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Review

Fault Location for Distribution Smart Grids: Literature Overview, Challenges, Solutions, and Future Trends

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Abstract: Thanks to smart grids, more intelligent devices may now be integrated into the electric grid, which increases the robustness and resilience of the system. The integration of distributed energy resources is expected to require extensive use of communication systems as well as a variety of interconnected technologies for monitoring, protection, and control. The fault location and diagnosis are essential for the security and well-coordinated operation of these systems since there is also greater risk and different paths for a fault or contingency in the system. Considering smart distribution systems, microgrids, and smart automation substations, a full investigation of fault location in SGs over the distribution domain is still not enough, and this study proposes to analyze the fault location issues and common types of power failures in most of their physical components and communication infrastructure. In addition, we explore several fault location techniques in the smart grid's distribution sector as well as fault location methods recommended to improve resilience, which will aid readers in choosing methods for their own research. Finally, conclusions are given after discussing the trends in fault location and detection techniques.

Keywords: fault location; smart grids; fault classification; low-voltage and DC smart grids; resiliency of smart grids; microgrids; artificial intelligence; local measurement-based techniques

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1. Introduction

Smart grids (SGs) are a "electric power system that utilizes information exchange and control technologies, distributing computing and associate sensors and actuators" [1] to empower customers and provide secure and reliable energy. The SGs integrate distributed energy resources (DER), advanced sensing technologies, control methods, and communication technologies into the electrical grid to offer an intelligent manner to operate with bidirectional power flow and self-healing capability [2,3]. As depicted in Figure 1, the SG is separated into different domains in accordance with the standard IEC 62913-1 ED2. These domains that are described in the Smart Grid Architecture Model (SGAM), using an architectural approach [4], include bulk generation, transmission, distribution, DER, customer premises, and cross-sectional domain. Additionally, the distribution domain has been divided into three categories: distribution grid management, microgrids (MGs), and smart substation automation.

The integration of more renewable energy resources (RER), storage systems, and controllers into the distribution grid will guarantee system reliability, improve system resiliency, and maintain the current and voltage in safe ranges. However, as an increasing number of different technologies are introduced into the grid, a growing number of important failure points, if not properly handled, will lead to cascading failures and subsequent blackouts [5]. Therefore, a suitable fault management system [6,7] is required to detect, classify, localize, diagnose, isolate, and restore the system to normal functioning.

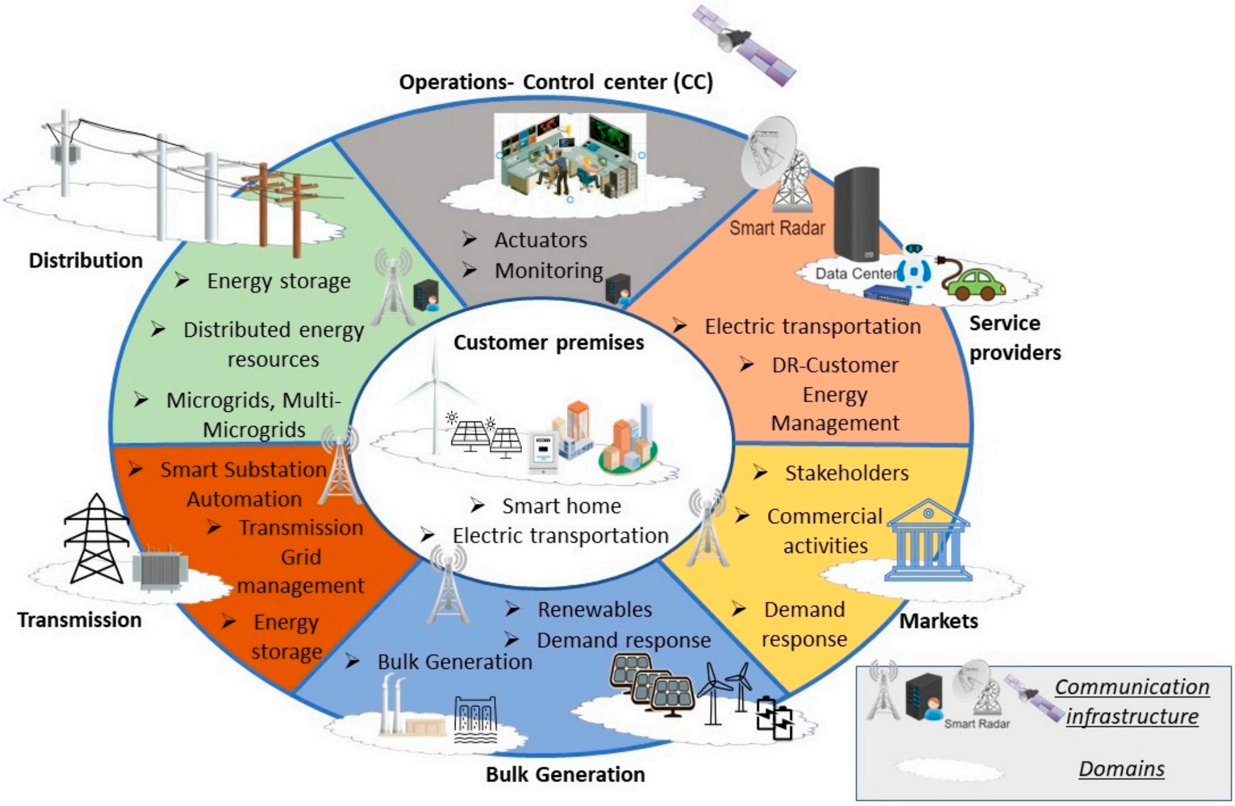

Figure 1. Smart Grid Domains. Vision for Smart Grid [8].

One of the key features of SGs is their self-healing ability to locate and isolate disturbances, reduce fault frequency, reschedule grid resources to avoid critical situations, maintain the service continuity of the electric grid under any conditions, and shorten the time needed for outage restoration [9,10]. Fault diagnosis and location are important to ensure this self-healing capability, stability, and enhanced system performance by reducing undesirable impacts such as power outages and component failures [11].

The detection and isolation of abnormal events are the focus of fault diagnosis [12]. The process of diagnosis begins after detection. The type of problem that is present and possibly what caused it can be determined by diagnosing the severity of the problem. It can also help assess whether a fault is developing but is not yet substantial enough to threaten the system [13]. The major considerations for developing a fault location strategy are locating the power outage inside the system to handle it, improving the fault detection procedure, and deciding whether an online or offline location approach will be employed [14].

The SGs systems need more accurate fault location algorithms, fault predictions, and privacy-preserving schemes [15,16], as more generation sources based on inverters, sensors, and communication systems are added. Since there are more dynamic and unbalanced loads, intermittent and unbalanced generation sources, various operating modes (connected, isolated, interconnected), different topologies (star, ring, mesh, or interconnected), different failure points will be created, and various conductor sizes will make fault locating a crucial task. Additionally, rapid communication is necessary for the integration of direct current (DC) MGs with small line impedance, significant fault current deviation, and high sampling rates [17]. Figure 2 displays a few of the challenges in fault location that have been discussed in the literature.

Several reviews on the fault management system of SGs have been conducted, taking into account, a wide range of fault types [11,18,19], MGs fault diagnostics and detection methods [20–22], fault management in hybrid MGs [23], fault tolerant control systems of AC/DC [24], MGs machine learning (ML)-based approach [25], fault detection, location, isolation, service restoration (FDIR), and protection methods in low voltage DC-grids

(LVDC) [17,26–28], in smart distribution grids [6,15,29–31], and power system protection [32]. There is still a need for a review of fault location methods and techniques in the SG's distribution domain, considering distribution grid management, MGs (AC, DC, and hybrid MGs), and smart substation automation (communication and attack failures). Table 1 compares the primary topics covered in this study to reviews from other SGs.

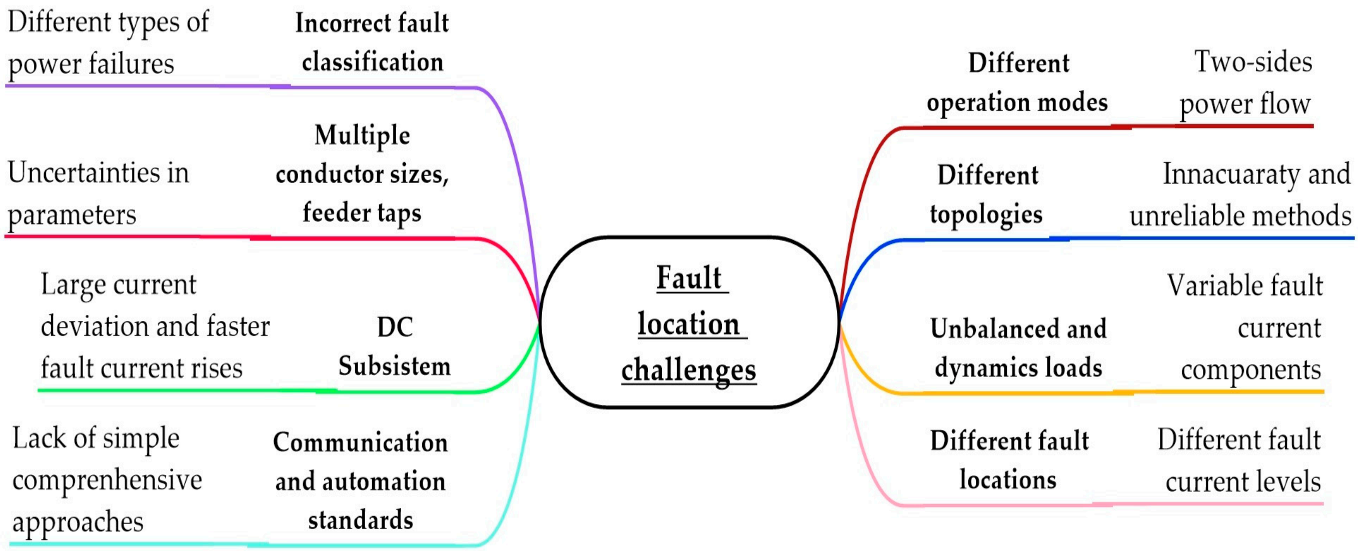

Figure 2. Fault location challenges in SG's distribution domain [21].

Various authors also discuss various fault location techniques and methods for SGs and MGs, including impedance-based methods [6], traveling wave-based fault location methods [33], high-frequency component-based methods (S-transform) [34], knowledge-based methods [35], intelligent approaches [36,37], adoption methods with load estimation [38,39], location via SCADA systems, and a lot of intelligent electronic device (IED) data [40,41], as well as using intelligent devices like smart meters, smart sensors, phasor measurement units (PMU), and switching devices [42,43]. However, these methods are still not enough to carry out a full investigation of fault location in SGs over the distribution domain. The contributions and increased value of this research can be summarized as follows:

1. This paper identifies recent publications on smart grids and microgrids to give readers an overview of the challenges these systems experience while dealing with different fault types and the methodologies used it to locate them;
2. The challenges with fault location techniques and the types of faults that impact electric power systems (EPS), SGs, and MGs are also briefly summarized. This subject has already been covered in depth in several articles, so here is a summary with a focus on the ones that cover it in depth;
3. This document also covers cutting-edge methodologies for troubleshooting SGs and MGs. considering fault monitoring systems, fault-tolerant controls, communication structures used to ensure self-healing and automatic fault location, and the application of intelligent algorithms used to detect and reduce risk;
4. This review also analyzes fault location techniques for DC and low voltage networks and fault location techniques to increase the resilience of these intelligent systems, considering meteorological factors and examining fault location techniques for storage systems and electric vehicles that support the systems' resilience but have been underexploited in prior studies;
5. We talk about the current research trends, problematic areas, and potential uses for fault location techniques in the future.

Table 1. Topics covered in this review.

Fault Location in	**Reference**																			
	[6]	[7]	[11]	[15]	[17]	[18]	[19]	[20]	[21]	[22]	[23]	[24]	[25]	[26]	[27]	[28]	[29]	[30]	[32]	**This Review**
Distribution grid	√ *	—	√	√	—	√	√	—	√	√	—	√	—	—	—	—	√	—	√	√
Microgrids	—	√	√	√	√	√	—	√	√	√	√	√	√	√	√	√	—	√	√	√
Distribute energy resources	√	√	√	√	√	√	—	√	√	√	√	√	√	—	√	√	√	√	√	√
Energy Storage System	—	—	√	—	—	—	—	—	√	—	—	—	—	—	—	√	—	—	—	√
Electric transportation	√	—	—	√	—	—	—	√	—	—	—	—	—	—	—	—	—	—	—	√
Communication infrastructure	—	—	√	√	√	—	—	—	√	√	—	√	√	√	√	√	√	√	—	√
Identification of sensor gaps for faults location	√	√	√	—	√	√	—	√	√	√	√	√	√	√	—	√	√	√	√	√

* Symbol √ indicates that the topic is covered in the article, while the symbol — indicates that the topic is not covered.

