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Review

Review on Artificial Intelligence-Based Fault Location Methods in Power Distribution Networks

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Abstract: This paper provides a comprehensive and systematic review of fault localization methods based on artificial intelligence (AI) in power distribution networks described in the literature. The review is organized into several sections that cover different aspects of the methods proposed. It first discusses the advantages and disadvantages of various techniques used, including neural networks, fuzzy logic, and reinforcement learning. The paper then compares the types of input and output data generated by these algorithms. The review also analyzes the data-gathering systems, including the sensors and measurement equipment used to collect data for fault diagnosis. In addition, it discusses fault type and DG considerations, which, together with the data-gathering systems, determine the applicability range of the methods. Finally, the paper concludes with a discussion of future trends and research gaps in the field of AI-based fault location methods. Highlighting the advantages, limitations, and requirements of current AI-based methods, this review can serve the researchers working in the field of fault location in power systems to select the most appropriate method based on their distribution system and requirements, and to identify the key areas for future research.

Keywords: fault location; artificial intelligence; power distribution networks

Citation: Rezapour, H.; Jamali, S.; Bahmanyar, A. Review on Artificial Intelligence-Based Fault Location Methods in Power Distribution Networks. *Energies* **2023**, *16*, 4636. https://doi.org/10.en16124636

Academic Editor: Javier Contreras

Received: 20 May 2023
Revised: 6 June 2023
Accepted: 8 June 2023
Published: 11 June 2023

1. Introduction

Following to a short-circuit fault in distribution networks, the fault should be located and isolated before restoring the supply. A fast and accurate fault location method can help to improve the continuity of supply considerably. In general, the distribution-network fault location methods can be categorized into impedance-based methods, state estimation-based methods, traveling wave-based methods, and artificial intelligence-based (AI-based) methods.

The impedance-based methods determine the location of faults by measuring the apparent impedance seen from one or more measurement points. These methods estimate the fault location by comparing the measured impedance for the probable fault paths in the network with the measured one [1–5]. These methods can provide fault location estimations with acceptable accuracy, although they might estimate several candidate locations in the networks with several laterals. They require detailed data about the network topology, line impedances, and loads and are, hence, very sensitive to network-model inaccuracies.

State estimation-based methods consider a fault as bad data and try to locate it using the data collected from different measurement points of the network [6–8]. Similar to the impedance-based methods, these techniques need the distribution-network data. While they are less sensitive to input data inaccuracies, they can only be applied to networks with considerable measurement infrastructures.

Traveling wave-based methods estimate the fault location by calculating the sweep duration of the wave traveling from the measurement point to the fault location [9–12].

These methods are practically applicable to long transmission lines. However, their application to distribution networks with short line sections demands very high measurement sampling frequency which is not practical. Moreover, the application of these methods to networks with various laterals is challenging.

AI-based methods can be trained in off-line procedures to make fast online estimations of the fault location or faulted section. These methods need a considerable amount of training data which can be based on historical records or be generated in a simulation process. Research show these methods are less sensitive to noise in input data and considerably more accurate in comparison to the other methods. However, they suffer from challenges in practical applications where big data needs to be used and analyzed in detail. This review surveys the AI-based fault location methods, discusses the advantages and disadvantages of recently published methods, and highlights the corresponding challenges to be considered in future studies.

AI-based algorithms are widely used in various fault diagnosis applications. In [13], an artificial neural network (ANN) based on ACO-DWT is developed for fault identification and classification in HVDC networks. In [14], a method combining attention mechanism and long short-term memory (LSTM) is proposed to investigate tool condition monitoring in milling applications. A tangent hyperbolic fuzzy entropy measure-based method for determining the most sensitive frequency band to easily identify defective components in an axial piston pump is proposed by [15].

Although there are review papers on fault location methods for distribution networks [16,17], it is essential to highlight that AI-based approaches require specific considerations that distinguish them from other methods. These considerations encompass tailored training requirements, distinct analysis models, and unique factors to consider regarding their outputs, such as generalization capability. In this context, the primary focus and the contribution of this paper is to provide a comprehensive review specifically dedicated to AI-based fault location approaches in power distribution networks. By concentrating on this specific subject, it aims to emphasize the distinct characteristics and challenges associated with the application of AI techniques in fault location in this domain.

From the perspective of input and output variables, each AI-based method is a mapping from inputs to outputs. The input variables are electrical data including voltage, current, or frequency, and each method may use one or more of these variables. The output is fault location in the form fault distance or variables indicating the fault distance such as the reactance from fault point to the main substation. In this context, the type of input data and the data-gathering system is important because it determines the applicability of a method. Dealing with fault type and the presence of distributed generation (DG) units assigns the applicability level of each method. Table 1 compares the published research in this field based on different perspectives. In the first column, papers are compared in terms of the utilized AI method, where most proposed methods use ANNs as their main algorithm. The second and third columns compare the papers in terms of input/output variables. The fourth column presents the data-collecting system and the feature of the processed data. The considered fault types are shown in the fifth column and the DG inclusion is given in the sixth column. All these terms are explained in detail in the following sections.

Table 1. Comparison of recent papers in the field of artificial intelligence-based fault location approaches.

Ref	Method	Input Variables	Output Variables	Measurement Points/Measurement Feature	Fault Type	DG
[18]	SVM\ANN	Current, Voltage, and Frequency	Fault reactance to the main sub	Main Substation/ Main frequency features	All	No
[10]	ANN	Voltage	Fault distance to the main sub	Main Substation/ High-frequency features extracted by Wavelet	SLG	No

