

Review Article

Review and Performance Evaluation of Photovoltaic Array Fault Detection and Diagnosis Techniques

Albert Yaw Appiah ^{1,2}, Xinghua Zhang,¹ Ben Beklisi Kwame Ayawli ^{1,3}
and Frimpong Kyeremeh^{1,2}

¹College of Electrical Engineering & Control Science, Nanjing Tech University, Nanjing, China

²Department of Electrical/Electronic Engineering, Sunyani Technical University, Sunyani, Ghana

³Department of Computer Science, Sunyani Technical University, Sunyani, Ghana

Correspondence should be addressed to Albert Yaw Appiah; appibert@yahoo.com

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The environmentally clean nature of solar photovoltaic (PV) technology causes PV power generation to be embraced by all countries across the globe. Consequently, installation and utilization of PV power systems have seen much growth in recent years. Although PV arrays of such systems are robust, they are not immune to faults. To guarantee reliable power supply, economic returns, and safety of both humans and equipment, highly accurate fault detection, diagnosis, and interruption devices are required. In this paper, an overview of four major PV array faults and their causes are presented. Specifically, ground fault, line-line fault, arc fault, and hot spot fault have been covered. Next, conventional and advanced fault detection and diagnosis (FDD) techniques for managing these faults are reviewed. Moreover, a single evaluation metric has been proposed and utilized to evaluate the performances of the advanced FDD techniques. Finally, based on the papers reviewed, PV array fault management future trends and possible recommendations have been outlined.

1. Introduction

In recent years, there has been an increasing demand for clean energy resources due to climate change concerns and dwindling fossil resources. Towards this demand, PV technology presents itself as a suitable candidate due to its desirable characteristics such as its environmental compatibility, decreasing cost of PV modules [1], short installation time, and low maintenance cost [2, 3]. Consequently, global PV power plant installed capacity exponentially increased from 1.3 GW in 2000 to 177 GW in 2014 [3]. At the end of 2016, global installed PV capacity was reported to be about 310 GW [4].

Despite the attractiveness of the PV technology, its usage, especially for large-scale power generation, comes with multiple technical challenges. Notable among them are (1) the need to track and maintain the operating point of the PV module at its maximum power point (MPP) [5, 6] and (2)

the need to detect and mitigate the almost unavoidable PV array faults [7, 8]. Tracking the MPP requires the use of a device known as maximum power point tracker (MPPT). This tracking is important to guarantee a maximum achievable power under a given operating condition. Various algorithms exist in literature [9], and some of these algorithms have recorded tracking efficiency of almost 100% [10].

To minimize energy losses, improve reliable power supply, and safeguard PV installations from fire hazards on the other hand, PV system installations are fitted with protective devices. The role of these protective devices is to detect and isolate the faulty component from the rest of the system. Due to the necessity and numerous benefits of protection, various national and international standards make the installation of protective devices mandatory. For instance, the US National Electric Code, article 690, mandates the protection of PV arrays against faults. Unfortunately, in many instances, these protective devices responsible for the

PV power-generating units (arrays) have failed to detect and isolate faults, which among other things have led to loss of power, loss of revenue, and fire outbreaks. For example, on April 5, 2009, in Bakersfield, CA, USA, and on April 16, 2011, in Mount Holly, NC, USA, PV array fault incidences were witnessed [11]. In both cases, protective devices failed. The authors of [12] report that in the United Kingdom, annual energy loss as a result of faults in PV systems is evaluated to be around 18.9%. The inability of these protective devices to detect fault in some cases has been attributed to PV array fault behavior dependence on fault location, fault impedance, irradiance level, and use of blocking diodes [12]. The authors of [13] have argued that there is a deficiency in PV array fault analysis. The good thing, however, is that these reported instances of protection failure have exposed weaknesses in conventional PV array fault protective devices and schemes. To address these weaknesses, advanced PV array fault detection and diagnosis (FDD) techniques are needed. In a context of a fault management system, these FDD techniques are required to (1) detect faults, (2) classify faults, (3) localize faults, and (4) trigger fault isolation.

Although many PV array faults exist, line-to-line fault (LLF), ground fault (GF), arc fault (AF), and hot spot fault (HSF) have gained more attention than the others. For easy reference, these faults shall be referred to as the *four major PV array faults* in this paper. The reason for the attention gained by the four major PV array faults could be attributed to their effects. For example, LLF, GF, and AF in most cases have the potential to cause fire hazards and a significant energy loss. These three faults have been collectively referred to as catastrophic faults [14]. The attention towards HSF can also be attributed to its ability to create hot spots in PV cells, which if remain undetected can permanently damage the PV cell.

The problem of designing and implementing effective FDD techniques for the four PV array faults has received research interest in recent years. As a result, many advanced FDD techniques now exist. While some of these FDD techniques solely concentrate on one specific fault, others are for managing multiple faults. In response to these many techniques, a couple of review papers that seek to present the state-of-the-art of FDD techniques and to compare the performances of individual techniques have been published. In [15] for example, the authors discussed and compared different techniques and the features used for the detection of faults in PV systems. Although comprehensive, the scope of [15] is narrow as it concentrated solely on AFs. Next, in [14], the authors presented a discussion and analysis of the catastrophic PV array faults along with their protective devices. In addition, some advanced FDD techniques were also reviewed and compared. Again, in [16], the authors presented a review on protection challenges and fault diagnosis in PV systems. Moreover, the authors conducted a performance review of various fault detection techniques. In all these papers, performance evaluation and comparison of individual studies have been performed using important engineering design considerations such as cost, implementation complexity, sensor requirements, and computational

complexity as evaluation metrics. Although this paper acknowledges the usefulness of these comparisons, it must be, however, noted that using such multiple evaluation metrics does not easily help identify the best FDD technique for managing PV array faults. Moreover, these evaluation metrics are not scored in numerical terms, which makes it difficult to choose a particular FDD technique for a given application. For example, it is common to find an FDD technique evaluated as either low, medium, or high under the cost metric in reference to no base cost.

In the light of the above discussion, this paper aimed (1) at reviewing both conventional PV array protection schemes and the advanced FDD techniques specifically for LLF, GF, AR, and HSF in order to present their state-of-the-art and (2) at performing a performance evaluation of the advanced FDD techniques using a single evaluation metric called Fault Management Score (FM score). This metric seeks to measure the capability of an FDD technique to manage the four major PV array faults. To the best knowledge of the authors of this paper, this evaluation metric has never been used to evaluate FDD techniques in the context of PV array faults. This evaluation metric combines four evaluation criteria into a single metric.

The rest of the paper is organized as follows. Section 2 presents an overview of a PV power system. Typical PV array faults are considered in Section 3. This is followed by a review of conventional PV array fault protection techniques in Section 4. Next, an overview of an FMS is presented in Section 5. Section 6 provides a review of the advanced FDD techniques. Performance evaluation of the advanced FDD techniques is presented in Section 7. PV array fault management future trends and recommendations are given in Section 8. Finally, Section 9 concludes the paper.

2. Overview of a PV Power System

A PV power system is one that generates electric power from sunlight through the use of PV modules. Based on the power application, PV power systems are usually classified as follows: (1) stand-alone system, (2) grid-connected system, and (3) hybrid-power system [17]. The grid-connected system, which represents 95% [12] of the worldwide installed PV capacity, is the focus of this paper. Figure 1 [12] depicts a typical grid-connected PV system, which is composed of a PV power source and a centralized inverter having MPPT functionality.