The objective of this paper is to provide a thorough review of SG fault location methodologies by considering the challenges that come with SG disruptions and addressing any obvious faults. Additionally, we provide a thorough analysis of the advantages of several fault location methods and techniques suggested in the literature on SGs and MGs. We also review the challenges and offer suggestions for further initiatives.

This document's remaining sections are structured as follows: Section 2 describes the challenges in fault location in SGs and MGs. Section 3 focuses on the potential solutions for fault location. Methods for locating faults to increase resilience are covered in Section 4. Section 5 offers some trending topics and conclusions.

2. Research Methodology

This study provides a thorough analysis of the SG and MG fault location-based methodologies. To choose and combine top-notch research articles in this single review work, a thorough search of research databases and repositories was conducted. The process for researching and choosing the papers for this review can be summed up as follows:

- Some of the databases or digital libraries used in this work are MDPI, ELSEVIER, IEEE Xplore, IET Digital Library, and Springer Link;
- The following research questions to search databases' papers was: ("fault location* OR " "fault mitigation*" OR "fault detect*", OR "fault monitor*" OR "fault diagnosis*" OR "fault tolerance*" OR "Cyberattack*") AND ("smart grid*" OR "MG*" OR "micro-grid*" OR "microgrid* cluster*" OR "distribution system*" OR "DC* microgrid*" OR "hybrid* MG*");
- A bibliometric analysis of several databases, including the Web of Sciences and Scopus, was done using the software "Bibliometrix". Using this tool, we can identify the tendency and classify the information using a factorial technique, a conceptual structure map, a topic dendrogram, and knowledge of the most significant and referenced papers [44];
- When it was decided that the literature was directly relevant to the review criteria, it was added to this study;
- The period considered for the revised work was 2010–2023, and its abstracts and conclusions were checked first. Numerous pieces of academic literature on the use of fault location in power systems are identified using online databases;
- We also examine a few book chapters, standards, and technical papers published by forums with an emphasis on smart grids.

Out of 167 reviews of research literature in the final document, 122 are journal papers, 25 are conference papers, and the remaining are books, technical reports, and standards.

3. Fault Location Challenges

Conventional protection systems' methods for fault location can be problematic when there are bidirectional faults, so protection systems for SGs must use methods for fault location that can be based on scalable mathematical models and supplement them with cutting-edge technology like numerical relays to ensure sensitivity and operational speed.

The SG is susceptible to the same kinds of failures that can happen in a traditional centralized network; when this happens, the intelligent system must handle the tasks of swiftly managing, diagnosing, and isolating the type of failure to safeguard the system's components and maintain normal operations. The SG requires the integration of several components, such as failure indicators, equipment automation, a control center, signal monitoring through intelligent devices, and advanced communication techniques to carry out the correct diagnosis, identification, and protection of the system. This is done to ensure that all the protection systems (PS) operate as expected [45].

3.1. Common Electrical Power System Failures

Lightning, winds, storms, contamination of insulation materials, cable deterioration, physical contact with animals, falling trees, overloads, and protection failures caused by factors like current fluctuation and bidirectionality are just a few of the many things that can lead to failures in both a traditional system and an SG [6,45]. According to [46] "An electrical fault is defined as an abnormal electrical current in the electrical power system", which can be further classified into two categories. Internal faults that can happen, for instance, on the AC side of a converter or on the DC system of energy storage, as well as external faults like a phase-to-ground fault [45].

3.2. Common Types of Smart Grid Power Failures

Open circuit faults (series faults) and short circuit faults (shunt faults) are the two principal types of power failures that can occur in an SG. Shunt faults are, for instance, generated by the union between two phases, but series faults might be created by broken conductors that result in broken lines [45]. According to [47,48] short-circuit failures account for between 75% and 80% of power outages in an SG. The typical types of power failures in SGs are depicted in Figure 3. Symmetric and asymmetric faults are two different categories of short circuit failures. Three-phase ground faults (ABCG) and three-phase faults (ABC) are examples of symmetric faults. Phase-to-ground faults (P-G), phase-to-phase failures (P-P), and faults of two phases to ground (P-P-G) are examples of asymmetric faults.

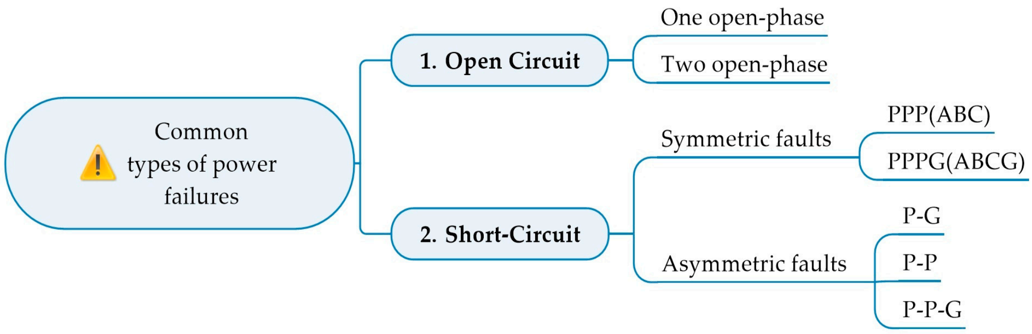

Figure 3. Common types of power failures (open circuit and short circuit failures).

Other faults and/or abnormal conditions in the power system include the magnetizing inrush current of a transformer, the starting current of an induction motor, and conditions during power swing. However, it can be difficult to distinguish between normal and non-normal conditions. There are some inherent operating conditions in the electrical system that are abnormal.

The authors in [49] divided the SGs failures into three categories according to the various SGs layers, including physical or component faults, communication faults, and software or hardware level faults. In addition, they provide sufficient details about different failures for various physical systems and components inside the SG architecture. Figure 4 displays the type of faults in the SG infrastructure described in [49].

In conventional energy sources like diesel generators and synchronous machines, problems with the stator, rotor, crankshaft, and fuel leaks are all possible. Localized overheating, winding faults, and core faults in conventional power transformers can reduce their dielectric capacity and cause damage to the transformers. Likewise, smart transformers are susceptible to the same defects, such as short and open circuit failures, that affect DER and power converters. Underground cables in the distribution grid may have mechanical problems, thermal runaway, and general wear and tear. Furthermore, there are a variety of reasons why overhead lines can fail, including lightning strikes, short circuits, human error, and lack of maintenance [49]. Reduced output power from cells, modules, and by-pass diode defects in DER resources like photovoltaic (PV) panels resulted in decreased voltage and current signals in MGs. Faults in the gearbox, generator, power electronics, and power converters in wind turbines can result in deterioration, imbalanced voltage, and current, and low generation efficiency [49].

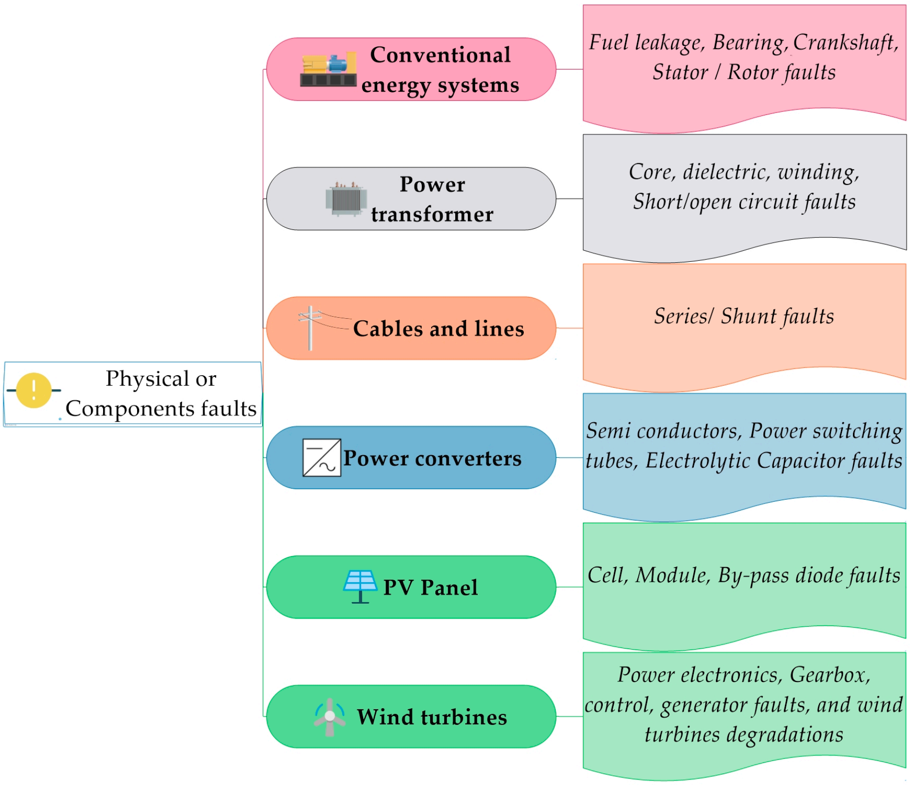

Figure 4. Types of power failures in SGs physical components [49].

3.3. Categories of Power Failures in a SG

SG power failures are classified based on their duration and how the network operated at the time of the disturbance. The following categories are listed in [45]:

3.3.1. Incipient Failures

It is a system failure that happens for a predetermined amount of time. The Fourier and Laplace wave transforms, among others, are used to detect and classify failures by controlling the amplitude and duration of the failure. Impedance-based techniques are also employed, which are helpful for identifying and categorizing problems in underground cables [45].

3.3.2. Abrupt Failures

Abrupt failures are those sudden changes in signals brought on by a system power supply malfunction. Digital relays and digital process transform techniques like wavelet transform (WT) are frequently employed for the classification and detection of these errors, but they are frequency-sensitive [45].

3.3.3. Intermittent Failures

These are short transitory failures that can be related to an incipient failure that ultimately results in a permanent failure. In order to detect this type of failure, EPS nodes typically use distance relays and carrier signal monitoring systems [45].

3.4. Power Failures in Microgrids (MGs)

An MG is part of the distribution domain of SGs and can operate in both grid-connected and island modes, the latter of which means it can operate independently without being connected to a main power source. Because the faults seen in island mode are less than those seen in MG connected to the network, traditional PS cannot distinguish between the fault and network disturbances and does not perform as well [50].

Currently, several methods have been put forth to create a protective system that enables the MG to be protected, considering general characteristics like reliability, but more importantly, the ability to respond to any change in the load. In general, the right technique for an MG should consider protecting the main network and power equipment in addition to acting rapidly in the case of failures within or outside the MG [50].

3.4.1. AC Microgrids

The active power, reactive power, imbalance component, and harmonics are the four primary parts of an ACMG that need to be synchronized. However, as the distributed energy sources are DC, power converter implementation is necessary, which has an adverse effect on the way in which harmonics appear. Additionally, the protection against failure in AC circuits is based on so-called overcurrent principles. The fact that microgrids can operate in both island mode and grid-connected mode presents a challenge for protection systems because of the large short-circuit current variation [51]. The majority of ACMG failures are transient and very short-duration [52,53]. Shunt and series faults are the two types of faults seen in the MG power line [54]. Some of the faults that can occur in an ACMG include high- andlow-impedancee faults [55,56], short circuit faults [25], and voltage sag faults [57].

3.4.2. DC Microgrids

In terms of dependability, efficiency, ease of control, integrating renewable energy sources, and connecting DC loads, a DC microgrid outperforms an AC microgrid; it must be considered that most distributed energy sources are DC-powered (photovoltaic panels, energy storage, electric vehicles, etc.). Despite the many benefits of DC microgrids, it can be difficult to design a trustworthy protection system due to the fault current's characteristics. In a DC MG, the fault current is quite large and can reach excessive values in a matter of seconds since the line impedance is relatively low [58]. The faults in DC MGs can be classified into two categories Short-circuit fault and arc fault, as shown in Figure 5. DC bus faults, DC feeder faults, and source faults are the potential locations for failures in a DC system [27,59].