Table 1. *Cont.*

Ref	Method	Input Variables	Output Variables	Measurement Points/Measurement Feature	Fault Type	DG
[19]	ANN/fuzzy	Current and Voltage	Fault type and distance to the main sub	Not specified/ High-frequency features extracted by Wavelet	ALL	Yes
[20]	ANN/fuzzy	Voltage	Fault distance to the main sub	Sparse measurement/ High-frequency features extracted by Wavelet	SLG	Yes
[21]	ANN	Current	Fault distance, section, and resistance	Not specified/ High-frequency features extracted by Wavelet	All	No
[22]	ANN/fuzzy	Current and Voltage	Fault distance to the main sub	Main Substation/ High-frequency features	SLG	No
[23]	ANN	Current and Voltage	Fault type and distance to the main sub	Main Substation/ High-frequency features extracted by FFT	All	No
[24]	ANFIS	Current	Faulted zone	Main Substation/ High-frequency features extracted by Wavelet	All	No
[25]	ANN	Current	Fault type and distance to the main sub and DGs	Main Substation and DGs/ Main frequency features	All	Yes
[26]	Data mining (KNN)	Current and Voltage	Fault detection, type and section	Not specified/ High-frequency features extracted by Wavelet	All	Yes
[27]	KNN, Random Forest, ANN	Current and Voltage	Faulted line	Main Substation/ High-frequency features extracted by Wavelet	All	Yes
[28]	SVM\ANN	Current and Voltage	Faulted line	All buses measurement/ High-frequency features extracted by Wavelet	LLL	Yes
[29]	DNN	Current and Voltage	Fault detection, section, and location to the main sub	All buses measurement/ Main frequency features	All	Yes
[30]	ANN	Current and Voltage	Fault location to the main sub	All buses measurement/ Main frequency features	SLG and LLL	Yes
[31]	ANN	Voltage	Fault type and nearest bus	Measurement in all end users/ Main frequency features	All	No
[32]	GCM	Current and Voltage	Faulted bus	Sparse measurement/ Main frequency features	All	No
[33]	Deep RL	All nodes voltage and DGs real power	Faulted bus	All buses/ Main frequency features	LLL	No
[34]	ANN	Current	Fault location to the main sub	Sending feeder/ High-frequency features extracted by Wavelet	All	No
[35]	ANN	Current	faulted phase and distance to the main sub	Sparse measurement/ High-frequency features extracted by Wavelet	All	Yes
[36]	KNN/fuzzy	Voltage	Nearest bus	Sparse measurement/ Main frequency features	All	No
[37]	PSO/SVM/ Extreme Learning	Current	Fault distance to the main sub	All laterals/ High-frequency features extracted by S-transform	All	No
[38]	ANN	Current	Fault distance to the main sub	Distributed generation terminals/ High-frequency features extracted by Wavelet	All	Yes

Table 1. *Cont.*

Ref	Method	Input Variables	Output Variables	Measurement Points/Measurement Feature	Fault Type	DG
[39]	ANN	Current and Voltage	Faulted zone	Main Substation/ Main frequency features	SLG	No
[40]	ANN/KNN	Current and Voltage	Faulted line and Fault location to the main sub and DGs	Main Substation, DGs and Microgrids/ Main frequency features	All	Yes
[41]	ANN	Current and Voltage and Real Power	Fault distance to the main sub	Main Substation/ Main frequency features	All	No
[42]	ANN	Current and Voltage	Fault distance to the main sub	Main Substation/ Main frequency extracted by DFT	All	Yes
[43]	ANN	Current and Voltage	Fault distance to the main sub	Main Substation/ Main frequency extracted by FFT	All	Yes
[44]	ANN	Current and Voltage	Faulty section	Main Substation/ Main frequency features	All	No
[45]	SVM	Current and Voltage	Faulted zone	Main Substation/ Main frequency features	All	No
[46]	SVM	Current and Voltage	Faulted Section, fault type, fault impedance, and fault distance to the nearest nodes	Main Substation and DG terminals/ Main frequency features	All	Yes
[47]	SVM	Current and Voltage	Faulted zone	All substations/ Not specified	SLG and LLL	No
[48]	SVM	Voltage	Faulted zone	All DG terminals/ Not specified	LLL	Yes
[49]	CNN	Current and Voltage	Fault type, faulted section, and exact location of the fault	Main substation and all laterals/ High-frequency features	ALL	No
[50]	CNN	Current and Voltage	Fault distance to the measurement point	Main substation and all laterals/ High-frequency features	ALL	Yes

This paper is organized as the following: Section 2 discusses the papers in terms of the utilized method. Section 3 describes the papers in terms of input/output variables. Section 4 explains the data-gathering systems. Section 5 discusses fault types and Section 6 discusses DG consideration. Finally, Section 7 presents some concluding remarks, research gaps, and future trends.

2. AI-Based Methods

The application process of AI-based methods is illustrated in Figure 1. The first step of applications is to choose the input variables which comprehend the network condition. In the second step, the features of voltage or current are adopted by using transforms such as Wavelet, Stockwell, and Fast Fourier to generate informative features. Some features are based on high-frequency spectra of signals, and some are based on the fundamental frequency spectrum of the signal such as the root mean square (RMS) value of the fundamental signal. Finally, in the last step, the main algorithm analyzes the input features and gives an estimation of the fault location as the output. In the following, some of the main algorithms employed by the AI-based fault location methods are discussed in details and discussions about each of these steps are provided in their corresponding sections.

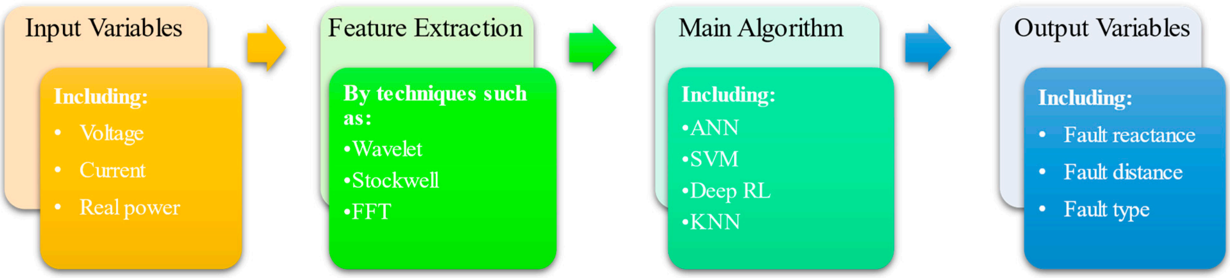

Figure 1. The process of AI-based fault location methods.