The PV power source contains PV modules, which are electrically connected in a series-parallel manner to form a PV array. Although PV arrays are known to be robust for lack of no moving parts, they still suffer from many faults. To mitigate the negative effects of these faults, PV arrays are often protected with devices such as overcurrent protection devices (OCPDs) and ground-fault protection devices (GFPDs). Details of PV array faults are presented next.

3. PV Array Faults

Fault is a deviation of a component operation from the expected manner [18]. Therefore, this paper refers to any

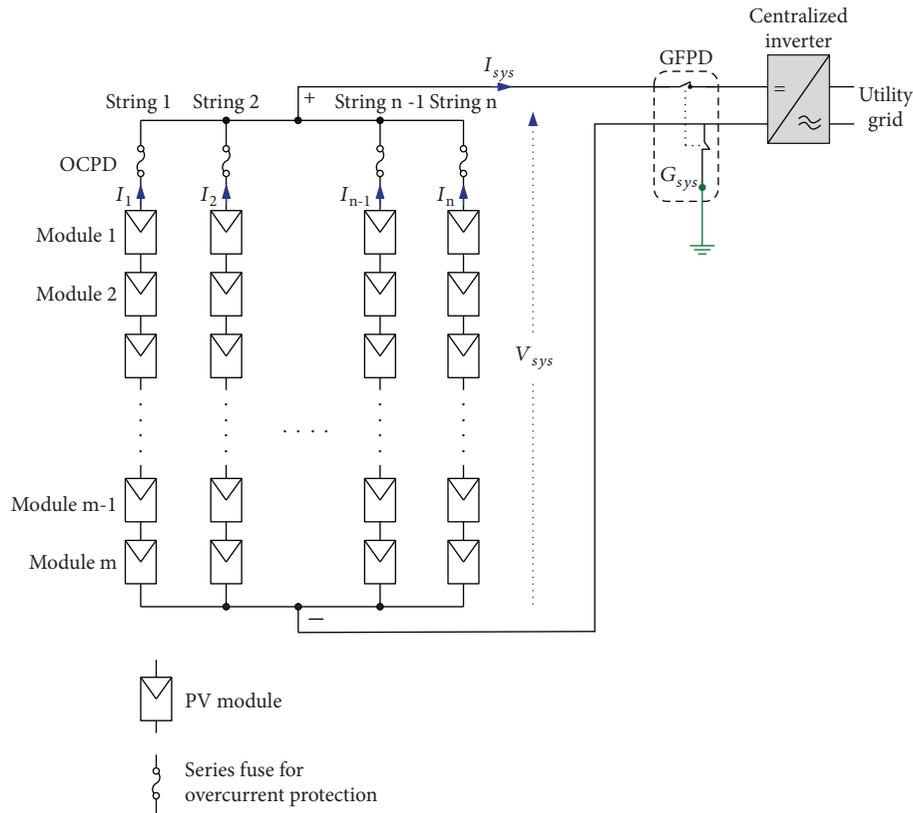


FIGURE 1: Typical grid-connected PV array with a centralized inverter.

act or operation which causes a PV module or array to deviate from its expected manner as a fault. The cause of a PV array fault can be physical, electrical, or environmental as shown in Figure 2. For better detection, diagnosis, and mitigation, it is important for one to understand what PV array faults are and their causes. Therefore, the rest of this section explains PV array faults and their root causes. A blind-spot fault, which is a special case of LLF or GF, is also explained. As stated in Section 1, this paper is focused on GF, LLF, AF, and HSF, so no attempt has been made to explain the other faults captured in Figure 2. Readers interested in the other faults can refer to [16].

3.1. PV Array Ground Fault. A common practice in electrical installation is to connect all normally nonconducting uninsulated metallic (NNUM) parts of the installation to a third conductor called equipment-grounding conductor (EGC). This practice ensures that any unintended current flowing through the NNUM parts goes to the ground to avoid electric shock. A GF, which causes such unintended current flow in the NNUM parts, is defined as any accidental connection between a current-carrying conductor and an EGC that leads to flow of current to ground [19, 20].

The severity of a GF depends on fault location. In Figure 3 [3], F_5 and F_6 are the instances of GFs. By virtue of location, F_5 and F_6 represent upper and lower GFs, respectively. Due to the existence of a high potential difference between the location of F_5 and the ground, a substantial amount of current ensues. In contrast, the existence of low

voltage between F_6 and the ground leads to a lower fault current. Another indicator of GF severity is percentage mismatch, which specifies the number of PV modules involved in the fault. Given that each string of Figure 3 contains 10 PV modules, percentage mismatches for F_5 and F_6 are 10% and 20%, respectively. Detection of lower GF or high percentage mismatch GF tends to be more difficult due to lower fault current magnitude. In [21], it is reported that cable insulation failure, accidental short-circuiting of normal conductor and ground, PV module encapsulation deterioration, water corrosion, and impact damage are some of the causes of GF.

3.2. PV Array Line-Line Fault. An LLF is defined as an accidental short circuit between any two points of different voltage potentials [21]. In a PV array, accidental short circuits could be created within a PV string giving rise to intrastring LLF or across PV strings, giving rise to interstring LLF. In Figure 3, F_1 shows an interstring LLF while F_2 , F_3 , and F_4 show intrastring LLF. Like GF, the severity of an LLF depends on fault location or the percentage mismatch. Given that each PV array string shown in Figure 3 has 10 PV modules, then F_1 and F_2 have a mismatch of 10% each. Likewise, F_3 and F_4 have a mismatch of 20% and 90%, respectively. LLFs create a voltage drop in the affected PV array string(s), which leads to a flow of back-feeding current from the other unaffected strings. Contrary to GF, an LLF with high percentage mismatch leads to high fault current. Reported causes of LLFs include water ingress, animal chewing of cable

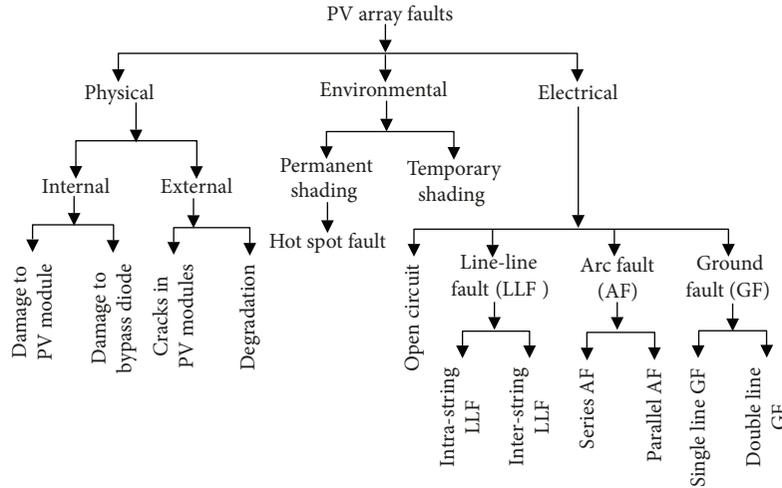


FIGURE 2: Classification of PV array faults.