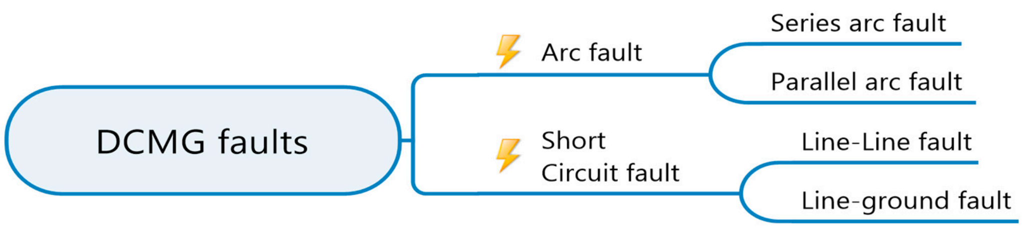

Figure 5. Classification of DCMGs faults [59].

3.4.3. Hybrid Microgrids

The hybrid MGs reduce the number of conversion stages and interface converters while combining the benefits of both ACMGs and DCMGs to increase efficiency, power quality, and reliability. Like ACMGs or DCMGs, hybrid MGs are susceptible to short-circuit faults that result in converter switch faults and distribution line faults [60]. As soon as the MGs start to run, they are vulnerable to the occurrence of fault modes in the plants, sensors, or actuators. Due to the similarity of voltage/current profiles produced by the converter switching activity, unintentional tripping happens.

Islanding faults [61] and cyberattacks [62] on the communication systems represent another challenge to the MG's regular operation.

3.4.4. Islanding Faults

Microgrid islanding fault is a condition where the microgrid unintentionally disconnects from the microgrid due to a power system fault [61]. Techniques for islanding fault detection are divided into two categories: remote and local. The operating points of the generation units and storage units typically change when microgrid failures occur. The microgrid may eventually become disconnected from the power system due to faults on the power system side [61]. The term "islanding" refers to the intentional or unintentional disconnection from the power system. The islanding fault in the microgrids poses the following drawbacks [61]:

- It is a hazard for personnel, as they may consider the systems inactive while the generation units are feeding power to the loads;
- The voltage and frequency may not be kept at an acceptable standard;
- When the microgrid is out of phase, circuit reclosers re-connect it to the utility grid. As a result, the ideal solution to this highly significant problem should be quick and accurate detection of the islanding fault.

The functionality of microgrid control and protection may eventually be decentralized or centralized. Fault detection and location determination could be coordinated between these units to ensure always selective islanding detection by using real-time synchronized high-speed communication, measurements from multiple locations at the same time, and knowledge of the type, status, and location of various DER units. The effective operation of the protections in MGs will depend on how well communication and control work to solve faults [61].

3.4.5. Cyberattacks

Another risk to the regular operation of MG controllers is cyberattacks on the communication systems, which disrupt the information flow between smart sensors, local actuators, and controllers [24]. This is due to the widespread use of IoT devices and insecure protocols, which expand the attack surface. A specific case could be a false data injection (FDI) attack on the synchronization system of an MG, which plays a crucial role in the daily operation of power systems and the connection of isolated MGs to the main grid [63]. These synchronization systems typically employ open data transmission protocols such as IEC 61850, Modbus, or DNP3, which lack encryption and authentication mechanisms and provide remote access to control the generator governor [62,63].

A cybercriminal could send corrupted control commands to cause a generator to trip, which could lead to stability issues or a possible outage, even if the attacker could exploit system resonance, this could pose a greater risk to the MG [63]. It is necessary to use a fault detection metric to differentiate between cyberattacks and current sensor or actuator faults [64,65]. The Kalman filter, state estimation methods, and computational intelligence tools like intrusion detection systems (IDS) and intrusion protection systems (IPS) are the most frequently used methods for detecting cyberattacks [63,66]. IEC 62351 standard recommendations could be used to assist in the application of TLS, X.509 certificates, and digital signatures to secure the transfer of messages within devices in the MG [64] to protect communications [67].

In the literature, there are different protection models for microgrids both in DC and AC, that follow the conventional principles; some of these are:

- Overcurrent protection: It works on the same theory as traditional overcurrent protection in that a maximum programmed current value must be considered such that if it is exceeded, the protection operates; however, MR in DC cannot apply this theory. The selectivity of the PS is directly impacted by this function, which may lead to extremely long fault-clearing durations or the disconnecting of EPS components that are not expected during the fault. The issue can be resolved by using a self-adjusting relay that is configured using optimization techniques and improves the speed of data transmission and reception in the PS to handle the dynamic fault current [58,68];
- Directional overcurrent protection: it is the principle that is most frequently applied since the current in a system with DG can flow in any direction. This rule can be used to ensure selectivity in the case of a mesh topology. Additionally, if a quick communication system is connected to this, it can aid in more quickly locating the fault [58];

- Differential overcurrent protection: it is one of the most suitable for an MR since it only measures the amplitude current at the ends of the device to be protected and operates quickly. However, to effectively utilize this protection, quick communication and advanced relays are required [58,69];
- Distance protection: In the case of the distance principle, it must be considered that, for instance, a DC line behaves differently from an AC line because the conductor's inductance has a considerably smaller impact and there is no fundamental frequency default. This protection requires measuring the voltage and current at the measurement site, the voltage at a closed point and then estimating the fault distance iteratively [58,69].

4. Fault Location Methods in Smart Grids and Microgrids

The fault distance and the faulty section must be in the distribution domain of SG. A fault location method's objective is to identify the precise area of the system that is being impacted by the fault occurrence and to determine the fault's specific location with accuracy, precision, and quick restoration [70].

There are three fault location methodologies for power systems: traditional, observant, and intelligent, according to [70]. It is essential to reduce fault-location technique errors in the SGs by ensuring the accuracy of the information relating to the system with a fast, secure communication infrastructure, fault-tolerant control, and innovative decision-making algorithms. Observation is an example of conventional methodology; in this scenario, a customer notifies the operator when they notice downed wires or a burned-smelling cable. Under the observant methodology, we found intelligent meters or local detectors that alerted the system operator through communication feedback. Finally, there is the intelligent methodology, which uses smart sensors or expert systems (expert systems, ANN, GA) to find the fault. Figure 6's fault location methodologies are described in [70].

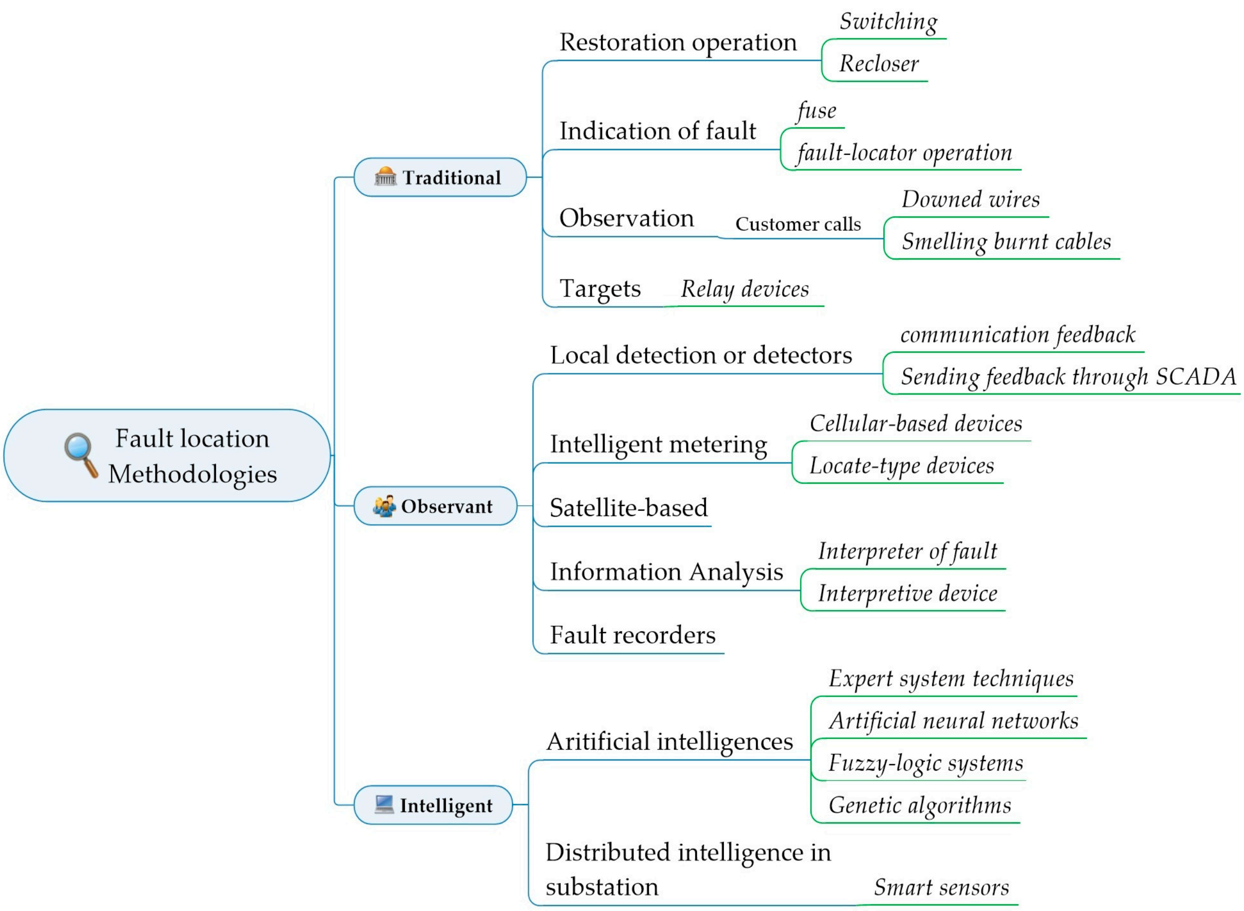

Figure 6. Fault location Methodologies for power systems [70].

Prior to the fault location, it is important to detect the fault (fault detection) and determine the fault type (fault classification).

4.1. Fault Detection and Classification-Based Methods in SG

Several reviews have been published on fault detection and classification methods in SGs [9,21,25,45,71–73]. Model-based, knowledge-based, and signal-processing techniques are among the most widely used for fault detection [74]. The safety and stability of the EPS are ensured by a quick and accurate failure detection technique. The magnitudes of current, voltage, and frequency [75] must be continuously monitored before, during, and after the failure enters the SG to locate and identify the type of failure that entered the system. Additionally, there needs to be a self-adjusting technique that enables the electrical magnitudes to be returned to the values established before the fault occurred.

The fault classification methodologies are based on logic flow or learning algorithms (intelligent techniques) using Artificial Neural Network (ANN), data mining techniques, and hybrid methods that combine artificial intelligence and signal processing tools [73,76,77].

The authors of [78] proposed a real-time hierarchical architecture for frequency disturbance occurrences in power systems utilizing PMUs data. Recurrent neural network (RNN) and long short-term memory (LSTM) were employed in this strategy to precisely identify and localize the fault. PMUs are used in 118, 38, and 14 IEEE bus systems to monitor, protect, and control the system. This technique, which can categorize and localize the event in real time, utilizes rate-of-change-of-frequency (ROCOF) data obtained by PMUs and deep learning (DL) method. Information loss and cyberattacks are potential problems with this approach that must be handled in SGs applications. It is suggested in [79] to use wavelet packet transform (WPT) and extreme learning machines (ELM) to classify fault events in grid-connected PV systems. At the point of common coupling (PCC), the sample of the post-fault voltage signal is processed using the WPT. A logarithmic energy entropy criterion is implemented to reduce the dataset size. The ELM is used to classify the different fault events. The method was validated on a 250 kW grid-connected photovoltaic model, which demonstrated its ability to quickly identify different fault resistances and fault locations.

The authors in [80] developed a classification-based traveling wave feature fault location in an active distribution system. The correlation between the transient waveform of traveling waves and the fault location is examined using the WT. A linear discriminant analysis (LDA) is used to reduce the dimension of fault data and to select the representative fault features. Additionally, the fault data set is trained and tested using the naive Bayesian classification model based on kernel distribution to identify the faulty area. This method improved the accuracy of the fault localization for a single-phase ground fault, but it still must be tested in other kinds of failures to determine its efficacy.

The authors in [81] proposed an algorithm for fault location and classification based on mathematical morphology (MM) and random forest (RF). The MM is used to pre-process voltage and current data, then, the signal norms are using as a feature for the RF algorithm for fault location and classification. To confirm this method's efficacy, a more complex system must be used for validation.