2.1. *Artificial Neural Networks (ANNs)*

ANN is the most used AI-based algorithm in the field of fault location due to its flexibility and high precision [10,18–23,25,27,28,30–35,38–44]. ANNs are a class of supervised regression algorithms that can be used as a prediction tool. The training procedure of ANNs is based on a series of experienced samples of the system. In a fault location method, the training samples are formed of tuples including inputs (e.g., current or voltage features) and outputs (e.g., fault distance or fault reactance). The training data is often adopted from simulations because this data is extracted from the fault condition, and it is not possible to apply several faults on real-world systems to generate data. However, there might be a record of previous fault signals; ANN needs a large amount of data in different network conditions and fault situations, and the recorded data are often insufficient.

An ANN is simply constructed of different layers. There are three types of layers in ANNs: the first as the input layer, the last as the output layer, and hidden layers in between. The input layer connects the input variables (features) to the neurons in the first hidden layer. The hidden layers construct a network connection from the input layer to the output layer and the output layer contains a number of neurons (equal to the number of outputs) connected to the last hidden layer. Figure 2 shows a typical example of an ANN.

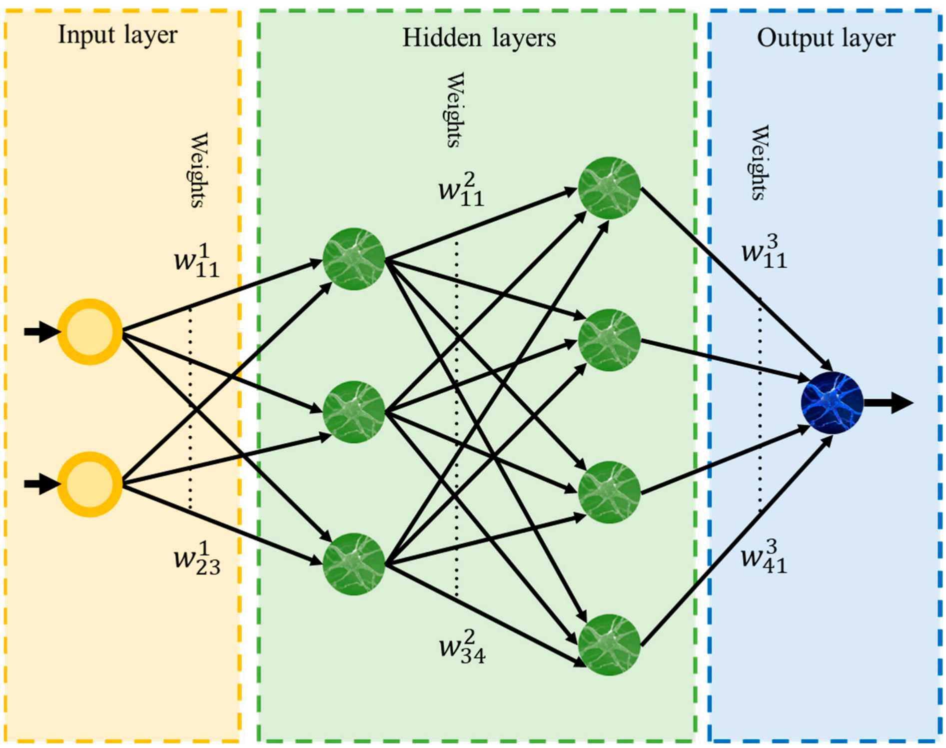

Figure 2. A typical ANN showing network layers connection.

In an ANN, each neuron acts based on its activation function as Equation (1):

$$y(x, w) = f(x) = f\left(\sum w_i x_i\right), \tag{1}$$

where y, x, and w are the output, input, and corresponding weights of the neuron.

The activation function is dependent on the type of the ANN and most papers proposed hyperbolic tangent. The number of hidden layers and the number of neurons in each hidden layer is modified based on the experience of the designer depending on the size and complexity of the problem. After determining the type of the network and the number of neurons, the weights should be determined within a training process [51].

There are different methods to calculate the optimized weights; Levenberg–Marquardt, backpropagation, and evolutionary algorithms (GA, PSO, ACO, etc.) are examples of these methods.

In addition to the fully connected ANNs, there are other novel neural networks such as conventional neural networks (CNNs) and recurrent neural networks (RNNs). The key components of a CNN include convolutional layers, pooling layers, and fully connected layers (basic ANN). In the convolutional layers, the network applies a set of filters to the input sample, producing a set of feature maps that highlight different aspects of the sample. The pooling layers downsample the feature maps, reducing their dimensionality and creating a more compact representation of the image. Finally, the fully connected layers use the features extracted by the convolutional and pooling layers to make predictions or classifications [32,52–54]. In fault location applications, first, a signal-to-image transform is performed to create images from recorded fault data appropriate for the convolutional process, and, then, the exact fault location is investigated by the fully connected ANN [49,50].

RNNs are a type of neural network that are designed to work with sequential data. Unlike fully connected neural networks that process inputs in a single pass, RNNs process inputs in a sequential manner, while also maintaining a hidden state that captures information from previous inputs. The key feature of RNNs is their ability to capture and learn temporal dependencies in sequential data. This is achieved by using recurrent connections that allow the network to pass information from one time step to the next. The hidden state of the network at each time step is a function of the current input and the previous hidden state, allowing the network to maintain a memory of past inputs [55–57].

2.2. Support Vector Machine (SVM)

SVM is a powerful tool for handling classification and regression problems [18]. This method determines hyperplanes for separating different classes. For example, in a two-dimension two-class problem, the SVM method determines the line separating the classes, as shown in Figure 3 [58,59].

For more complex systems, SVM adds an extra feature to the samples (maps the problem into a higher dimensional space) and proposes a hyperplane in the D-dimensional space [60]. In fault location applications, SVM is used as a regression tool to estimate the output value (fault location here). While SVM is a tool for linear systems, however, it can be applied to nonlinear problems using the kernel trick [28]. SVM maps inputs to outputs using the following equation:

$$y(x) = w^T \varphi(x) = \sum_{i=0}^{D} w_i] \varphi_i(x) \tag{2}$$

where y is the output, x is the input, $w = [w_0, w_1, \ldots, w_D]^T$ is the weight vector and $\varphi(x) = [\varphi_1(x), \varphi_2(x), \ldots, \varphi_D(x)]$ is the basis function.