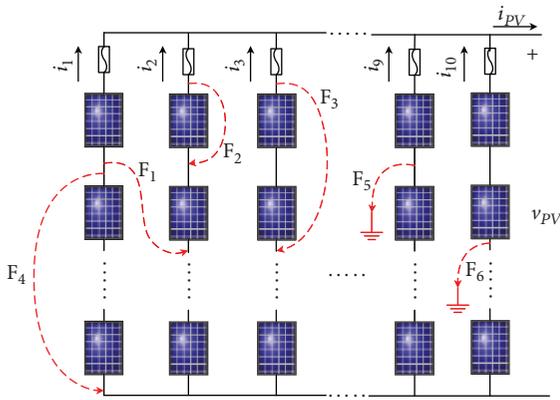


FIGURE 3: PV array configuration showing possible line-to-line faults and ground faults.

insulation, mechanical damage, and corrosion of DC junction box [22].

3.3. PV Array Arc Fault. AF is a high-power discharge of electricity across an air gap between conductors [19]. Arc across air gap is initiated when high electric fields ionize air molecule and accelerate the ion towards the opposite electrode. This ionization results in high-speed particle collisions which generates additional ions. The movement of ions from one electrode to the other converts the normally nonconducting air gap into a conducting medium [14]. Series AF is said to have occurred when the arc is initiated as a result of a discontinuity in any of the current-conducting conductors. On the other hand, an arc between adjacent conductors is referred to as parallel AFs. Figure 4 [15] illustrates possible locations of AFs in a PV array. According to Wang and Balog [23], causes of both series and parallel arc faults are as follows:

(a) Series arc fault: this fault is caused by a discontinuity in the current path due to a broken conductor,

loosened conductor, or a high impedance connection due to corrosion

(b) Parallel arc faults: parallel faults also occur due to mechanical damage, nesting rodents, or failure within the PV module

Contrary to AC systems, the current through DC arc does not possess a zero crossing [24, 25]; thus, there is a likelihood that a PV array arc will be sustained. Parallel AF draws large amount of fault current as compared to series AF due to large voltage potential difference involved in the former [26]. As a result, this large fault current of parallel AF detection is easy than series AF.

3.4. PV Array Hot Spot Fault. Hot spot is a condition which occurs in PV cells and modules when the electrical characteristics of series connected cells/modules of PV string become mismatched. A sustained hot spot gives rise to HSF. Although investigations into HSF dates back to the 1980s, it remains a challenge today [27]. In some literature, mismatch fault [28] and HSF are used interchangeably. The severity of HSF depends on the mismatch level and duration. In [29], the identified causes of HSF are (1) snow covering, (2) shading from trees or buildings, and (3) bird droppings. A manufacturing defect is another reported cause [30].

This section explains hot spot formation in terms of a PV string of series connected cells. All cells in a PV array string under a uniform distribution of solar irradiance exhibit identical current-voltage (I-V) characteristic, so the string operates at the MPP of each cell for optimal output power. However, a nonuniform distribution of solar irradiance introduces a mismatch in the cell characteristics. When a relatively few cells become mismatched in a string, the imposed string current reverse bias the mismatched cells. For example, given that cell PV3 is shaded while cells PV1 and PV2 are not as shown in Figure 5 [31], the I-V characteristic curve of PV3 moves down on the current (I) axis which results in a reduced MPP. Consequently, the string current (I_{string}) settles at a current value that is greater than PV3's short-circuit current,

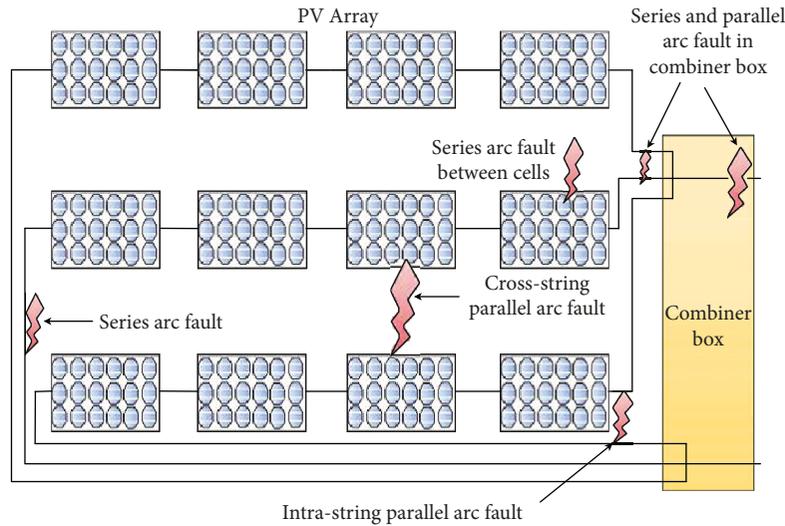


FIGURE 4: Possible locations of AFs in a PV array.

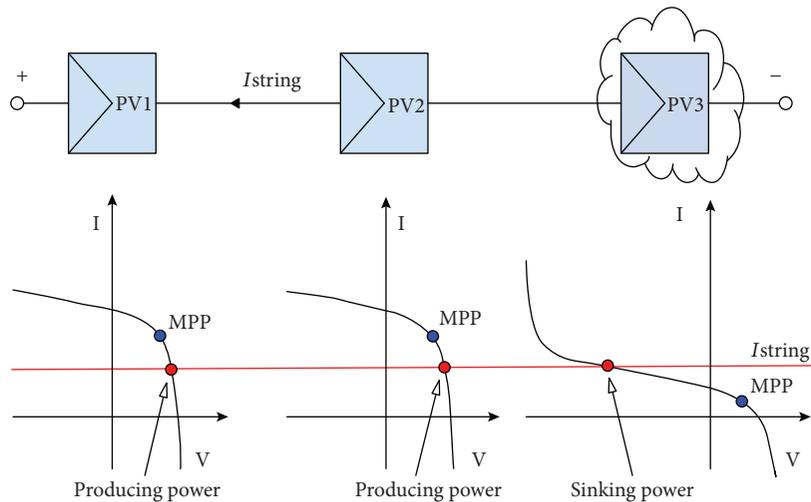


FIGURE 5: Partially shaded string of PV cells showing reverse bias voltage of the shaded cells. Each cell's electrical characteristics are shown with the MPP and the operating point according to the string I_{string} .

causing PV3 to become reverse biased [27, 31]. At this present string current, PV3 conducts with a negative voltage across it. From a circuit theory perspective, a conclusion to be reached is that PV3 is dissipating power instead of sourcing. At a sufficiently large power dissipation, the heat generated increases the localized cell temperature which can damage the cell. This process of increasing the cell temperature is known as hot spotting. The term hot spot refers to the portion of the cell with a higher temperature due to hot spotting.