A MG intelligence-based defect detection and categorization system is suggested in [82]. This technique utilized the Hilbert–Huang transform (HHT) and the boosting ensemble approach. The boosting ensembled approach is an adaptive machine learning technique that classifies the data space with high accuracy and low program complexity by using a non-convex optimization procedure. The HHT is used for feature extraction from signals' transient behavior to reduce noise sensitivity. Additionally, the accuracy of the proposed algorithm was compared with other intelligence-based studies, including decision tree (DT), support vector machine (SVM), k-nearest neighbor (KNN), Nave Bayes (NB), RF, deep neural network (DNN), and ELM, having simple topologies and close accuracy to them. This method can detect internal and external faults, making it suitable for backup MG protection.

The authors in [83] proposed an intelligent fault diagnostic system based on feed-forward neural networks (FF-NNs) and signal processing methods for distribution grids that considered the intermittent nature of renewable energy sources. The discrete wavelet transform (DWT) and Stockwell transform (ST) are used to decompose the time-domain current signals into the time-frequency domain to obtain the feature extraction. FF-NNs were trained and evaluated for fault classification after the features were collected. The suggested method's accuracy in classifying failures was shown to be more than 99.9%, demonstrating independence from the uncertainties of renewable energy sources. The authors in [84] suggested a signal-processing solution for ML fault classification that makes use of a fault type module. The ML models were trained with the three-phase voltage and current data. To identify the fault type, classification techniques such as the linear SVM, KNN, and baggage tree were utilized. A framework for fault localization, classification, and detection as provided in the literature is shown in Figure 7.

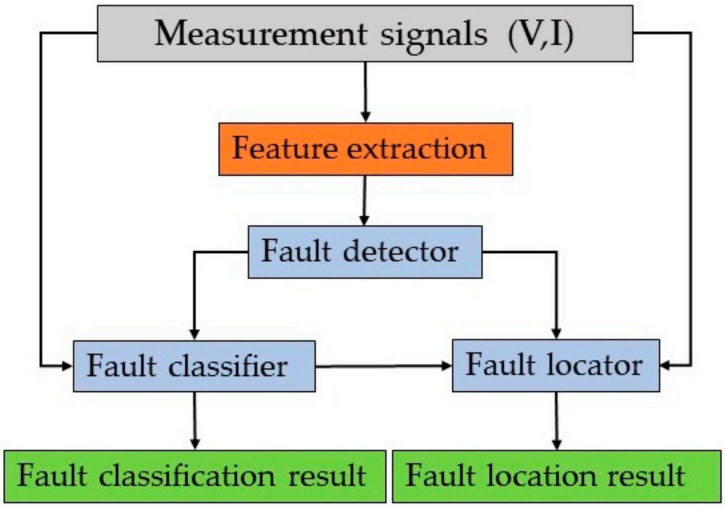

Figure 7. Fault location, classification, detection framework [73].

4.2. Fault Location Based-Methods in SGs

Due to the non-homogeneity of the branch circuits, the techniques described for the location of faults in transmission lines are difficult to apply to distribution systems; therefore, a method for locating faults in distribution systems must consider the constraints for obtaining the data and the costs of implementing these techniques.

There are many different methods for locating faults in the literature. One of these is based on the relationship between voltage and current in relation to the phases involved. However, this method is inaccurate due to the large number of estimates that must be made by only taking the substation's current and voltage measurements into account.

Extracting current and voltage measurements from each DG unit and submitting them to a multi-class support vector machine (MSVM) classifier is another method for locating faults in ACMG in mesh topology that's also proposed in [85]. The fault zone is located using a communication link between two neighboring DGs to compare their impedance during the injection of a high-frequency harmonic signal. The line with the lowest high-frequency impedance or the highest harmonic current at that high frequency is employed in this procedure [85]. This technology locates the fault more quickly and is resistant to topological changes, dynamic loads, and unbalanced circumstances, but it needs a communication system and sophisticated signal processing or filtering methods, which make it challenging to use in practical applications.

Therefore, it is crucial that the EPS generally have intelligent equipment installed that can provide effective monitoring, measurement, and protection. This includes equipment like digital relays, digital fault recorders, and intelligent measurement elements, among other equipment, which generates a high degree of confidence and high performance in intelligent applications. It is also important that each protection communication infrastructure be significantly modernized to detect and locate faults more quickly than a traditional PS.

Fault location methods are classified as automatic (intelligent) or traditional techniques. Table 2 contains the methods related to automatic fault location; they are described in detail in [15].

Table 2. Fault location methods and techniques.

Fault Location Methods	Techniques	References
Physical location of a fault waveforms values	Direct three-phase circuit analysis, Local current and voltages values	[40,70]
Travelling wave phenomenon	WT, Double terminal, Principal component analysis (PCA), Parks transformation, Teager energy operator (TEO), Ensemble empirical mode decomposition (EEMD), Mathematical morphology function (MMF)	[6,33,80,86]
Knowledge-based approaches	Artificial intelligence, ANN, Fuzzy, Expert systems, SVM, Multi Agent-based	[12,87–90]
Signal processing	Short time Fourier transform (STFT), WT. Differential equation-based approach, Laplace-transform	[6]
Phasor based algorithm	Impedance measurement	[11]
	Active impedance estimation (AIE)	[91]
	Apparent impedance measurement	[40]
	Sequence components	[40]
	High frequency impedance	[92]
Power quality data	Inject high frequency harmonics	[40]
	Measurement of high harmonic impedances	[85]
Hybrid methods	Communication-based	[93,94]

The most popular approaches for fault location in the SGs domain include impedance methods, phasor-based methods, and signal processing-based methods. Hybrid methods with communication architectures are becoming more popular [93]. These methods incorporate the advantages of intelligent devices such as switches, fault sensors, power probe units (PPU), etc., with intelligent algorithms that analyze signals in transient and steady states, power flow, synchronization angles, and create pattern recognition in a large database.

Sequence components, synchronized voltage and current, graph marking, multi-agent-based, decision tree, impedance-based, travelling wave, fuzzy logic, SVM, expert system techniques, and genetic algorithms are a few of the fault location techniques that have been used [21,45]. These techniques are depicted in Figure 8.

The authors of [95] offer a thorough analysis of ML-based EPS fault diagnostics. The authors of this paper examine many ML approaches used for fault diagnosis, including unsupervised, supervised, reinforcement learning, and various intelligent models that can be used for fault detection. Unsupervised learning is the method of training models to look for underlying structures or hidden patterns in data. Hard clustering and soft clustering are the two sorts of strategies used in this learning to solve issues where there is only input data and no goal class labels. We can use K-means, K-medoids, and hierarchical techniques for hard clustering, and fuzzy C-means and Gaussian mixture models for soft clustering.

The use of supervised learning is appropriate when the model can be trained using both input and output data, and when the trained data can predict the behavior of observed data. It is utilized for regression or classification, depending on the needs. The following methods are employed for classification: Logistic regression (LR), KNN, SVM, neural networks (NN), NB, discriminant analysis (DA), DT, and ensemble methods (EM) models.

Regression models include gaussian process regression (GPR), regression tree (RT), and support vector regression (SVR).

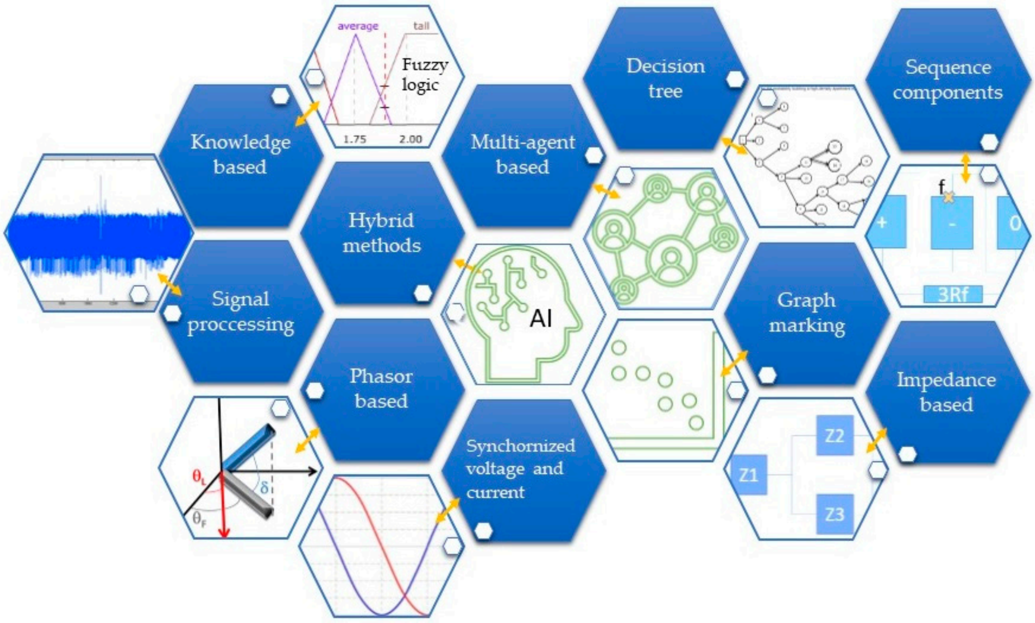

Figure 8. Localization techniques in SG [21,45].

On the other hand, reinforcement learning is a reward and punishment-based learning method in which the critic serves as both a guide and a means of punishment and reward for proper behavior. Q-learning and deep reinforcement learning (DRL) are two examples of reinforcement learning algorithms used for defect diagnosis. The model, in contrast to supervised learning, focuses on the similarity between reference faults and sampling faults (action) as a reward for training. Regarding knowledge-based approaches for fault diagnosis, see [95] for more details. The various ML approaches for defect identification are shown in Figure 9 and are discussed and explained in [90].

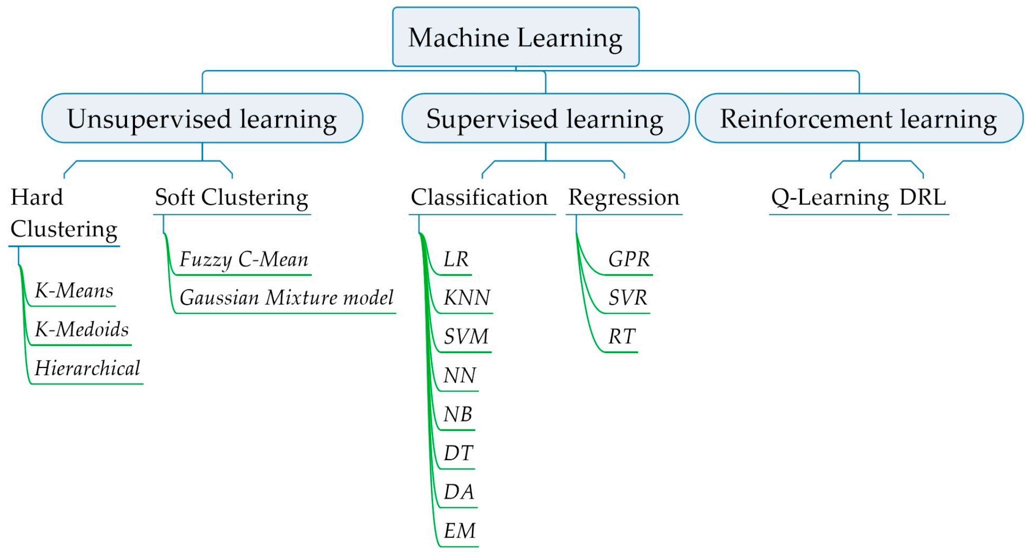

Figure 9. ML techniques for fault diagnosis in EPS [95].

In the SGs domain, creating an online fault location is becoming more and more crucial. The use of fault monitoring technologies, communication infrastructure, fault-tolerant control approaches, data feature extraction, and intelligent algorithms has led to the development of many techniques for locating faults in SGs systems.

4.2.1. Fault Monitoring Technologies

The use of modern monitoring technologies with artificial intelligence data processing techniques enhances online fault detection and fault location [96–99]. Based on decision tree algorithm (DTA), the authors in [96] develop a fault monitoring system for electrical automation equipment. The fault monitoring system can detect the fault using the current monitoring data, and the DTA can improve fault classification accuracy. The authors in [97] present a technique for cloud-computing-based fault location for distribution lines that increases the grid's level of reliability and visibility. A front-end smart grid sensor, a back-end cloud computing platform to receive and store the sensor data, and wireless connectivity using 4G technology make up the monitoring system. With this approach, the operating status of the grid could be observed in real-time, and the status of the line (alarms, temperature, conditions), as well as the location of the fault, could be determined by statistical processing and analysis of the relevant data. However, the efficiency of handling faults on standard cloud service platforms may decline because of changes in SG or MG topology. Hierarchical fault monitoring [98] and artificial intelligence solutions [99] might increase efficiency.