To solve the problem, a loss function ($L_\varepsilon(y(x), \beta)$) is defined as below.

$$L_\varepsilon(y(x), \beta) = \begin{cases} 0, & if|\beta - y(x)| < \varepsilon \\ |\beta - y(x)| - \varepsilon, & if|\beta - y(x)| \geq \varepsilon \end{cases} \tag{3}$$

where ε is a threshold for the loss function and β is the target value of the training sample x. Minimizing Equation (4) is the main task of the SVM can be handled using different optimization methods.

$$E = \frac{1}{N}\sum_{j=1}^{N} L_{\varepsilon}\left(y_j(x), \beta_j\right) \tag{4}$$

where N is the number of the training samples.

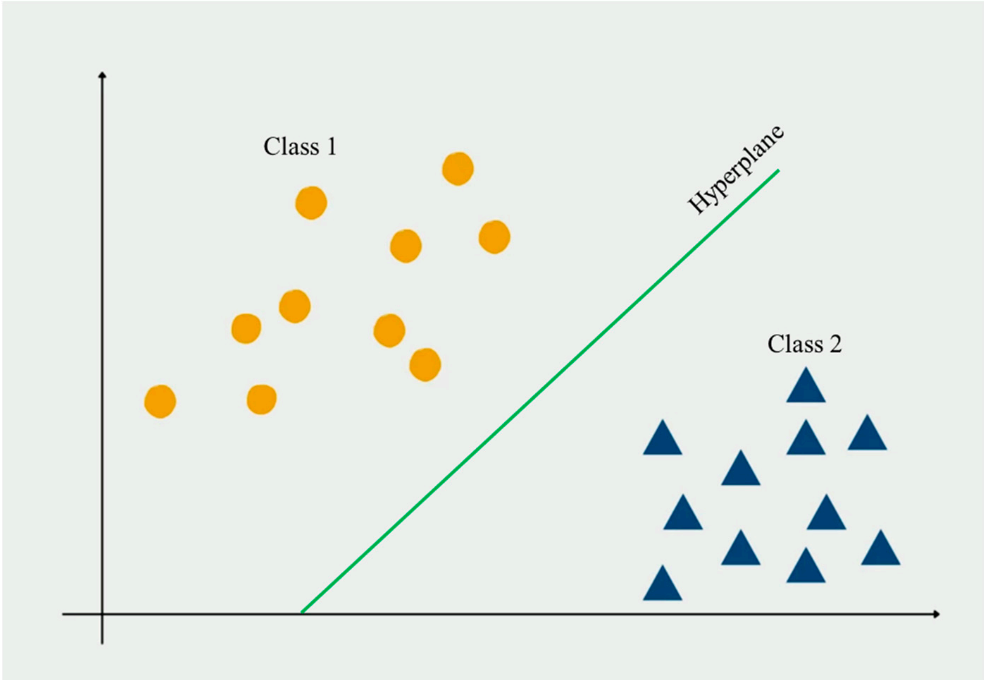

Figure 3. SVM method applied to a simple two-dimension two-class problem.

2.3. K-Nearest Neighbor

KNN is a simple supervised machine-learning algorithm for both objectives of regression and classification. In fault location applications, KNN is used for both classification and regression purposes, faulted line section and fault type detection are of the classification applications, and determination of fault location is of the regression applications [26,36]. In this method, the test sample is assigned to the nearest classes depending on the value of K, e.g., if K equals to 1, the sample will be assigned to the first nearest neighbor and if the K equals to 3, the sample will be assigned to the class that is more repeated in the three closest neighbors. Figure 4 shows an example to assign a sample (green square) into two classes; if k equals to 1 (dashed red circle) the sample assigns to class 2 (blue triangles) and if k equals to 3, (solid red circle) the sample assigns to class 1 (orange circles). In some applications, the sample is assigned using weights based on the distance of the sample to the class samples.

The main disadvantage of KNN is its slow response in high-dimension problems. To overcome this issue, the research used KNN in conjunction with ANNs [27,40]. In these methods, KNN processes the outputs of ANN to improve efficiency and the precision of ANN. Furthermore, this technique reduces the number of KNN input variables that are independent of the network structure and size.

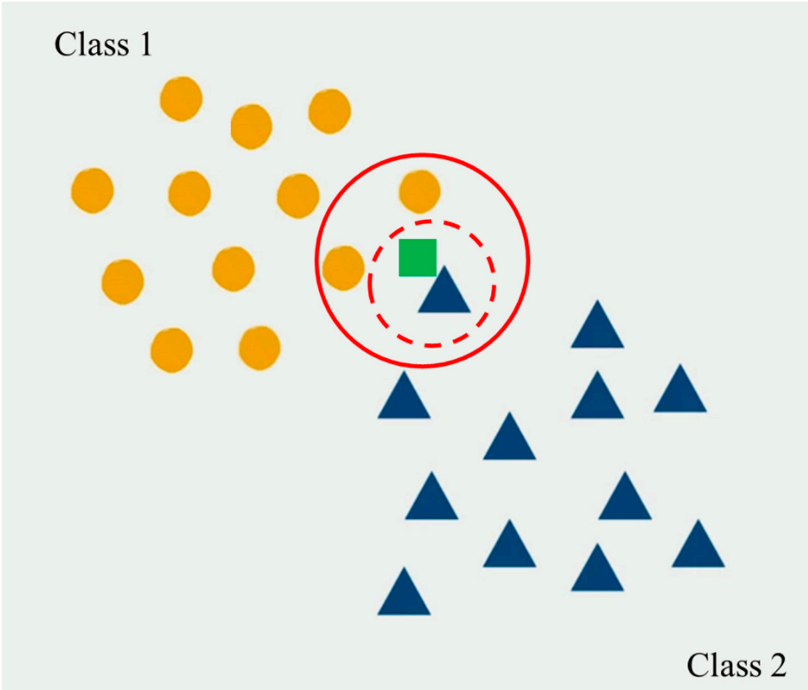

Figure 4. A typical example of the KNN classification method (the green square is the test data, and the red line shows the neighboring area).