3.5. Blind-Spot Fault: Special Cases of GF and LLF. As pointed out in Section 1, PV array protective devices are unable to detect some cases of PV array faults. Such faults are said to have occurred at the blind spot of the protective device and are referred to as blind-spot faults. The protective devices are unable to detect such faults due to low fault current

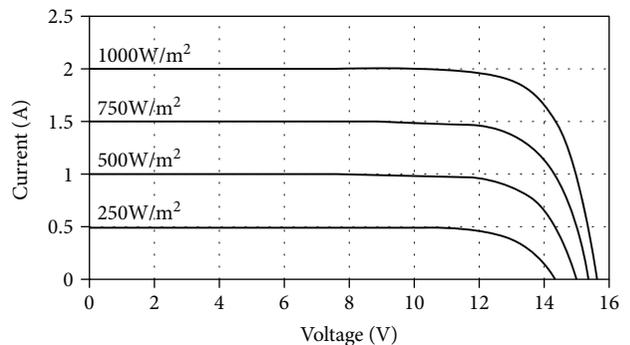


FIGURE 6: Current-voltage characteristic of solar PV module.

magnitudes. Causes of low fault current include solar irradiance and MPPT. A PV module output current has a nearly linear dependence on solar irradiance [32, 33] as shown in Figure 6 [34]. Since solar irradiance level does not stay

constant throughout the day, there is a chance for GF or LLF to occur at a low solar irradiance level, giving rise to a low fault current magnitude.

Although the use of MPPT is to optimize PV power utilization, its presence in PV systems poses a challenge to fault detection. When, for example, an LLF occurs in a PV array, it creates a back-feeding current in the affected string and at the same time reduces the output of the PV array. As shown in Figure 7(a) [3], at no fault condition, the PV array exhibits I-V characteristic curve (shown in a solid black line) having an operating point marked as MPP_{normal} . The moment the LLF occurs, if the MPPT is active, it will quickly sense the reduction in the PV array output power and attempt to optimize it. To optimize the PV array output power, the MPPT will operate the PV array on a new I-V characteristic curve having its operating point marked as MPP_{fault} as depicted in Figure 7(a). Comparing MPP_{normal} and MPP_{fault} , the latter operates the PV array at a reduced PV array output voltage. This reduction in PV array output voltage reduces the back-feeding current. A significant reduction in the back-feeding current will mask the LLF so as to prevent fault detection. Figure 7(b) [22] shows that in the absence of an MPPT, back-feeding current created by an LLF at 40% mismatch (shown as a black solid line) exceed the threshold of the protective device (usually a fuse) and will be detected. In the presence of MPPT, however, the occurrence of an LLF under the same mismatch percentage will create back-feeding current exceeding the fuse threshold but will immediately be reduced by the MPPT to a level lower than the threshold of the OCPD to mask the fault.

4. Review of Conventional Protection Techniques for PV Array Faults

Over the years, various conventional protection techniques have been implemented on PV arrays for detection and isolation of the four major PV array faults. Unfortunately, these techniques have some operational challenges. Therefore, this section seeks to review these conventional techniques along with their limitations in order to guide future research.

4.1. GF Protection Techniques and Their Limitations. The type of grounding configuration implemented on a PV array influences the choice of a GF protection technique. PV array grounding configurations are generally classified as either grounded or ungrounded as illustrated in Figure 8 [16]. Although both systems have metallic parts grounded, the grounded configuration has an electrical connection between its EGC and negative current-carrying conductor (CCC) of the PV array through a fuse in addition. In ungrounded systems, protection is enabled with the help of grounding electrodes. With this arrangement, however, isolation of GF fault is not possible [16]. To offer detection and isolation, residual current monitoring devices (RCDs) and insulation monitoring devices (IMDs) have been utilized along with grounding electrodes. An RCD is a relay, which uses a residual magnetism to detect GF and in turn opens a CCC [14]. The residual magnetism comes from a differential current

between the terminals of the PV array as a result of the GF. RCDs can falsely trip, so it is advisable to consider the sensitivity of the RCD with due regard to PV array leakage current. In [35], a formula for estimating a threshold at which RCDs should operate has been discussed. Interested readers can refer to it.

Similar to RCD, IMDs measure the resistance between a CCC and ground. If the resistance is lower than a threshold value, then the device can alarm the system. Because insulation resistance is influenced by the ambient conditions, references [35, 36] recommend a formula for setting the threshold value for the RCD.

Contrary to an ungrounded system, a fuse linking the EGC and the CCC serves as ground-fault detection and interruption (GFDI) fuse in ungrounded PV systems. The fuse is designed to melt when the fault current is greater than a given threshold. Generally, grounded PV systems are preferred to ungrounded PV systems. In spite of simplicity and relatively low cost, GF protection devices suffer the following limitations:

- (1) GFs coinciding with lower levels of solar irradiation or higher percentage mismatch can be masked and remain undetected
- (2) The response of MPPTs to GFs lowers the fault current magnitude which in turn masks the fault and remain undetected
- (3) External factors can initiate false tripping of both RCDs and IMDs
- (4) Performance of GFDI is poor in cases of blind-spot fault

4.2. LLF Protection Techniques and Their Limitations. The use of overcurrent protective devices (OCPDs), which are fuses, has been a conventional protection technique for LLF. In practice, each string of the PV array is fitted with its own fuse as shown in Figure 1. The fuse melts when the LLF current exceeds a threshold value for a certain duration. The fuse rating is usually fixed at 2.1 times the short-circuit current of the string [37]. Although OCPD benefits from less implementation complexity and cost, it has the following setbacks:

- (1) The response of MPPTs, low irradiance levels, and percentage mismatch can force an LLF to occur at the blind spot of the OCPD and remain undetected indefinitely
- (2) In PV applications requiring storage energy through batteries, it is important to install blocking diodes in each string to avoid the discharge of the battery through the PV modules in the night. The presence of these blocking diodes renders OCPDs dysfunctional due to blockage of back-feeding current

4.3. AF Protection Techniques and Their Limitations. AF protection is a concern to the PV industry, so it is required in any

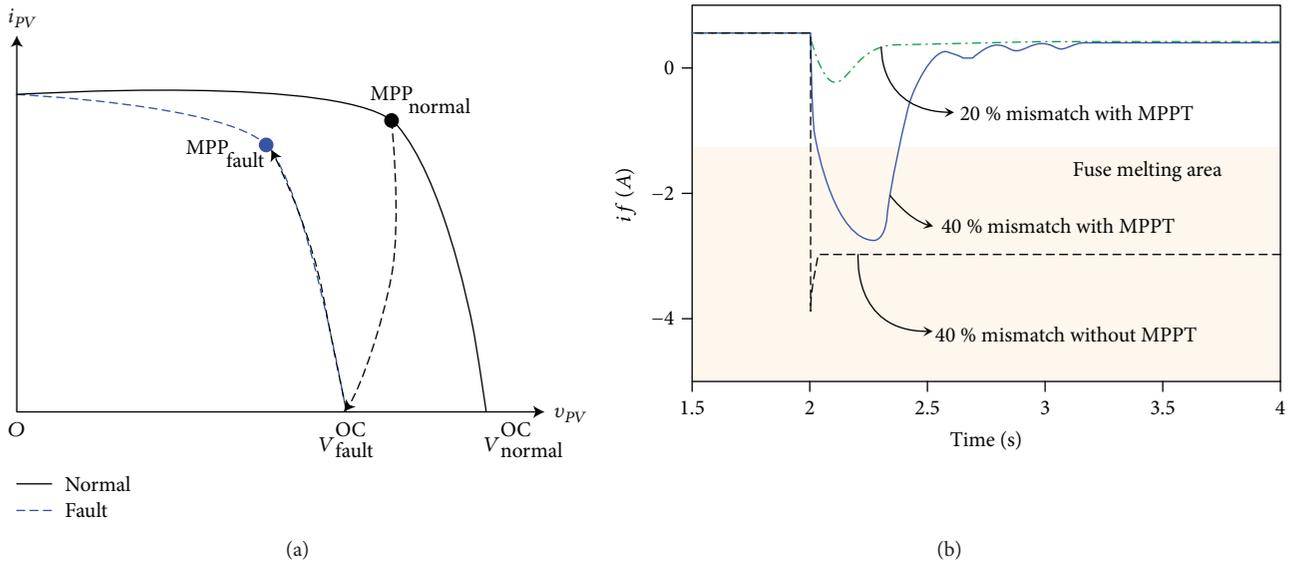


FIGURE 7: (a) Change of operating point due to the interaction between fault and MPPT algorithm. (b) Back-feeding current of a faulted PV string (LLF occurs at $t = 2$ s).