In [98], the authors suggested a fault location approach in a distribution network based on traveling waves and cloud-edge computing on a hierarchical fault monitoring and control system that is not impacted by the line parameter or topological changes. A traveling wave acquisition module (TWAM) situated at the end of each branch and an edge-computing gateway situated at the front end of each main feeder carry out the fault location with accuracy, reliability, and speed. A hierarchical fault monitoring and control system is created by the edge computing gateway, which identifies the defective branch by evaluating the traveling wave variation characteristics. The suggested hierarchical fault monitoring and control system is depicted in Figure 10. The authors of [99] proposed a fuzzy association rule-based fault monitoring system that can assess the system's fault condition. This technique improved the performance in monitoring alarms and fault judgment accuracy by utilizing edge computing technology and an expert knowledge base.

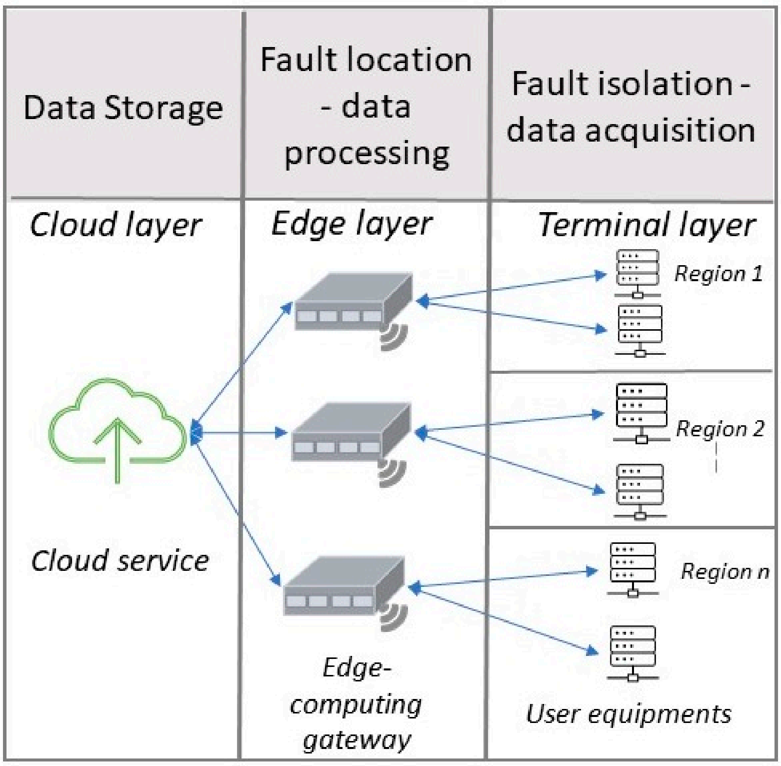

Figure 10. Hierarchical fault monitoring system [98].

4.2.2. Communication Infrastructure for Self-Healing and Automatic Fault Location

The communication infrastructure is crucial to guarantee self-healing and automatic fault location [100–103]. According to [100], there are two methods for implementing self-healing service restoration in SGs: distributed automatic fault location devices, isolation, and service restoration (D-FLISR), and centralized fault location, isolation, and service restoration (C-FLISR) [100]. D-FLISR used intelligent electronic devices (IEDs) to locate and clear the fault. Communication using IEC 61850 and the general oriented substation event (GOOSE) protocol will enable the switches that energize the faulty zone during a fault event. To make all the self-healing processes accessible in one location, C-FLISR requires a dependable communication infrastructure and high-performance computing. For the purpose of automatically locating faults and isolating fault sections, the C-FLISR takes data from fault indicators and fault records.

The authors in [101] proposed a hybrid peer-to-peer (P2P) communication system for fault location based on interactions between numerical relays and smart meters. In [80], a wide-area protection method with PMU was proposed to isolate the internal and external fault sections in an MG. The PMU sends the voltage and current phasor to the central controller through communication links, which identify the fault section according to the local measurements. The authors in [81] proposed a fault locator device for medium-voltage (MV) cable fault location by considering a traveling wave (TW) method and employing Wing sensors for sensing TW pulses associated with faults. This method used a LoRa communication module to interconnect the monitoring units. This solution shows the low complexity and low cost of electronic devices; it can be a solution for SGs, and its performance should be evaluated.

Artificial intelligence-based approaches and multi-agent strategies can enhance the automation process in these kinds of solutions [91,104,105]. The authors in [104] present a framework for fault location in a radial distribution system based on machine learning algorithms and a multistage approach to determining the occurrence of the fault region.

There are four steps in the framework: First, the voltage and current data are processed. Next, the fault distance is estimated using ANN via a multilayer perceptron neural network. Third, the fault is identified using a decision tree technique. Finally, the fault region is identified. However, further topologies and the incorporation of distributed generation (DGs) units are required for this methodology to be validated. In [90], the authors proposed a protection multi-agent scheme for a loop-based MG using IEDs. Traditional overcurrent relays were outfitted with IEDs to act as agents within a multi-agent architecture, and they used the IEC61850 standard using GOOSE technology to share the collected data between the relays. In addition, the proposed solution employed a token feature (operation permission) in the communication strategy to avoid adjacent zones from failing when loop MGs experience fault conditions. This approach ensures the functioning of the fault zone protection strategy regardless of MG topological changes, DGs capacity, or fault location and does not require a central controller or multi-layer structure.

Hybrid methods that combine knowledge and communication have been used for fault detection and isolation in EPS [105]. The authors in [105] proposed a bioinspired probabilistic Boolean network (PBN) model for an intelligent power router (IPR) device to fault detection and isolation of multiple faults. The PBN method that models the uncertainty of the gene interactions can characterize possible failure modes given the state of its variables This model can detect and classify single and multiple faults and provide a probability of fault and failure occurrence, which allows better maintenance planning. This method is a possible solution for smart grids and requires further study before the integration of MGs.

4.2.3. Control Methodologies for Fault Mitigation

A fault or failure may cause the system to operate incorrectly, perform poorly, or become unstable. With fault-tolerant controls (FTC), new control methods in SGs must ensure the reliability and accuracy of their main components [106–108]. The authors in [106] provide an overview of multiagent systems' (MAS) fault-tolerant cooperative control (FTCC) for locating and identifying faults. More work is required in FTCC for MAS susceptible to various fault categories as there are still some faults that are challenging to identify, such as intermittent, incipient, and compound faults, which can have serious effects on these systems. The authors in [108] present an adaptive fault-tolerant control technique, by using Takagi-Sugeno (T-S) fuzzy systems, fuzzy logic systems, command-filtered adaptive fuzzy tracking, and neural networks in nonlinear systems with actuator faults.

The authors in [85] describe a method for fault diagnosis method and a fault tolerant control framework with plug-and-play (PnP) capabilities. This method was centered on a data-driven approach to give reliability and flexibility for advanced monitoring and controlling methodologies which prevent changing the control that was predesigned while performing fault detection and fault-tolerant control. The effectiveness of the data-driven fault tolerant control design was tested on the DC motor benchmark test system and needs to be investigated in non-linear systems and SGs [109].

In [107] the authors describe a method for fault diagnosis and fault tolerant control framework in an integrated manner with PnP capabilities. This method was focused on a data-driven approach to provides reliability and flexibility for advanced monitoring and control methodologies because it avoids changing the predesigned control while realizing the fault diagnosis and fault tolerant control [107]. The effectiveness of the data-driven fault tolerant control design was tested on the DC motor benchmark test system and needs to be investigated in non-linear systems and SGs [109]. In [110], the authors presented a sensor failure detection system, an observer-based residual generation method, and recursive online model estimation for AC MG. In order to provide the residuals needed for fault detection, an observer is first established, which estimates a basic linear model using the control signal produced by the MG's secondary control. A warning signal can be generated as a result of the recommended technique's ability to quickly identify sensor issues. The authors in [111] proposed a "federal-Kalman-filter-based fault-tolerant controller" to ensure reliability in case of faults on sensors, actuators, or communication networks. The federal-Kalman filter used multiple independent Kalman filters to process corresponding data from several sensors. Also, this Kalman filter provides the capability of fault diagnosis and signal reconfiguration.

A fault-tolerant supervisory controller for a hybrid AC/DC MGs based on the state machine approach was proposed by [112]. This controller can achieve fault-resilient and optimal power flow in the hybrid AC/DC MG. Furthermore, it proposed a procedure to increase the tolerance of the supervisory controller towards different failures in solar, wind, and battery systems. This solution can determine the maximum available power under faulty conditions and increase the SC tolerance towards different failures and it also requires validation in hardware in the loop simulations to prove its effectiveness.

4.2.4. Data Feature Extraction for Fault Localization and Intelligent Methods for Fault Detection and Minimization

Identifying and extracting relevant features of the system characteristics during a failure condition is essential after data preprocessing. This feature mining assists in identifying the correct pattern in the acquired fault data. There are several data-feature extraction methods for fault detection and localization proposed in the literature based on time-domain methods, frequency-domain methods, and time-frequency-domain methods [113]. In [113], the authors provide an overview of fault detection and localization techniques and explain the different methods for feature extraction and anomaly detection. Figure 11 shows the methods discussed in [113].

Additionally, with the correct available data for feature extraction supervised or non-supervised learning algorithms have been utilized for fault detection and localization. ML [114], ANN [115], DNN learning methods, and MAS have been more popular in the field of fault diagnosis and location [116–118]. The authors in [114] review the application of ML in SGs and summarize the use of ML methods in fault diagnosis, such as convolutional neural network (CNN) for the distribution system, DNN with layer-wise relevance propagation (LRP) for nuclear power plant reactors faults, heterogenous graph attention network (HGAT) for power equipment failures, graph convolutional network (GNN) for cascading faults, and RF for photovoltaic grid-connected faults. In [116], the authors used grayscale images and then CNN and LSTM to localize and diagnose the fault. This method was applied in a spacecraft system and should be a solution for fault location in space MGs. The proposed method simultaneously transforms high-dimensional abnormal fault data from spacecraft into grayscale images for image-based fault diagnosis to precisely locate the component on which the fault has occurred and determine the type of fault. A CNN can extract features directly from images and simplify the computation process for fault diagnosis; the LSTM is a variant of an RNN that can learn and extract features from pattern fault data and complete the fault classification.

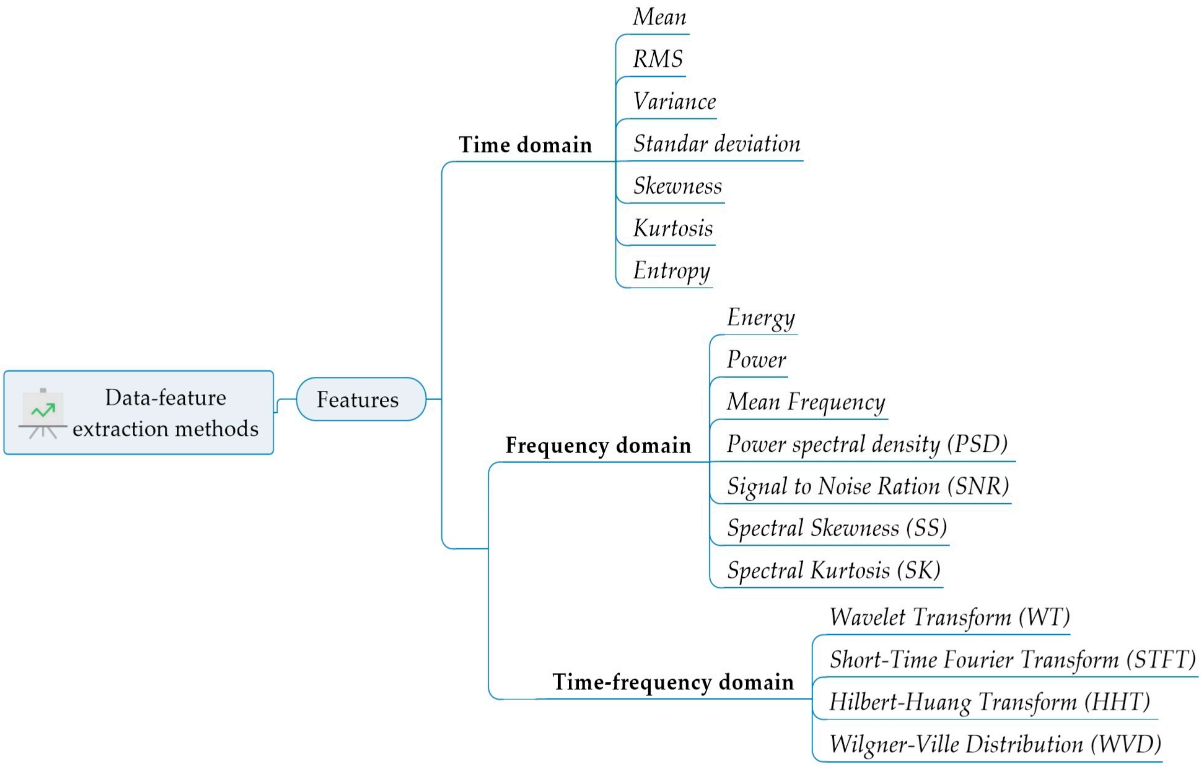

Figure 11. Data-feature extraction methods [113].