2.4. Deep Reinforcement Learning

Deep learning is inspired by the evolution of mammals' brains. In this method, an agent is trained based on its experiences where actions with rewards registered as good choices and actions with harm registered as unfavorable choices and the agent chooses its next action trying to maximize its reward. Favorable or unfavorable conditions are determined depending on the agent and the environment, e.g., for a mammal, finding food is a favorable situation, and falling from a cliff is unfavorable. In optimization or classification applications, favorability is determined by the operator. For example, for a can gatherer robot, finding new cans is a situation with pleasure, and losing battery is not encouraging.

The fundamentals of deep learning are based on reinforcement Q-learning. Q-learning is an efficient optimization tool for solving multistage problems. In each stage of the problem, the next stage (state) is a function of the present stage and the chosen action is based on the following:

$$x_{k+1} = f(x_k, a_k) \tag{5}$$

where x_k is the present state, a_k is the chosen action, and x_{k+1} is the next state.

In this method, each state-action tuple (x_k, a_k) has a related Q-value and the agent in each state chooses the action with maximum Q-value and reaches the next state. The Q-values are in relation to rewards or penalties the agent gained during its training process (experiences). Q-value for each state action is dependent on its immediate reward and those it might gain in the following next states based on the following equation:

$$\begin{aligned} Q^{n+1}(x_k, a_k) = Q^n(x_k, a_k) + \alpha[g(x_k, a_k, x_{k+1}) \\ +\gamma \cdot \arg \max_{\alpha' \in Ax_{k+1}} (Q^n(x_{k+1}, a')) - Q^n(x_k, a_k)], \end{aligned} \tag{6}$$

where n is the number of the training iteration, $g(x_k, a_k, x_{k+1})$ is the immediate reward, α is the training rate, and γ is the discount factor. $Q^n(x_{k+1}, a')$ is dependent to the situation of the next state representing what the agent will experience.

Due to the curse of dimensionality, determining $Q^n(x_{k+1}, a')$ is not an easy job in high dimension or continuous problems and needs high calculation efforts. To cope with this problem, deep neural networks are hired as a regression tool to estimate $Q^n(x_{k+1}, a')$ for each state-action tuple. The training procedure of DNNs can be performed by using batch-constrained sets of data, including agent experiences, that simulate the behavior of the agent and responses of the environment.

In fault location applications, the agent should be able to classify the fault type and determine the fault location. Hence, the agent should be trained as a tool for regression and classification applications. The input variables can be voltage or current features and the output variables are fault type (e.g., the line to ground (LG), line to line (LL), line to line to ground (LLG), three phase (LLL)), and fault location (a continuous value).

In [29], the authors developed a deep neural network-based (DNN-based) method for fault location and identification in low-voltage grids that is topology independent and can also localize high-impedance faults. In [33], the authors presented a DRL algorithm for fault diagnosis applications that is goal-oriented and independent of a large amount of labelled data.

3. Input/Output Variables

The input variables can help to identify the behavior of the system. During fault incidence, the voltages and currents of the network are affected by the network condition and fault characteristics, including fault distance, fault resistance, and fault type. The optimization or regression algorithms should be able to determine fault characteristics based on the recorded signals. As mentioned before, applied algorithms need a preprocessing procedure called feature extraction that extracts single or multiple features from fault signals (voltage-time or current-time curves).

In comparison to voltage signals, current signals are more instructive because current signals are directly related to the load and the condition of the network. However, in some types of networks, such as islanded microgrids or inverter-based distribution networks, voltage fluctuations are significant during faults and voltage features may present valuable information about fault characteristics. Hence, some papers use current features, some voltage features, and some features extracted from both signals. Generally, it is better to use features of both current and voltage signals to be able to consider the different conditions of the networks and different types of networks.

From the perspective of required devices for data registration, current-based approaches are more complicated due to higher fluctuations of fault current signals that make current transformers (CTs) more expensive in comparison to voltage transformers (PTs) that record voltage signals. Note that during a fault incidence, the current magnitude may increase to multiple times the nominal current while voltage signals are either reduced, or in some rare cases, increased less than the $\sqrt{3}$ times the nominal voltage. Hence, choosing the input variables is a trade-off between cost and precision.

Output variables in fault location applications are selected to give an estimation of the exact location or the fault area. In most of the published research, the distance to the fault from the main substation or a variable representing the distance such as fault reactance is calculated. The main idea of these approaches is inspired by the impedance-based methods that estimate the fault location based on the measured impedance during fault incidence. Determining fault impedance is helpful in the estimation of fault location but it may cause a multiple-location estimation. Due to the presence of different laterals in the network, two or more locations may show an equivalent impedance. Figure 5 shows such a condition that different fault locations are estimated for a single estimated fault impedance (e.g., Z1, Z2, and Z3 are three estimated impedances for three different fault cases).

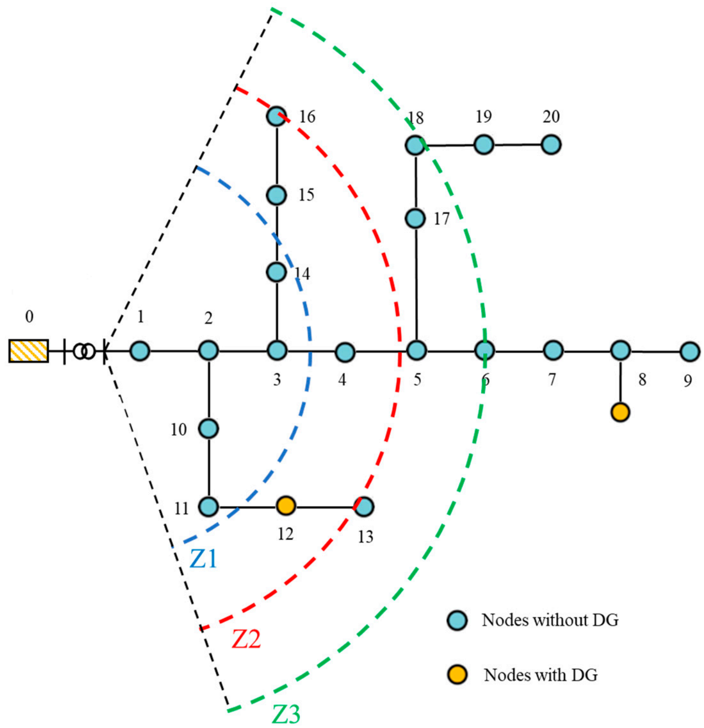

Figure 5. How determining fault location based on fault impedance may cause false estimation.