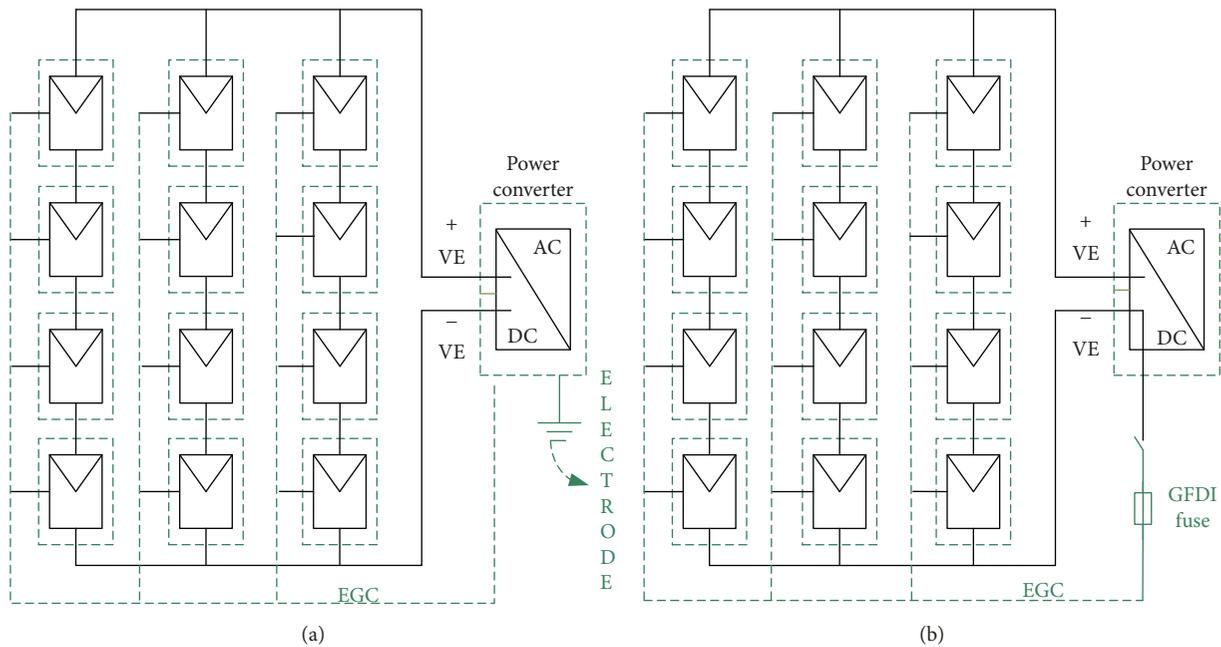


FIGURE 8: Schematic diagram of (a) grounded and (b) ungrounded PV systems.

rooftop PV array installation operating above 80 V to have arc-fault circuit interrupter (AFCI) for series AF protection [24, 38]. AFs distort PV array output current and voltage waveforms. Hence, AFCI’s detection of AF is based on the analysis of these waveforms for sustained atypical patterns in the current and voltage waveform. AFCIs do not localize faults, so arc-fault detectors (AFDs) are often used to detect AFs in specific PV array strings. However, AFDs lack fault isolation capability. In order to reduce the protection cost, a single AFCI or AFD is usually located in the central inverter for small PV systems or in the combiner box for large PV

systems. Although cost reduction is a good engineering design practice, it compromises the reliability of protection. It must be noted that AFCIs and AFDs are solely meant for series AFs. Detection and mitigation of parallel AFs are done by the use of GFPDs and OCPDs [16]. When PV array terminals become isolated, the flow of series AF current stops which extinguishes the series AF. In contrast, this isolation increases parallel AF current since the operating voltage of the PV array reaches open-circuit voltage. It is, therefore, an important design consideration to distinguish between series and parallel AFs. Towards this end, [39–

41] have offered ways to do so. Conventional AF techniques suffer the following limitations:

- (1) For series AFs, the propagation of the fault current from fault point to the AFCI in the central inverter suffers attenuation which can mask the fault
- (2) In order not to trade off the reliability for optimal cost, it is important to combine multiple devices. This strategy increases the cost of protection
- (3) The switching frequencies of the MPPT and inverter switches can interfere with the operations of the protective devices to cause false tripping

4.4. HSF Protection Techniques and Their Limitations. After hot spot was identified as a condition that could cause permanent damage to PV cells in the early days of satellite systems [42], a preventive method popularly known as the bypass diode technique was invented and remains in use today. This method places bypass diodes in parallel with a string of modules or a single module to provide an alternative current path around the PV module or string during HSF. Placement of such diodes in parallel with the modules is illustrated in Figure 9(a) [43]. The bypass diode creates an alternative current path for the PV modules during permanent or partial shading to prevent the shaded PV module from getting hot spotted. Although using bypass diodes for the prevention of hot spotting has the advantages of simplicity and low cost, it has the following limitations:

- (1) In [44], it is reported that bypass diodes only mitigate hot spotting problem but do not prevent hot-spot damage. Field studies have confirmed that hot spotting is the major cause of PV cell performance degradation even in systems employing bypass diodes [45, 46]. The authors in [44] are of the view that hot-spot damage could be avoided by placing bypass diodes over a small number of cells. Implementation of this recommendation demands that the bypass diodes are integrated into PV modules rather than in the junction box. Presently, PV module manufacturers have not adopted this idea likely due to cost implications
- (2) The introduction of bypass diodes in PV arrays has a side effect of creating multiple MPPs in the PV array output characteristics during partial shading conditions [6, 47]. Figure 9(b) [47] illustrates the presence of multiple peaks in a PV array power-voltage characteristic curve. These multiple MPPs render most conventional MPP tracking algorithms ineffective for MPP tracking during partial shading conditions [48–53]
- (3) Increased temperature of bypass diodes as a result of long-term operation of the bypass diodes may result in the degradation of the adjacent cells of the PV module [27]

5. Overview of Fault Management System

To address the various limitations of the conventional FDD techniques, it is important to develop advanced FDD techniques with capabilities of functional fault management systems (FMS). An FMS is a system designed to monitor the current operating status of an electrical power system, identify fault at inception stage, and take suitable actions to abate the effects of the fault for reliability, safety, and restoration [54]. Functionalities of a PV arrays FMS must include fault detection, classification, localization, and isolation. Fault detection is the task of discovering the existence of a fault. Classification is a process of classifying the faults into categories. When a fault is detected, isolation of the faulty component must be performed to disconnect the affected part from the rest of the system. This task of locating the faulty section or component of the PV array is referred to as localization. The role of isolation is to isolate the fault and impede its propagation. Figure 10 is a workflow diagram of a PV array FMS. An essential feature required of any FMS is its ability to execute its functionalities in real time.