The authors in [117] proposed a MAS system and Big-Data storage and mining technology for fault discrimination, location, isolation, and service restoration in active distribution network (ADN) based on inverter-based DGs. The MAS system is used for service restoration. To process the data, the big data platform uses distributed computing, distributed storage, and mining technologies. A feature extraction module extracts the local features from the voltages and current series, and the agents process the remote features. Then, a differentiated operation examines both local and remote properties simultaneously. Finally, a statistical classifier will then decide based on differential or local features (fault or not fault). The microprocessor-based relays perform fault discrimination and fault location using this local and remote electrical information. An RF algorithm was used for fault classification. This method can reduce fault processing time and increase system reliability. The author in [118] proposed a fault diagnosis-optimized method of building electrical systems based on a radial basis function (RBF)-backpropagation (BP) neural network. The fault information is clustered using fuzzy c-means, and fault future data mining is done using a singular value decomposition (SVD). The RBF-BP then decides which classification to allocate the faults based on the clustered fault data. This technique, which increases the reliability of fault diagnostics in building electrical systems, should be examined in a real-time simulation. Figure 12 shows a proposed flowchart of ML methods for SGs fault diagnosis.

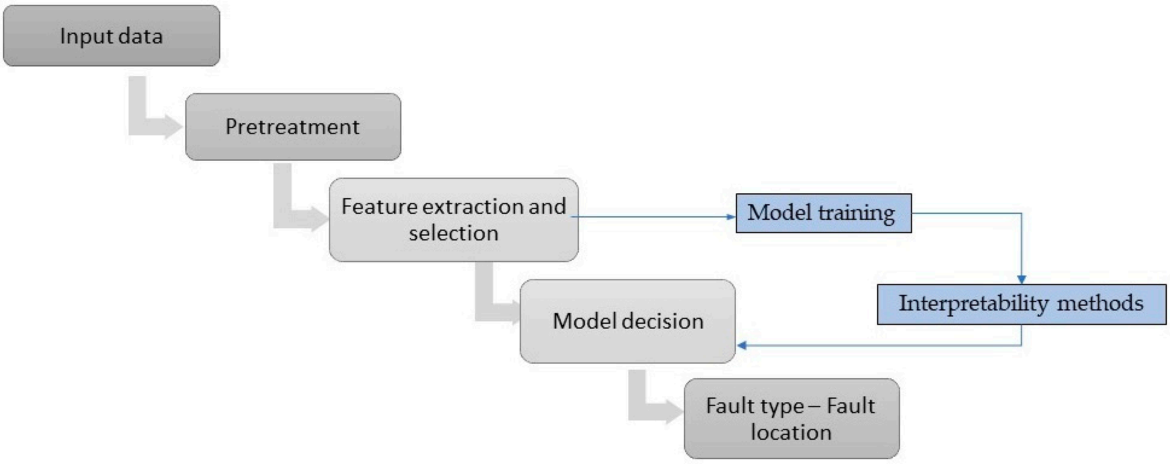

Figure 12. Flowchart of ML fault diagnosis methods [114,118].

For fault detection, intelligent protection techniques have been deployed. To identify the location of the fault, the authors in [119] use LSTM networks and empirical wavelet transforms. The authors in [120] proposed a hybrid clustering algorithm based on the KNN algorithm and K-means algorithm to provide reduced computational complexity in fault scenarios and aim to enable real-time data processing for fault localization. The authors in [121] proposed a noise-based decomposition technique called "ensembled empirical mode decomposition (EEMD) technique" and "adaptive multi-kernel extreme learning machine" (AMKELM) for high-impedance faults (HIFs) location in MGs. The EEMD technique is used to decompose the fault current and extract the current amplitude signal to calculate the differential energy profile. The extracted features are used to formulate the data matrix, and the AMKELM is implemented in HIF locations in MGs with different topologies, connections, and DG variations. This method provides efficient and reliable results for fault location; however, it needs to be applied in a larger system to see its performance.

4.3. Fault Location Based-Methods in Low-Voltage and DC Smart Grids

In LVDC, the main challenge for a fault protection strategy is to quickly detect, locate, and isolate the faults to minimize voltage collapse since DCMGs components are particularly sensitive to disturbances and faults [59]. To identify and locate short-circuit faults, many protection strategies have been employed, concentrating on local, measurement-based protection algorithms and integrating fault indicator measurements [122–126]. The authors of [122] proposed a numerical calculation method to analyze the fault behavior of the system and obtain fault indicator sets and their thresholds to develop a protection algorithm. This protection algorithm still must be tested in various grid topologies or conditions besides pole-to-pole midpoint short circuit faults. For the purpose of fault detection in DCMGs, the authors of [123] proposed a threshold-based protection method based on local measurements of voltage and current. The suggested approach relies on a threshold violation in the i–r plane detected by the system's installed IEDs to generate a trip signal for the corresponding CB. The protection scheme's reliability, security, and promptness (t = 0.500 s) are all guaranteed by this method without the aid of communication-assisted signals.

The authors in [124], presented a fault location method for high resistance faults using PPU units in DCMG. The fault location is obtained by considering the damping frequency and attenuation of the probe current. The damped resonant frequency is obtained using the fast Fourier transform (FFT), and the attenuation constant is calculated from the peak values of the underdamped probe current response by using the least-squares (LS) technique. This method improved the fault location accuracy using PPU for DC systems because it did not require online data to calculate the fault. Figure 13 shows the schematic diagram of low-voltage DCMG with PPU units. The authors in [125] proposed an offline fault location method for low-voltage DC lines. This method used a fault location module connected to the positive and negative poles of the DC line and used the residual current of the DC line after the tripping for fault location. This method only uses the local current to calculate the fault distance and can locate the fault points of DC lines accurately and faster (above t = 1 ms).

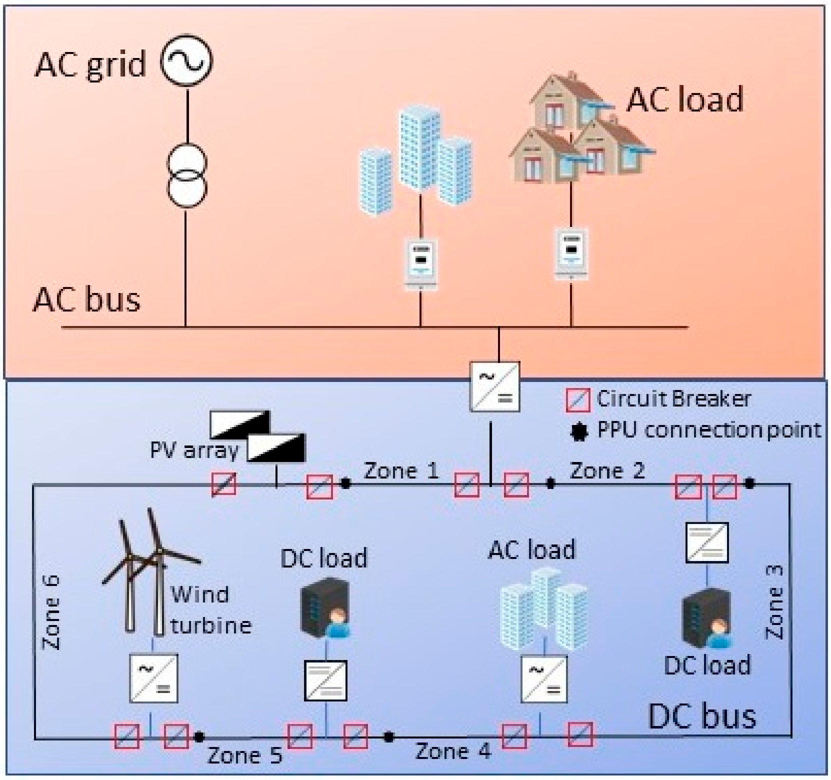

Figure 13. Schematic diagram of low-voltage DCMG with PPU units [124].

In [126] the authors proposed two methods, bus fault search and line fault search, respectively, for fault detection and isolation for LVDC networks in rural villages. Power protecting devices (PDDs) were employed to protect the LVDC in a ring topology and to isolate the faulty section for restoring the grid. Both methods can identify the faulty segment by looking at the sudden increase in current and drop compared with the rated threshold values of current and voltage simultaneously. The bus fault method used the voltage measurement through each CB bus to detect a faulty bus segment. In this method an active bidirectional converter is used to send the current signals in the grid for tripping the bus and measured the voltage. Once the measured bus voltage is not increased, the fault is detected. The second method (line fault search method) used the measurement line voltage and compared it with the rated threshold voltage, and again if the measured voltage was not increased the fault was detected. According to the simulation results, both methods could precisely identify and isolate the fault; however, the authors recommend the line fault searching method as it took a short amount of time to restore the grid after isolation of the faulty segment, improving grid performance. This method requires relays inserted at both ends of the grid lines and communication and may not be efficient in rural environments where there is no access to communications. This method should be evaluated under real-world conditions or in real time to observe its effectiveness.

Other authors [127] suggested a positive channel metal oxide semiconductor (PMOS) self-powering DC solid-state circuit breaker (CB) to protect against DCMG ground short-circuit fault events. This CB is adjustable in accordance with voltage levels and doesn’t need any additional auxiliary circuits or sophisticated control mechanisms. By cutting off the positive terminal in the event of a short circuit fault, the PMOS prevents an electric shock and achieves the short-circuit current blocking effect without the need for extra power supplies. In [128], the authors proposed a fault location principle for AC circuit breakers (ACCB) in a loop type DC grid based on steady-state currents and a fault isolation (2-step isolation) scheme. based on AC circuit breakers (ACCB) for a loop type DC grid. The voltage source converter (VSC) architecture's is altered by the primary isolation, but the connection between the AC/DC component and some of the fault current is kept. The DC fault current component is restricted enough to allow the natural zero-crossing to arise, and the secondary isolation removes the fault section by ACCB at the natural zero-crossing point. The fault can be identified using the cable's inductance between the fault and the measurement point along with the Fourier series of the fault current and voltage to determine its amplitude and phase from the measured impedance. This solution could be used in hybrid MG to avoid the installation of numerous DCCBs; however, it must be tested in real time to ensure its efficacy [128].

The authors of [129] proposed a fault location for flexible DC distribution grids based on traveling wave differential current and improved gray correlation degree analysis. In order to determine the location of the fault, this approach examines the traveling wave differential current in the positive and negative directions at the beginning and end of the line. It then calculates the similarity of the two waveforms using an improved gray correlation. This technique lowers investment costs and increases the accuracy of fault location in DC distribution networks.

Local and Nonlocal Fault Location Methods

- Nonlocal methods

The authors in [130] developed a data-driven method for fault location on active power distribution systems employing smart meters (SM) at the LV level and remote fault indicators (RFIs) at the MV level, as shown in Figure 14. This technique employed overcurrent notifications from RFI with directional elements at the MV grid and outage reports from smart meters at the LV grid to locate the faulted line sections fast. Combining outage reports and overcurrent notification, an optimization model based on mixed integer linear programming (MILP) is suggested to locate the faulty line section. This method increases the system's resilience and reliability, but it may have asynchronization problems and a lack of RFIs with directional elements that are not included in the system.

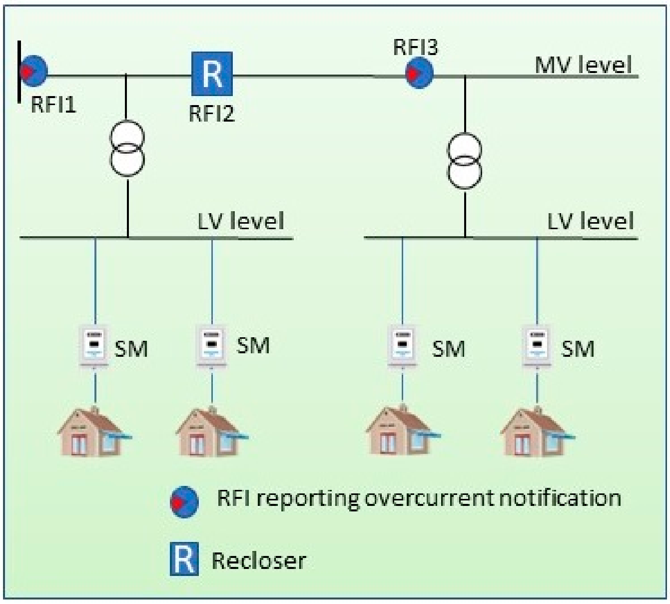

Figure 14. A simplified distribution network [130].

