification method concepts, a comparison of their benefits advantages and disadvantages of those methods is illustrated in **Table 1**.

Table 1. The fault types features.

Method	Advantage	Disadvantage
Traveling wave-based	There are no affections by the load changes and the higher grounding lines resistance and series capacitor.	The accuracy effected by other line parameters, which are line inductance and shunt capacitance.
Impedance-based	Low price and easy implementation	The high dependency on line parameters, line characteristics, load value system non-homogeneity, and measurement device.
AI basic methods	Fast, error limits are depending less on the space dimension. Easiest Artificial Intelligence method by implementation, and low complex.	Failing in single optimal point. Not accrue in some of the high complex issues.
AI modified methods	Medium in complexity, pass the failing in single optimal point in many applications.	High parameter dependence
AI hybrid methods	Low parameter dependences, high accuracy	High complex, difficult to implementation. Needs to high algorithm information.

In spite of the several types of power transmission lines and their complexity, tasks research on the AI solved many of power system problems[42,43]. The fault location still requiring for more location accuracy special for the cable distribution system. It is very important to summarize the general features of the literature methods to. The future recommendations can be summarized as:

1) Due to the increased number of new AI methods applications in power system, we recommending to use more than basic intelligent methods such as Garra rufa optimization, gray wolves optimization, and elephant herding optimization in fault location topic.

2) Due to the robust of hybrid methods via control, classification, and optimization, we recommending to implement the most successful methods for locating the fault, for example, GA-PSO, Fuzzy-PSO, and firefly-PSO.

3) The combination of the AI and conventional methods maybe reduce the data-driven knowledge that needs in the machine learning-based.

5. Challenges and future recommendations

Despite the numerous fault location methods available for power system lines, there are still several challenges associated with fault location. Some of these challenges include:

- Data quality: AI-based fault location methods require high-quality data to train accurate models. However, data quality can be affected by factors such as noise, interference, and measurement errors, which can impact the accuracy of the fault location model.

- Interpretability: One of the major challenges of AI-based fault location methods is their lack of interpretability. These methods often use complex models that are difficult to interpret, making it challenging to understand how the model arrives at its fault location prediction.

- Model robustness: AI-based fault location methods are vulnerable to adversarial attacks that can manipulate the data inputs to the model, leading to inaccurate fault location predictions.

Future recommendations:

- Data preprocessing: Developing effective data preprocessing techniques to improve data quality is crucial to the accuracy of AI-based fault location methods. These techniques should aim to reduce noise and interference and remove measurement errors.

- Explainable AI: Researchers should focus on developing explainable AI techniques such as decision trees, rule-based models, and neural networks with attention mechanisms. These techniques can help improve the interpretability of AI-based fault location models, providing insights into how the model makes its predictions.

- Model robustness validation: Validation techniques such as adversarial training, robust optimization, and input perturbation can improve the robustness of AI-based fault location models, making them less vulnerable to adversarial attacks.

- Data sharing: The availability of high-quality data is essential for the development and testing of AI-based fault location methods. Therefore, utilities and researchers should collaborate to share data, facilitating the development of more accurate and reliable fault location models.

- Integration of AI-based fault location methods: Finally, the integration of AI-based fault location methods into power system operations is crucial for their successful implementation. Utilities and researchers should work together to develop guidelines and standards for the integration of AI-based fault location methods into existing power system infrastructure.

6. Conclusions

Fault location in power system lines remains a critical task for power system operators, as it helps to reduce outage times and improve the reliability of the power system. However, locating faults in power system lines can be a challenging task, particularly in complex power grids with numerous transmission lines and distributed generation sources. This paper has presented a review of the challenges and solutions of fault location methods in power system lines. The review has identified several challenges associated with fault location, including the impact of distributed generation on fault location, the need for accurate fault location in underground power cables, and the impact of system complexity on fault location accuracy. The review has also highlighted several fault location methods, including time-domain reflectometry, traveling wave-based methods, and model-based methods. To improve the accuracy and efficiency of fault location in power system lines, future recommendations include the integration of advanced technologies, standardization of fault location methods, development of comprehensive fault location strategies, and improved communication infrastructure.

Author contributions

Conceptualization, AHZ and KSY; methodology, AHZ; formal analysis, AHZ; writing—original draft preparation, AHZ; writing—review & editing, KSY; visualization, AHZ; supervision, KSY.

Conflict of interest

The authors declare no conflict of interest.

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