To cope with this issue, the research proposed fault location estimation from different locations in addition to the main substation. DG terminals are suitable candidates for being chosen as an additional locator point because DGs often have metering devices at their interface point. Figure 6 shows a multiterminal fault location scheme that determines the fault location from different points (main substation and DG terminals) and determines the exact location by analyzing the estimated fault impedances from all terminals.

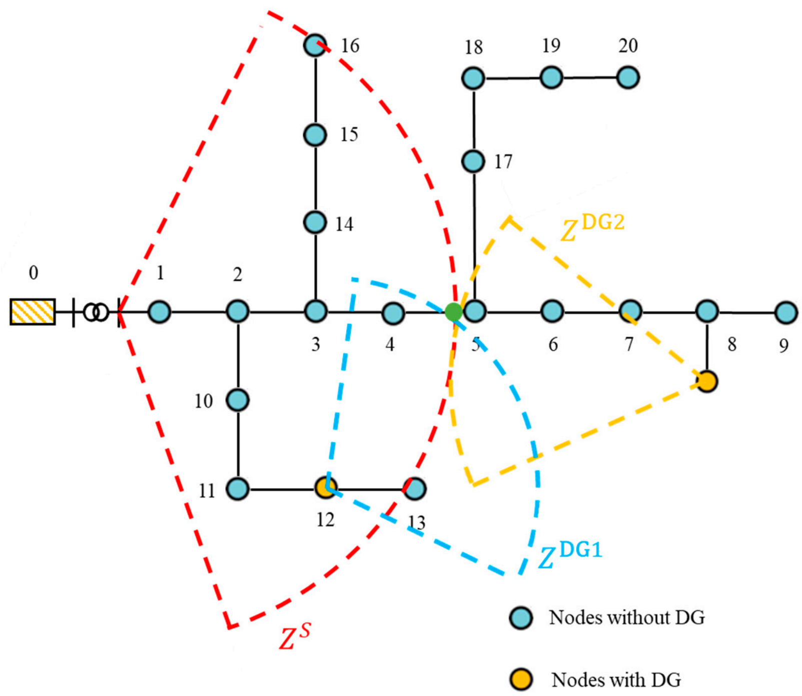

Figure 6. Multiterminal fault location scheme.

4. Data-Gathering System

A data-gathering system, which may include one or multiple metering devices, sends recorded fault signals to the network processor. Recent fault location methods are mostly based on multiple metering devices where data from different locations of the network are gathered by a communicational system. The communication links connect the metering devices (installed on power-network elements) to the main processor unit (distribution control center), as shown in Figure 7.

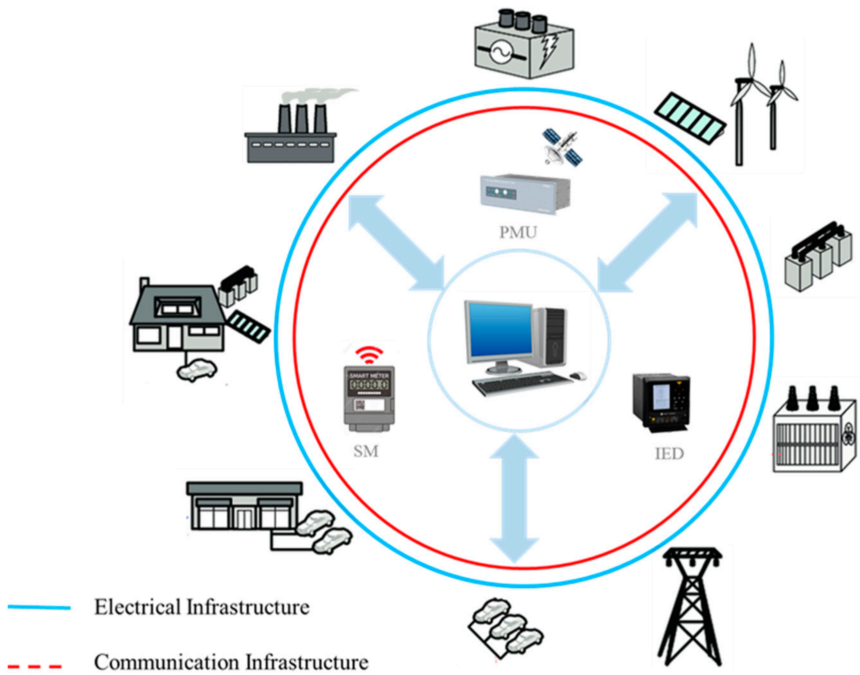

Figure 7. Electrical and communication infrastructures in smart grids.

The communication system may be a wireless network or a wire-based network. Wire-based supervisory control and data acquisition (SCADA) systems are widely used in power system applications [61]; however, other types of architectures such as mobile cellular data [62–64] and WiMAX [65–67] are also proposed in some approaches. The IEEE 802.16 Standard defines requirements and means for the replacement of conventional wire-based networks with wireless broadband networks.

There are three main types of data-collecting devices in power systems known as smart meters (SM), intelligent electronic devices (IEDs), and phasor measurement units (PMUs). SMs are mostly used for energy-management purposes and do not record the high-frequency features of the fault signals but they can be exploited to estimate the network loads [8]. IEDs are intelligent programmable elements that can record, process, and transmit information over a communication network. IEDs have different applications in power networks including protection, control, monitoring, and measurement [68]. IEC 61850 proposes a process bus communication network between process-level equipment and bay-level IEDs used for power systems protection and control. PMUs measure synchronized phasors. Synchronization of PMUs can be achieved either by internal clocks or external clocks (e.g., GPS) [69]. The sampling rate of PMUs is high enough to record voltage and current features needed for protection purposes [70]. In [71], a real-time protection approach for microgrids based on the distributed dynamic state estimation using PMUs is proposed. In [72], a supervisory protection framework based on PMUs is developed that performs feature extraction techniques for speedy classifiers. PMUs are used in the transmission voltage level while μPMUs are developed for distribution networks [73–75].