6. Review of Advanced PV Array FDD Techniques

This section presents a review of advanced FDD techniques, which are usually classified into (1) visual and thermal methods and (2) electrical methods [55–57]. The latter is the focus of this paper, and it is further categorized into (1) comparison-based techniques, (2) statistical and signal processing-based techniques, (3) reflectometry-based techniques, (4) machine learning-based techniques, and (5) other techniques.

6.1. Comparison-Based Techniques (CBTs). In this category, detection and diagnosis of fault is based on a comparison of quantities. The comparison can be (1) between a real-time measured quantity of the PV array and its corresponding model-predicted quantity, (2) between real-time measured quantities, or (3) between some derived quantities from either measured or model-predicted quantity. It must be noted that the detection and classification accuracy of a CBT depends on the quality of the model used for the predicted quantity. Figure 11 gives an overview of CBTs. Reviews of papers drawn from this category are presented as follows.

In [58], the authors proposed a practical fault detection approach for PV systems intended for online implementation. Fault detection was based on a comparison between measured and model-predicted results of AC power production. A significant difference between the measured and model-predicted value was considered as a fault. The AC power predicted from the model was based on solar irradiance and temperature as model inputs. A fault detection rate greater than 90% was reported. Although this approach has a merit of low cost and less implementational complexity, it suffers the following setbacks: (1) it does not reveal the identity of the fault type on the PV array which can be useful for isolation and (2) it does not offer fault localization. In [59],

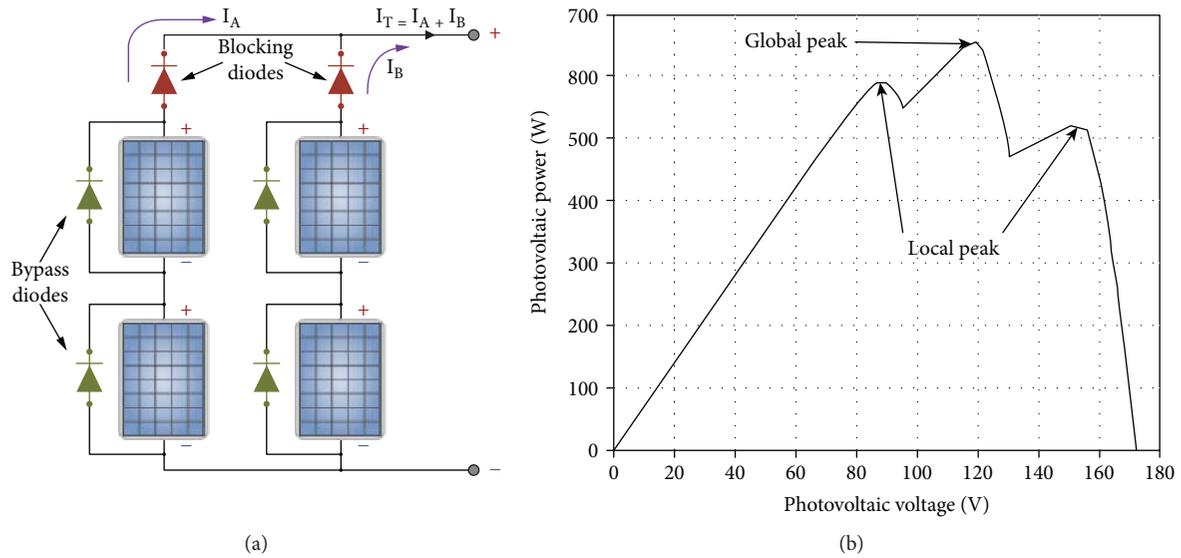


FIGURE 9: (a) Bypass and blocking diode application. (b) Power-voltage characteristic curve of six PV modules connected in series under partially shaded conditions featuring multiple peaks.



FIGURE 10: Workflow diagram of PV array FMS.

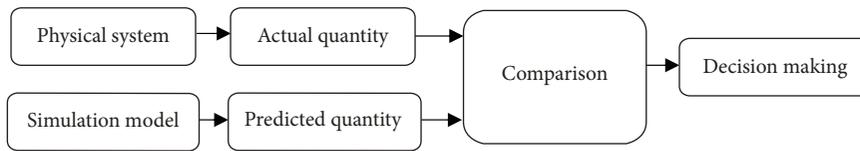


FIGURE 11: Overview of CBT detection process.

the authors developed a fault detection system using CBT. Three detection methods were proposed by the authors as follows: (1) comparison of measured output value and estimated value derived from measured irradiation, (2) comparison of present and past performance ratios (PRs), and (3) comparison of present and past output differences in an intersystem. PV module bypassing emanating from partial shading fault was considered in the study. Each of the three methods was evaluated against four case studies. Method three was reported to be superior to the other papers. One merit of this fault detection system is the ability to localize faulty strings. The authors of [60] proposed an automatic fault detection and diagnosis system for inverter disconnection, partial shadowing, and string disconnection faults. Fault detection was based on a comparison between simulated and measured yields through the analysis of losses, while fault identification was by the analysis and comparison of error deviation of both DC current and voltage with respect to a set of error thresholds. A simulation model of the PV system utilized was based on the studies presented in [61, 62]. Although this study offers a simple detection and diagnosis algorithms, it could be expensive due to a large number of sensors required. In a similar study reported in [63], the

authors have presented automatic supervision and fault detection based on loss analysis, where thermal capture losses (L_{ct}) and miscellaneous capture losses (L_{cm}) were introduced as power loss indicators. Fault detection was based on the processing of these indicators. Two additional indicators, namely, current and voltage ratios were introduced. Fault identification was based on the analysis of a faulty signal and the ratios. Faults considered in the validation of this study were disconnected PV strings and partial shadowing. This detection technique could suffer from high cost as it senses both DC and AC parameters of the PV system as well as environmental parameters.

A model for detecting PV array faults and partial shading was proposed in [64]. The model introduced two new parameters: gamma (γ) and array losses (L_{array}). Fault detection was based on a comparison of these two parameters with their corresponding thresholds to detect partial shading and LLFs, respectively. The proposed model was experimentally validated. An interesting feature of the model is its ability to detect a blind-spot fault. In [65], a method for fault detection of PV panels in domestic applications has been presented. The method utilizes the difference between actual power and model-predicted power to detect HSF, GF, LLF, and

open-circuit fault. One disadvantage of this method is that it sometimes fails to make diagnosis decisions. In [66], a technique for monitoring PV systems at the panel level has been presented. The technique is reported to be capable of detecting temporary and permanent shadowing, dirtying, and anomalous aging. Fault detection was based on a difference between the measured efficiency of each panel and the nominal one estimated in real operating conditions. Although the technique offers a simple methodological approach, it requires multiple sensors which can result in implementational complexity and cost. Moreover, it does not offer fault localization.