The author in [131] developed a SG fault identification algorithm (SGFI) that can detect the problem's location and identify the fault device using information gathered from smart meters and customer announcements. A tree graph is employed to simulate the LV network, and big data analysis is applied to examine the fault probability database created from actual network data. The fault location attribute table with the defective device's identification number is sent by the SFGI algorithm to the operations control center. This approach was used in a network with a tree structure, and it must be tested with the incorporation of MGs or distributed generation.

The authors in [132] proposed a big data-supported MG fault diagnosis and analysis technology. In order to extract the MG's fault feature information, this technique combined Rayleigh entropy, wavelet decomposition, and a back propagation neural network (BPNN). The fault type and phase can be forecast by the BPNN. This big data approach is tested in an experimental setting using hardware-in-the-loop simulation tests, and it produces accurate results for five-line fault categories in MG. To see the method's universality, it must, however, be applied to other faults.

- Local methods

The authors in [133] presented a local-measurement-based technique for online fault location estimation in multi-source DCMG. Without requiring communication, this model-based approach considers sources and loads that are connected at both cable ends. This model is used along with the local measurement to estimate the fault location and is independent of the MG topology. This method can differentiate between external and internal faults based on estimated fault distance.

A high-speed directional pilot protection for MVDC distribution systems is proposed in [134], which determines the fault direction based on high-frequency differences between traveling waves on the fault cables and (backward) adjacent cables. The practical implementation of this approach is greatly simplified, and it is appropriate for MVDC systems. The authors in [135] proposed a local-measurement-based distance relay for fault detection in DCMG. The protection scheme used a DC distance relay with directional capabilities, also integrated an inductor at the end of each line. Furthermore, the relay includes an auxiliary circuit for processing local voltage and current measurements at the fault instant. The proposed relay can provide backup protection during forward external faults, assess selectivity under bolted faults and various fault resistances, and work properly in the presence of energy storage systems. Additionally, this method provides an estimation for fault location and can identify different types of faults within their threshold settings under high fault resistance.

5. Fault Location Methods to Improve Resilient Power Generation

When we discuss faults, we're referring to various short circuits that happen across the grid. Fault-finding techniques must be capable of quickly and precisely identifying the precise location of a breakdown in the grid to restore service, ensure supply continuity, and provide quality assurance. Resilience is the capacity to anticipate, react to, and recover from external failure events, including natural disasters, extreme weather, and man-made attacks because improving the electrical system's reliability is more crucial than ever.

Natural disasters are predicted to increase in frequency and intensity because of climate change [136]. In this continuously changing environment, power systems must be designed and operated to tolerate extreme events like these and recover from them, maintaining supply quality and minimizing outages. The fundamental elements of a resilient power system have several meanings. According to [137], the main elements of resilience are robustness, resourcefulness, rapid recovery, and flexibility, and they apply to all essential infrastructures.

- Rapid recovery: contingency plans, emergency operations, returning to normal operation as soon as possible after a disaster [137];
- Robustness: continuing to operate and withstanding high-impact rare (HR) events [137];

- Resourcefulness: effectively managing a disaster as it evolves, identifying and prioritizing options to control and mitigate the damage [137];
- Flexibility: It is the capacity to adapt to abrupt and temporal events [138], allocating the resources to handle variations quickly and effectively in load and generation [139].

According to [140], the main characteristics of resilient critical infrastructure are resistance, reliability, redundancy, and response and recovery.

- Resistance: shield yourself from harm or interruption by building yourself up to withstand potential threats;
- Redundancy allows for the switching of regular operation using backup installations or extra capacity, while reliability ensures that the system and its components are correctly constructed to run under a variety of conditions;
- Response and recovery are contingency measures.

5.1. Fault Location Methods Considering Meteorological Factors

The following is a list of fault location techniques used in power systems, including hybrid, traveling-wave, knowledge-based, and impedance-based techniques. To learn more about the applications and conclusions derived using these methods, consult [141].

5.1.1. Impedance-Based Approaches

The impedance-based approaches use measurements of fundamental-frequency voltage and current along with network topology and electrical knowledge to identify the fault location.

5.1.2. Traveling Wave Methods

Traveling-wave techniques determine the location of the fault by using high-frequency components and precise temporal data.

5.1.3. Knowledge-Based Methods

This approach, which may be categorized as quantitative or qualitative, relies on a sizable amount of historical data to extract the underlying knowledge of the fault situations.

Like transmission systems, it is important to take the meteorological environment's information source into account while developing problem detection algorithms for SGs [142]. The authors in [142] proposed a knowledge-based fault diagnosis technique for transmission networks that considers climatic conditions. Typhoons, snow, wind, ice rain, and hail are only a few examples of the meteorology aspects that are considered by a knowledge-based method based on the spiking neural P system (SNPS). This technique employed the SCADA system's temporal order data, the action messages from the protection devices, and the weather data to identify the failures. This approach is efficient and effective for fault diagnosis in transmission networks, but it needs to be verified for fault events and self-healing techniques for catastrophic weather events in distribution networks.

5.2. Mitigating Energy System Vulnerability

It may be possible to combine operational and hardening measures to encourage the power system's resilience. The former is used for resilience-based planning of power systems, whereas the latter is used for resilience-based reaction and restoration actions. The amount of time until an incident happens must be considered in forecast-based operational and hardening plans. Table 3 provides a convenient summary of the planning, response, and restoration time scales for actions to improve the electrical system's resilience.

Table 3. Outage comparison between typical and natural disaster outages [143].

Sr Number	Typical Outage	The Outage Was Caused by a Natural Disaster
1	Low impact, high probability	High impact, low probability
2	Few faults (component failures)	Multiple faults (catastrophic damage)
3	No Spatial-temporal correlation	Spatial-temporal correlation
4	Most power plants remain in service	Generation units may be out of service
5	Supported by contingency analysis tools—Unforeseen event	The network remains intact Network was damaged/collapsed
6	Only involve infrastructure for the electrical grid	Interdependent infrastructures
7	Quick and complete restoration	Long restoration

The many resilience-based planning, response, and restoration techniques that are frequently used at the transmission and distribution level are listed in the following sections. You can read [143–145] for more information.

The robustness of SGs is increased by energy storage systems and demand response [146,147]. Therefore, it is essential to ensure the functionality of these systems and manage any faults [148].

5.3. Energy Storage Systems

To preserve the efficiency, reliability, and health status of batteries, electric vehicles (EV), etc., a reliable fault detection, localization, and isolation strategy for energy storage systems (ESS) is necessary [149–151]. ESS fault modes are divided into three categories: battery faults, sensor faults, and actuator faults [149,152]. According to [149] there are different studies on battery fault diagnosis, and the most widely used is the model-based method. Signal processing methods are more commonly used in a data-driven approach than machine learning methods. A phenomenological model like the equivalent circuit model (ECM) is used to diagnose sensor and actuator faults. The fault diagnostic methods are classified into knowledge-based, model-based, and data-driven.

- Knowledge-based methods: used battery system knowledge and observation to detect, isolate, and estimate the fault section. The most widely used knowledge-based methods are graph theory, fuzzy logic, and expert systems [149];
- Model-based methods: Methods that use a model: A residual signal is obtained by contrasting the measurable signal with the signal produced by the model. Due to the development of high-fidelity battery models and a better knowledge of battery system dynamics, model-based methods are the most frequently utilized for diagnosing faults in lithium-ion battery systems. It is possible to categorize these techniques into four groups: state estimation, parameter estimation, parity space, and structural analysis theory;
- Data-Driven methods: These techniques did not rely on a precise analytical model or the experience of experts to detect faults; instead, they exploited data to do so. The most popular data-driven techniques include information fusion, machine learning, and signal processing.

The sensor fault diagnosis methods used in a battery system are divided into sensor-topology-based, model-based, and fusion. The actuators' fault diagnosis methods include model-based and signal-processing techniques. A thorough comparison of these methodologies is also provided by the authors in [149]. Figure 15 displays the several methods examined in that review for battery, sensor, and actuator faults.

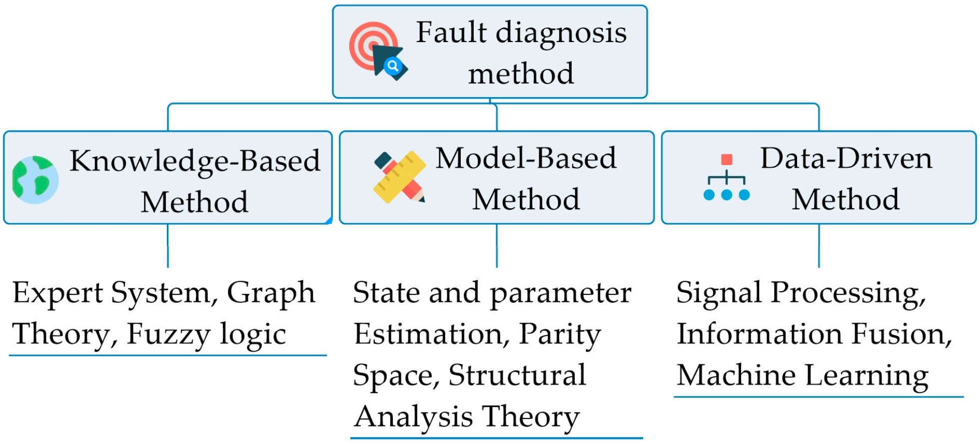

Figure 15. Fault diagnostic methods classification [149].

For the batteries of a hybrid electric car, the authors in [150] proposed a nonlinear fault detection and isolation method. The battery management system in this technique was generated using a nonlinear parity equation residual generation (NPERG) methodology. As a comparison to the fault signals, the NPERG scheme generates residual values for the voltage and fan setting sensors in a healthy system. To create an inverse model and prevent nonlinearities in the system, a sliding mode observer is additionally used. More dynamic systems would make it more difficult to adopt this strategy because it necessitates the creation of models and prior knowledge of several failures.

Electric Vehicles

The current, voltage, and temperature sensors as well as the fan motor frequently develop failures in these systems. The only fault that is considered for the motor fan is total failure, which occurs when it is unable to cool the battery continuously. Sensor faults include intermittent signal loss caused by bad wiring connections and sensor bias caused by time or temperature drift.

The authors in [151] presented a fault diagnosis method for lithium-ion batteries in EVs based on signal processing and two-dimensional feature clustering. Discharging voltage signals are divided up into intrinsic mode functions using the symplectic geometry mode decomposition (SGDM) technique. Comprehensive anomaly detection employs a correction step known as a density-based spatial clustering of applications with noise (DBSCAN). The distinction between faults and inconsistency may be made based on the clustering results, which also reveal the battery fault evolution process and the type of voltage anomaly. As much as 43 days before the thermal runaway, this approach can detect faults early, identify the fault cells, and determine the type of voltage anomaly.

The authors of [153] presented an examination of a distribution system's faults because of the widespread integration of plug-in electric vehicles (PEVs). According to this research, the node where the PEVs are connected has an increase in voltage and current. The system and loads may be affected by wave distortion caused by high switching frequencies that can generate too much heat.

The authors in [154] proposed a signal-based fault diagnosis method for lithium-ion batteries in EVs based on voltage signals. The variational mode decomposition (VMD) algorithm is a signal-based technique that is used to identify voltage signal characteristics related to either long-term battery state variations or local responses to external excitation. Then a generalized dimensionless indicator (GDI) is used to reduce the impact of the quality and quantity of training data. Finally, a clustering algorithm is utilized to find the outliers that represent battery cell abnormalities in feature sequences and diagnose the fault. This approach can reliably identify the fault types, duration, and magnitude as well as the initial state of the fault.

In [155], the authors proposed an online semi-supervised-data-driven approach for EV battery fault detection based on Bayesian optimization (BO) and support vector data description (SVDD). To train the SVDD and create a base fault detection model, the proposed method employed unlabeled data like temperature and voltage. The BO iteration is used to find the optimal parameter by iteratively training the model using a small amount of battery management system (BMS) data or manually labeling samples and maximizing the fault detection capability. Figure 16 shows the proposed model described in [155]. This technique can be utilized in the real-world operation of an EV to offer real-time alerts for minor and early battery system faults and has a low modeling cost and high modeling efficiency. It also increases the safety of the battery system. This method's following step requires validating the fault location capabilities and acquiring more advanced fault diagnosis in battery systems.