In terms of the required measurements, there are generally two classes of fault location techniques. The first class, such as impedance-based fault location methods rely on fundamental frequency phasor of recorded voltages and currents. The second class comprises techniques such as travelling-wave-based fault location methods which rely on recorded fault waveforms and often extract high-frequency information and features. In AI-based methods, both classes are used; e.g., Refs. [29–32] rely on fundamental frequency measurements and [19–22] rely on high-frequency measurements. The required input measurement is a key factor in determining the prerequisite infrastructure to implement each of the fault location methods.

5. Fault Type

Short circuit faults are the main reason for power outages in electrical networks. They are mainly categorized into four main types: LG, LL, LLG, and LLL. Fault analysis at the transmission level is usually limited to these four types. However, due to its imbalance and asymmetry, at the distribution level, the mentioned fault types constitute 10 combinations for the three phases to be studied. The fault type has a considerable effect on the fault location analysis. For example, Figure 8 compares the fault current path for LG and LL faults. For an LG fault, the fault current flows to the fault point and then bypasses to the ground, whilst for an LL fault, the fault current flows to the fault point through one phase and returns through another. This considerable difference in the fault current passage leads to considerable differences in the measured network variables and hence in the fault location method inputs. The AI-based methods address this problem with two distinct approaches. The first method involves training individual AI models for each specific fault type, which may result in more accurate estimations but requires the use of a fault classifier prior to implementing the AI. The second method involves training a single AI model to estimate the fault location for all fault types, which may be easier to train but could potentially result in lower estimation accuracy.

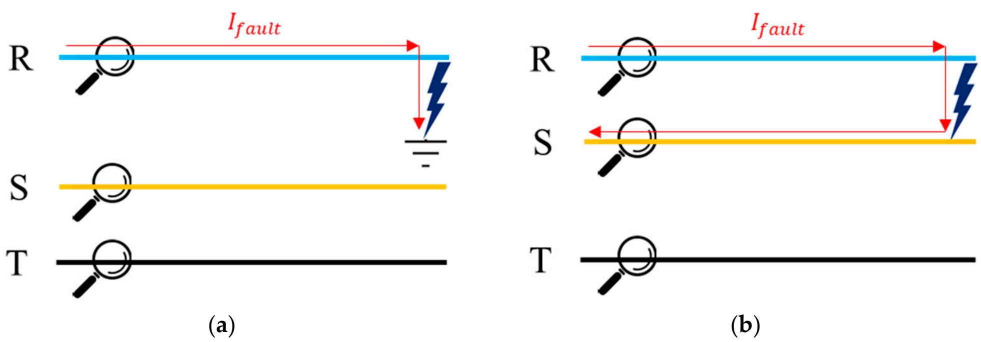

Figure 8. Fault current path in 3-phase RST system: (**a**) an LG fault and (**b**) an LL fault.

As can be seen in Table 1, a considerable number of the proposed AI-based fault location methods only focus on a single type of short-circuit faults. For the others, a preprocessing for fault type identification is often necessary. In distribution networks, discrimination of short-circuit fault types is not very complicated because the current flowing through the faulted phase or phases will increase following the fault occurance. However, in ungrounded or weakly-grounded networks, and distribution networks with multiple DGs, the increment in the short-circuit fault current might be minor, making the fault detection and fault type identification challenging. There are several research studies of fault detection and type identification in such networks [76–79].

6. Presence of DG Units

Integration of DG units into power distribution networks causes critical challenges to the distribution network protection and fault location. These critical challenges are as follows [80–84]:

- *Dynamics and variations of fault current magnitude*: smart grids (especially microgrids) can operate both in grid-connected and isolated modes. In grid-connected mode, the fault current magnitude is much greater due to the high short-circuit power of the upper grid. On the other hand, the type of DG units also affects the fault current contribution. Inverter-interfaced DG units contribute to fault currents up to 1.5 times of their nominal current while synchronous generators can generate fault currents about 5 times their nominal current. These challenges cause fault current magnitude variations which make the fault location and protection challenging;

- *Loss of selectivity:* In cases of placement of a DG unit close to the main substation, the DG unit may contribute to the fault current of a fault occurred in a parallel feeder. Figure 9 shows such a condition that, due to the fault current contribution of DG, relay R1 may operate faster than R2 which is not necessary and is known as maloperation. The operation of R1 will trigger the fault location process for its downstream feeder which might lead to misleading results;

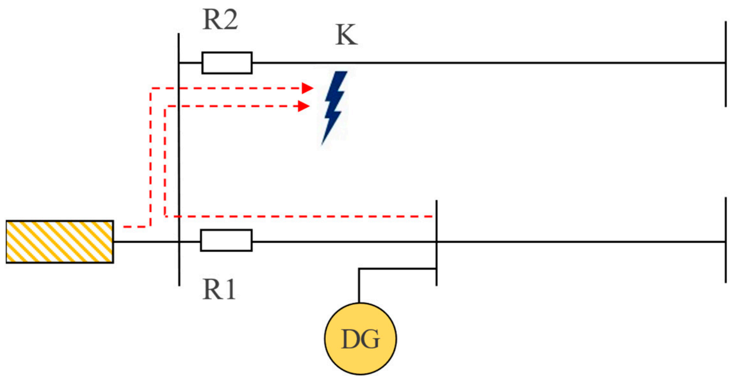

Figure 9. Maloperation of over-current protection relays (R1 & R2) in the presence of DG units.

- *Blindness:* As shown in Figure 10, in the cases of fault occurring at the end of a feeder containing a DG unit, the magnitude of fault current seen by the feeder relay is decreased due to DG impedance. The reduction of fault current magnitudes results in underestimation of fault current, and the relay may not act to isolate the fault.