In another study [17], authors proposed a power comparison-based algorithm to detect GF, LLF, HSF, and OCF. In the study, the difference between an MPPT estimated power and a meter-read power was further analyzed by a fractional-order color relation classifier to determine output degradation and fault. Simulation results indicated the suitability of the algorithm for real-time applications. Although the algorithm is effective, a failure of the MPPT will render the fault detector ineffective. In a slightly modified form, [67] proposed fractional-order dynamic error-based Fuzzy Petri Net (FPN) for fault detection in PV array. Although this FPN-based fault detection is reported to be promising for detecting LLF, OCF, GF, and mismatch fault, only lower and upper GFs cases were validated through simulation. The authors of [68] reported a method to detect and diagnose LLF and OCF based on an evaluation of three coefficients. Fault detection was based on a comparison between real measured coefficients and simulation model-predicted coefficients. The study was validated through simulations. Although this study benefits from simplicity, it can easily suffer from inappropriate threshold setting. CBT-based FDD techniques can suffer the following setbacks [3, 37]:

- (1) Simulation model errors can affect fault performance of the detection technique
- (2) Low percentage mismatch, partial shading, and low irradiance can cause false tripping
- (3) Lack of frequent model updates can affect detection performance since PV parameters change with seasonal variations

6.2. Statistical and Signal Processing-Based Techniques (SSPBTs). It has been recognized that PV system faults influence the output characteristics of the PV array, and one of such influences is distortions in the output current and voltage waveforms [16]. As a result, many papers have analyzed such output characteristics using SSPBTs to extract the features representative of specific faults. These features are then used for fault detection. This section presents reviews of papers based on SSPBT.

In recent years, many signal-processing techniques have been explored for the extraction of features for fault detection. In [69], a time domain discrete wavelet transform (DWT-) based series DC AF detector has been reported. The detection algorithm uses current change from time domain analysis and a normalized root mean square (RMS)

values from wavelet as inputs of the detector to differentiate between normal and AF conditions. The fault detector was tested at a different load current, DC source voltage, and gap length to evaluate the impact of each parameter on DC arc. Experimental results indicate that the proposed algorithm can achieve 100% detection accuracy at load current not greater than 15A. However, detection of errors was recorded at a load current of 25A with a DC source voltage at 230 V and 300 V. In a similar study based on wavelet transform and reported in [70], the authors proposed a fault detection algorithm for photovoltaic systems. However, instead of PV array faults, the study concentrated on faults in the power conditioning systems of the PV array. In [37], the authors had a preference for a wavelet packet transform (WPT) over DWT and accordingly proposed a WPT-based online PV array fault detection. The WPT was utilized to extract input features for the fault detection algorithm from PV array voltage and current data. PV array faults considered in the study were LLF and HSF. An interesting feature of this technique is its ability to detect faults under low solar irradiance conditions. The detection algorithm has many threshold values which if not set properly can impair performance. Using another signal-processing approach, the authors of [71] proposed a joint fault detection method for PV series AF, where short-time Fourier transform (STFT) and statistics were each utilized to extract the features as inputs to the detection algorithm. Just like in [68], getting a suitable threshold for the algorithm could be difficult. Studies in [3, 22] have both utilized multiresolution signal decomposition (MSD) technique to extract the features for PV array fault detection. In [3], the extracted features were fed into fuzzy inference systems (FIS) for the detection of LLF and LGF. On the other hand, in [22], the extracted features were fed into a two-stage support vector machine (SVM) for the detection and classification of LLF. In both studies, effort has been made to detect fault at low irradiance levels. The use of multiple filters in MSD can make both studies costly. In a comparative study, the authors of [72] have established that wavelet transform requires a much smaller sampling rate than Fourier transform. In general, using signal-processing techniques for feature extraction depends much on prior knowledge in signal processing and human expertise, which is time consuming. Next, features extracted based on a specific diagnosis might be unsuitable for others.

As an alternative to signal processing, a couple of studies have also utilized statistical methods. According to [15], statistical features such as mean, standard deviation, RMS value, and entropy of an input signal can be used for DC arc fault detection. In light of this, various statistical methods have been explored for PV system fault detection. In [73], a real-time statistical signal processing-based fault diagnosis technique for HSF in PV panels has been reported. The fault diagnosis technique utilizes Wald test to observe a clear signal from an arbitrary captured data. In [74], a series AF detection algorithm for PV systems has been discussed. The decision of the algorithm is based on calculating the modified Tsallis entropy of the PV panel current. In an experimental validation, the algorithm was able to detect both sustained series arcs and small sparking series arcs. The experimental

validation utilized a PV panel simulator whose behavior can be different from actual PV panels. A statistical method called exponentially weighted moving average (EWMA) has been utilized in [75] to develop a fault detection technique for PV systems. The technique first computes residuals, which capture the difference between the measured and the predicted parameters of the PV system. Then, the EWMA monitoring chart is applied to the uncorrelated residuals obtained from the PV model to detect and classify the type of fault. Measurements from a 9.54 kWp PV plant were used to validate the technique. Fault cases considered in this study were LLF, HSF, and OCF. Similar to study [75], the authors of [76] have proposed an interesting fault detection algorithm based on univariate EWMA (UEWMA) and multivariate EWMA (MEWMA) for LLFs, OCFs, HSFs, and degradation fault (DF) detection. In another study [19], a vector autoregressive- (AR-) based fault detection model has been proposed for LLFs and GFs in a grid-connected PV system. Although the study presents a novel approach, it has a high computational burden. In studies [77, 78], *t*-test statistical-based fault detection technique has been proposed for the detection of a faulty PV module, faulty string, faulty bypass diode, and faulty MPPT.

6.3. Reflectometry-Based Techniques (RBTs). Reflectometry-based fault detection has been used for fault detection in an electric power system particularly in transmission lines for a long period. Inspired by its success, some researchers have, in recent times, investigated its applicability in PV system fault detection. The working principle of time-domain reflectometry (TDR) is that a uniform impedance and properly terminated electric transmission line will have no reflections of its injected signal, so the signal will be absorbed in the termination end. Conversely, variations in line impedance will cause the incident signal to be reflected back to the source. The injected signal into the transmission line and the reflected signal caused by the impedance mismatches in the line are compared. Signal delays and the change of waveforms observed are translated into the failure position in the line and the type of failure through autocorrelation analysis. An interesting feature of a TDR method is that it does not require the measurement of parameters such as voltage, current, and temperature. Next, detection is possible in the absence of solar irradiance. Reviews of a couple of papers based on reflectometry are presented as follows.

In [79], a TDR-based technique has been investigated for detection, identification, and localization of OCF, short circuit to ground, and insulation defects. The technique was validated on a 1 MW PV plant. Although the technique is reported to have a merit of low cost, its performance can be affected by the switching devices of the inverter. In a similar study [80], a TDR-based technique has been proposed, where a PV string was considered as a transmission line on which PV modules and other devices are distributed. An observed signal response waveform from the transmission line after an injection of voltage signal was analyzed to detect fault and its location. Getting an equivalent transmission line model for a PV string could be a challenging task. Furthermore, in [81], a TDR-based technique for finding the

position of a failed PV module in an array was investigated. The objective of the authors was to develop a protection system which could be integrated into the power conditioner. Using an improved version of TDR, the authors of [82] have presented a spread-spectrum time-domain reflectometry (SSTDR) technique for the detection of both series and parallel arc faults. One distinctive difference between TDR and SSTDR is that a TDR uses an analogue signal as the injected signal, while an SSTDR uses a pseudorandom binary signal. An interesting feature of this SSTDR technique is that it does not only detect PV AF but also predicts AF. Similarly, study [83] also presented an SSTDR-based technique for ground-fault detection. The proposed technique has been validated in a real-world PV system. The advantage of this SSTDR technique is its ability to detect specific ground faults that may go unnoticed using conventional GFDI fuses. In general, RBT performances can be impaired by noise and signal attenuations.