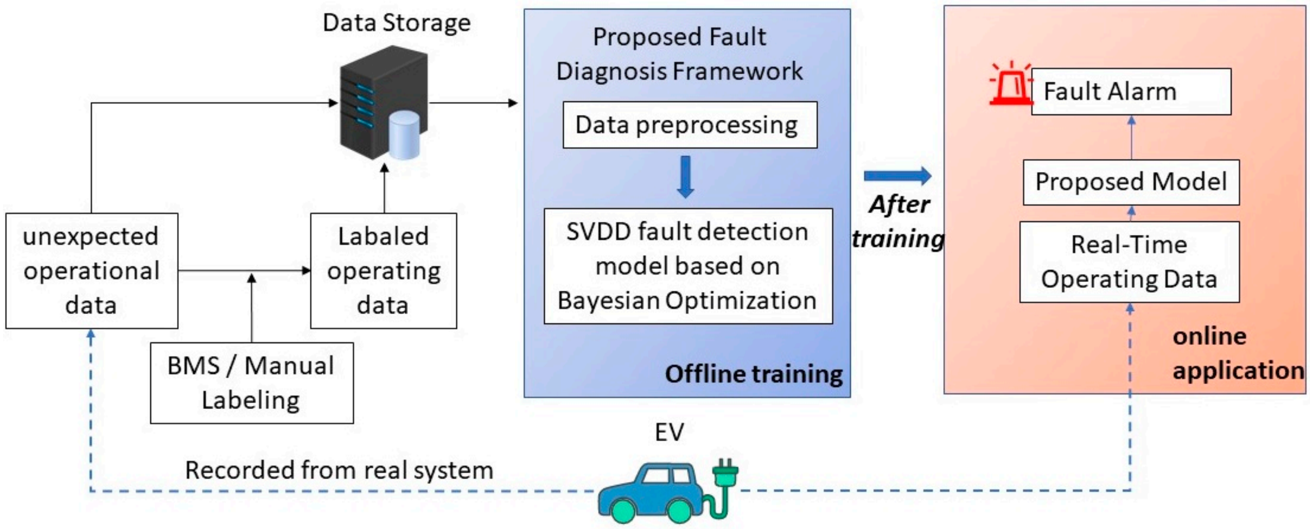

Figure 16. Fault detection proposed application for EV battery by [155].

The authors of [74] proposed a data-driven fault diagnostic technique for connecting a series lithium-ion battery pack based on SVM. There are four steps in this procedure. The method can successfully diagnose faults by first employing an optimal filter based on the discrete cosine transform (DCT), then analyzing the covariance matrix (CM) of the filtered data, then using a grid search method to optimize the kernel function parameter and penalty factor. Finally, the method can successfully diagnose faults by training the SVM parameters using condition indicators. This method can reflect the severity of the system fault and detect the voltage in real-time.

The authors in [156] proposed a fault detection classification scheme based on DWT and LDA for hybrid MGs integrated with battery energy storage systems (BESS). The DWT provides localization in the time and frequency domain, and LDA is a robust classifier for fault diagnosis in large datasets. It is capable of detecting, classifying, and identifying the faulty line in connected and islanded hybrid MG and it should be evaluated in interconnected or networked MGs to validate its effectiveness. In [157], the authors proposed a fault location approach for distribution networks with charging load access based on graph theory and DL. To create the model, the distribution network topology is first divided up into a number of Y-shaped structures using graph theory. Next, a generalized network learning (GNL)-based DL technique is used to extract the mapping relationship between the collected data and the fault location. A complex physical model and data analysis are used to detect the fault type and location. This technique is adaptable to various distribution network structures with charging loads and is unaffected by topological changes.

6. Future Works and Conclusions

6.1. Future Works

6.1.1. Real-Time and Online Fault Location

The SG's domain fault localization methodology must consider comprehensive, sophisticated deep learning models, multi-agent systems, and fault-tolerant controls in real time to detect and locate the concurrent occurrence of multiple fault events or cascade failures in the SG system [158]. Furthermore, for online fault location, it is critical to consider an artificial intelligence model for detecting cyberattacks and updating missing or inaccurate data [78], as well as topics that could continue to be developed, such as neural networks, deep learning, discrete wavelet transforms, and signal processing.

In order to identify online faults in these systems, it is also important to create a multicriteria fault detection and localization system that is based on rapid communication systems and incorporates adaptive emotional learning techniques [159].

Additionally, it's important to design adaptive protection schemes for these SGs that incorporate rapid restoration and on-line fault location utilizing more sophisticated algorithms.

6.1.2. Adaptable Fault Location Techniques and Hybrid Techniques

It is important for fault location methods to be resilient and adaptive, working properly regardless of the network's operating mode. A comprehensive framework for network failure detection can be created using a combination of heuristic network data, meteorological data, and geospatial data. Another practical option that has the potential to significantly increase the effectiveness of the fault prediction methods using only data from existing infrastructure, such as a smart meter [160], independent of the effects of controller devices and DG controllers, is the use of chemical analysis and electrical data associated with equipment [161].

In order to test the effectiveness of hybrid methods based on communication, such as the wide area traveling fault location (WATWFL) technique using IEC61850 and SCADA systems, they must be implemented in real-time applications for MGs. This is because traveling waves require effective devices for data collection [162].

Furthermore, it may be necessary to use more reinforcement learning or advanced machine learning-based fault location techniques using Micro-PMU [162] or intelligent sensors in other types of MGs, such as ad-hoc or networked MGs, to evaluate their efficacy.

6.1.3. Energy Storage Systems

The traditional battery management system (BMS) primarily focuses on simple faults, such as thermal faults and sensor faults; however, in the years ahead, the BMS fault diagnosis should be focused on an AI algorithm to achieve battery system fault detection and location, a large-scale battery array, accurate state estimation, and a fault diagnosis algorithm for battery health management [163]. The voltage at the feeder's beginning should be the focus of methods for fault location for electric vehicles in both grid-to-vehicle (G2V) and vehicle-to-grid (V2G) operation modes. Fault isolation, which protects a specific fault from battery, sensor, and actuator faults, is a requirement for a safer battery system [163]. To ensure long life, high energy, and low cost, stand-alone EV charging stations require attention to automatic fault detection and location [164].

Investigating a battery pack's temperature distribution can produce valuable fault features. The nature of the problem on the thermal runaway vehicle is still unknown, but acceptable fault features can also be produced through feature transformation and the merging of various electrical and thermal characteristics. Accurate early defect warning and diagnosis, as well as efficient fault decoupling with accompanying mechanism illustration, will be accomplished after the development and statistical analysis of the fault pattern library [151].

Another future direction is the development of an intelligent infrared detection and location system for SGs using an edge-cloud framework [165,166]. This solution combines the infrared technology used for fault diagnosis with a data-driven approach to achieve automatic and intelligent methods.

6.2. Conclusions

In this article, we review both fault location methods proposed in SG's domain and fault location approaches to improve resilience. While considering numerous literature articles on the subject, we also looked at the challenges of troubleshooting and the most typical types of distribution system failures. This article also covered the problems caused by these failures, as well as the challenges in locating the fault for various MG types, communication systems, and energy storage systems. Along with these issues, we also highlighted the main sources of fault location methods in SGs and MGs based on traveling waves, knowledge-based signal processing, and a phasor-based algorithm, among others.

According to the reviewed literature, the main challenges faced in fault location techniques are the following: (i) Several operation modes and diverse types of power failures; (ii) Existing gaps in hybrid solutions that use communication infrastructures and adaptive protections. (iii) More practical experience with this kind of intelligent system.

Future research should focus on developing studies that examine the performance of more intelligent algorithms made to deal with self-recovery, communication issues, and meteorological conditions. It is also necessary to test and validate the use of various localization approaches based on local or non-local measurements, fault-finding strategies for storage systems, and fault-finding strategies for electric vehicles in real-time scenarios.

Future research should also concentrate on the possibility of online techniques and approaches based on expert systems or bioinspired algorithms, such as multi-agent systems or emotional learning, to improve the resilience and autonomy of the autonomous restoration capabilities of future power systems.

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Nomenclature

Indices	
t	milliseconds
Abbreviation	
AC	Alternating Current
ACCB	AC Circuit Breaker
ADN	Active Distribution Network
AIE	Active Impedance Estimation
AMKELM	Adaptive multi-kernel extreme learning machine
ANN	Artificial Neural Networks
BESS	Battery Energy Storage System
BMS	Battery Management System
BO	Bayesian Optimization
BP	Back Propagation
BPNN	Back Propagation Neural Network

CB	Circuit Breaker
C-FLISR	Centralized Fault Location, Isolation, and Service Restoration
CM	Covariance Matrix
CNN	Convolutional Neural Network
DA	Discriminant Analysis
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DC	Direct Current
DCCB	DC Circuit Breaker
DCT	Discrete Cosine Transform
DER	Distribute Energy Resources
D-FLISR	Distributed Automatic Fault Location, Isolation, and Service Restoration
DG	Distributed Generation
DL	Deep Learning
DNN	Deep Neural Network
DRL	Deep Reinforcement Learning
DT	Decision Tree
DTA	Decision Tree Algorithm
DWT	Discrete Wavelet Transform
ECM	Equivalent Circuit Model
EEMD	Ensemble Empirical Mode Decomposition
ELM	Extreme Learning Machines
EPS	Electrical Power System
EM	Ensemble Methods
EV	Electric Vehicles
FDI	Fault Data Injection
FDIR	Fault Detection, Location, Isolation, Service Restoration
FF-NNs	Feedforward Neural Networks
FFT	Fast Fourier Transform
FTCC	Fault-Tolerant Cooperative Control
G2V	Grid-to Vehicle
GDI	Generalized Dimensionless Indicator
GNL	Generalized Network Learning
GNN	Graph Convolutional Network
GOOSE	General Oriented Substation Event
GPR	Gaussian Process Regression
HGAT	Heterogenous Graph Attention Network
HHT	Hilbert-Huang Transform
HIF	High-Impedance Faults
HR	High Impact Rare
IDS	Intrusion Detection Systems
IED	Intelligent Electronic Device
IoT	Intelligent Electronic Device
IPR	Intelligent Power Router
IPS	Intrusion Protection Systems
KNN	K-Nearest Neighbor
LDA	Linear Discriminant Analysis
LR	Logistic Regression
LRP	Layer-Wise Relevance Propagation
LS	Least-Squares
LSTM	Long Short-Term Memory
LVDC	Low-Voltage DC
MAS	Multi Agent systems
MGs	Microgrids
MILP	Mixed Integer Linear Programming
ML	Machine Learning
MM	Mathematical Morphology
MMF	Mathematical Morphology Function

MSVM	Multi-Class Support Vector Machine
MV	Medium-Voltage
MVDC	Medium-Voltage DC
NB	Nave Bayes
NN	Neural Networks
NPERG	Nonlinear Parity Equation Residual Generation
PBN	Probabilistic Boolean Network
PCA	Principal Component Analysis
PCC	Point of Common Coupling
PDD	Power Protection Devices
PEVs	Plug-in Electric Vehicles
PMOS	Positive Channel Metal Oxide Semiconductor
PMU	Phasor Measurement Units
PnP	Plug-and-Play
PPU	Power Probe Units
PS	Protection Systems
PV	Photovoltaic
RBF	Radial Basis Function
RER	Renewable Energy Resources
RF	Random Forest
RFI	Remote Fault Indicators
RNN	Recurrent Neural Network
ROCOF	Rate-of-Change-of-Frequency
RT	Regression Tree
SCADA	Supervisory Control and Data Acquisition
SGAM	Smart Grid Architecture Model
SGDM	Symplectic Geometry Mode Decomposition
SGFI	SG Fault Identification
SGs	Smart Grids
SM	Smart Meter
SNPS	Spiking Neural P System
ST	Stockwell Transform
STFT	Short Time Fourier Transform
SVD	Singular Value Decomposition
SVDD	Support Vector Data Description
SVM	Support Vector Machine
SVR	Support Vector Regression
TEO	Teager Energy Operator
T-S	Takagi-Sugeno
TW	Travelling Wave
TWAM	Travelling Wave Acquisition Module
V2G	Vehicle-to-Grid
VMD	Variational Mode Decomposition
VSC	Voltage Source Converter
WATWFL	Wide Area Travelling Fault Location
WPT	Wavelet Packet Transform
WT	Wavelet Transform

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