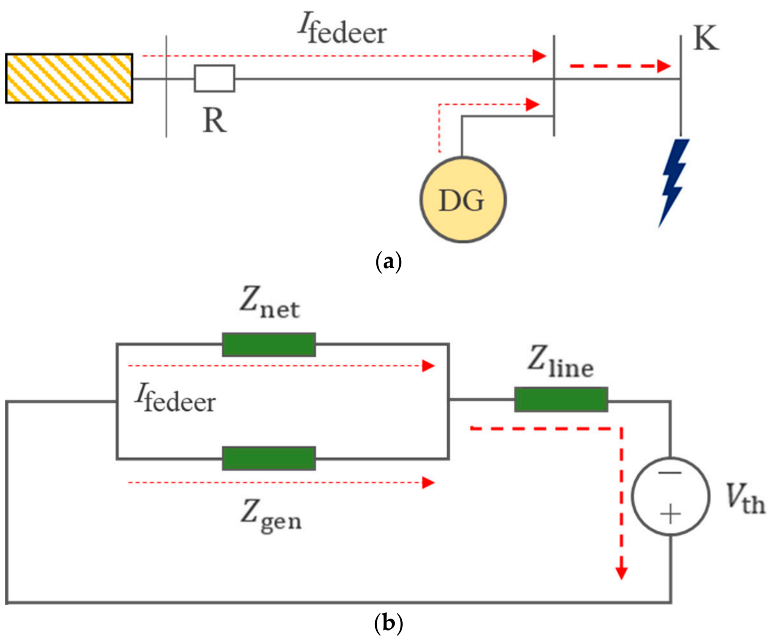

Figure 10. Protection blindness for relay R, (**a**) single-line view, (**b**) impedance view.

In this condition, the fault current magnitude in the absence of DG unit is:

$$I_{feeder} = \frac{V_{\text{th}}}{Z_{\text{net}} + Z_{\text{line}}} \tag{7}$$

Whilst in the presence of DG unit, it becomes:

$$I_{feeder} = \frac{V_{th}}{Z_{\text{net}} + \frac{Z_{\text{line}} \cdot Z_{\text{net}}}{Z_{\text{gen}}} + Z_{\text{line}}} \tag{8}$$

where I_{feeder}, Z_{net}, Z_{line}, and Z_{gen} are the current seen by the feeder relay, upper grid impedance (short circuit impedance), feeder impedance, and DG impedance, respectively.

Comparing the equations clearly shows the effect of DG units on the underestimation of the fault current at the protection point, resulting in the so-called protection blindness. This underestimation might hinder protection-system reaction and subsequent fault location. Moreover, it might affect the estimation accuracy if not considered.

7. Conclusions

Based on the literature review of AI-based fault location methods, this paper presented a comprehensive analysis of the advantages and disadvantages of various AI techniques proposed in the literature considering the types of input data required, the outputs generated, the data-gathering systems employed, fault type, and DG considerations. A detailed review and comparisons are presented to highlight the requirements and the research gaps in the field of AI-based fault location methods.

In general, the required input data, measurements, and the data-gathering infrastructure are the most important factors determining the applicability of each of the fault location methods for a specific distribution system. In terms of the output special care should be taken to the fact that just having an estimation of the distance to fault from a single measurement point might lead to multiple fault locations estimation in the branched structure of the distribution networks. Then, methods of estimating the faulty point or giving an estimation of the fault zone, together with the distance, are more desirable.

The review also highlights that a considerable number of proposed AI-based fault location methods focus on a single type of short-circuit faults which limits their application range. Although some have proposed training a single AI model to cover all fault types, this approach may result in lower estimation accuracy. Alternatively, separate AI models could be trained for each fault type but this would necessitate preprocessing for fault type identification.

In addition, the paper highlights that the integration of DGs into power distribution networks poses critical challenges to the distribution network protection and fault location, including dynamics and variations of fault current magnitude, loss of selectivity, and blindness. Considering the effect of DGs in the fault locator design will, of course, help to have a more reliable estimation. On the other hand, it often requires a more sophisticated measurement and data-gathering system. Such methods often require measurements with fault signal recorders with higher sampling rates than the most common ones in practice (e.g., smart meters), and a reliable communication capable of handling high amount of recorded signals.

The prominent obstacle associated with AI-based fault location algorithms pertains to their reliability in the training process. For instance, impedance-based techniques employ relevant equations that can be applied across various network typologies, whereas AI-based approaches necessitate tailored training procedures for each network individually. Furthermore, AI-based methods are perceived as less transparent than other methods, particularly impedance-based techniques.

In general, the presented comparisons were aimed to provide valuable insights for researchers working in the field of fault location in power systems to select the most appropriate method based on their distribution system and requirements and to identify the key areas for future research. Further research is necessary in two directions. The first is to address the critical challenges caused by the integration of DGs into power distribution networks and to develop more accurate and robust AI-based fault location methods that can handle multiple types of short-circuit faults in such networks. It should be noted that distinct categories of DG units exert diverse effects on the condition of short-circuit faults. Therefore, it is recommended that forthcoming approaches take into account the presence of various types of DGs in their investigations. The other direction is to design such methods to be able to be implemented with the minimum infrastructural investments. The infrastructural investments encompass both the type of data-acquisition tools (recording devices) and their location.

Author Contributions: Validation, S.J.; formal analysis, A.B. and H.R.; investigation, H.R. and S.J.; writing—original draft preparation, H.R.; writing—review and editing, A.B. and S.J.; visualization, H.R. and A.B.; supervision, S.J. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

ACO: Ant Colony Optimization, AFIS: Adaptive Neuro-Fuzzy Inference System, ANN: Artificial Neural Networks, CNN: Convolutional Neural Network, DNN: Deep Neural Networks, GA: Genetic Algorithm, GCM: Graph Convolutional Method, KNN: K-Nearest Neighbor, LLL: three-phase fault, PSO: Particle Swarm Optimization, RL: Reinforcement Learning, SLG: Single Line to Ground fault, SVM: Support Vector Machine.

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