6.4. Machine Learning-Based Techniques (MLBTs). Machine learning (ML) is a kind of data analysis which uses algorithms that learn from data via a process called training. Over the years, ML algorithms have been applied successfully in many applications in areas such as natural language processing [84], computer vision [85], and healthcare [86]. Inspired by these examples, ML applications have now been extended to PV systems fault detection and diagnosis. Figure 12 depicts a generic procedure for ML-based techniques for detection and diagnosis. The remainder of this section provides a review of PV fault detection diagnosis systems based on ML algorithms.

A two-layered artificial neural network (ANN) model along with an analytical technique for PV array FDD technique was presented in [2]. The idea is to predict the output power of the PV array using ANN model with solar irradiance and temperature as inputs. If the difference between the predicted power and the actual measured output of the PV array is greater than a given threshold, the system is considered faulty which then triggers a fault diagnosis algorithm. Simulation data was used to validate the effectiveness of the FDD technique. In [87], a three-layered feedforward ANN model was also investigated for a short-circuit fault detection and localization. Solar irradiance (E), cell temperature (T_c), maximum power point voltage (V_{mp}), and current (I_{mp}) were utilized as inputs to the model to estimate the terminal voltage of each module. The merit of this study is its ability to accurately detect the exact location of the fault. The technique has been validated using a 3×2 PV array. However, for very large PV arrays, the ANN model could have a huge computational burden. In a similar study [88], the authors have presented a Multilayer perceptron (MLP) neural network model for fault detection of partially shaded PV modules. Inputs to the model were the same as in [87]. The model was validated using a training data from a real-world PV installation. Although this technique offers a simple detection algorithm, the MLP model requires periodic training to maintain accuracy. In [89], a probabilistic neural network- (PNN-) based FDD technique model has been proposed for open- and short-circuit faults. The technique is

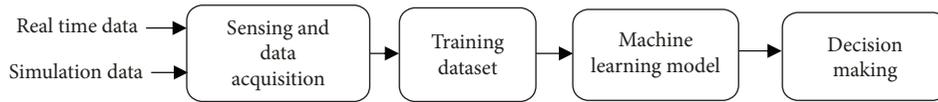


FIGURE 12: Overview of MLT detection process.

composed of two stage PNN models in which one is for detection and the other for diagnosis. The validity of the proposed FDD technique was tested using both simulation and experimental data. Recorded PNN classifier efficiency for the detection and diagnosis networks were 82.34% and 98.19%, respectively. In a comparative analysis, it was reported that the PNN model offers better classification than a traditional ANN. The feasibility of the model in real PV array has not been established. Similar to study [89], the authors of [90] have proposed a PNN model for monitoring and diagnosis of LLFs and OCFs where mean classification accuracy was reported to be 98.53%. Both studies share similar merits and demerits. Another variant of ANN called Laterally Primed Adaptive Resonance Theory (LAPART) neural network [91] has been investigated for PV fault detection and diagnosis in [92]. Although the study presents a novel model, it only classifies a PV system into healthy and faulty status without giving any clue to the fault type for the purposes of isolation, localization, and maintenance.

Another category of ML algorithms called extreme learning machine (ELM) has also been utilized in PV array fault diagnosis in recent times. In [93], a variant of the ELM called kernel extreme learning machine (KELM) was implemented for the detection and diagnosis of short-circuit fault, open-circuit fault, degradation fault, and partial shading fault. Both simulation and experimental data were utilized to validate the proposed KELM model. The merit of the model is its high detection accuracy and speed. Close to 100% detection and classification accuracies were recorded for all tested cases. A major setback of the model presented in [93] is that it relies on the features which are dependent on the PV module and as a result might not generalize well across different PV modules. In a similar study [94], a radial basis function kernel ELM model for PV array fault diagnosis was investigated, where simulated annealing algorithm was employed to optimize the parameters of the ELM. Diagnosis results of classification for normal condition, short circuit, aging, and shadow faults were reported as 99.9%, 93.64%, 90.91%, and 91.55%, respectively. As indicated in the results, the study benefits from high accuracy and short training time; however, its feasibility in real PV systems has not been validated.

To further explore other ML techniques, the authors of [95] have investigated the use of Elman neural network model for PV fault detection and diagnosis. PV array output voltage, current, inverter output voltage, DC load voltage, irradiance, and temperature were chosen as input features for the model. Open circuit, total, and partial shading faults were considered in the investigation. A data size of 1600 drawn from a 2×4 PV array simulation model was utilized for training the network. This data size is not sufficient for the model to generalize well in a real-world PV plant. In

[96], a decision tree-based fault detection and classification model was investigated for the detection and classification of LLF, shade fault, and open-circuit fault. The model was trained using data from a real-world PV system. Fault detection and classification accuracy on test data were 99.98% and 99.8%, respectively. However, it was acknowledged by the authors that the model might not perform well with unknown data. In an effort to get a better model, the authors of [13] also presented three statistic outlier detection rules for PV array fault detection. Specifically, 3-sigma rule, Hampel identifier, and Boxplot rule were investigated for the detection of LLFs, OCFs, degradation faults, and partial shading. The 3-sigma rule emerged as the best of the three rules. A major setback of these statistic outlier detection rules is that they at times signal false alarms. To address this problem, the authors of [97] suggested a local outlier factor (LOF) for fault detection. The authors have reported that the LOF does not give false fault alarm signals.

So far, all MLBTs reviewed learn via supervised learning, which means they are trained on labeled data. Acquiring training data can be time consuming and costly. To move away from the use of a much labeled training data, a graph-based semisupervised learning model for PV array fault detection and classification was proposed in [98]. Semisupervised learning models require few labeled data samples and many unlabelled data samples for training. Experimental results for both LLF and OCF yielded detection and classification accuracy of 100%. Again, the model has the ability to detect blind-spot faults that could come from low irradiance levels.

6.5. Other Techniques (OTs). This subsection expands the review of the advanced FDD techniques to include studies that have been reported in literature but do not fall into any of the categories already discussed. In [31], a hot-spot detection technique for solar panel substrings based on AC parameter characterization has been presented. In this technique, mismatch is detected using AC impedance of the panel. The AC impedance is usually detected at a frequency ranging from 10–70 kHz. The feasibility of the technique has been validated for a typical subpanel string lengths of Si PV cells. Conduction losses of inverter switches and implementation complexity are the drawbacks of this method. Contrary to [27, 31] that has presented a technique for detecting permanent partial shading in PV panels based on equivalent DC impedance of the panel. After detection, the shaded panel is open circuited via a simple relay. The merit of the technique is its ability to confirm permanent partial detection using Thevenin impedance, which is calculated from the open-circuit voltage and short-circuit current of the panel. These measurements can negatively influence the operations of the MPPT. Neurofuzzy (NF) models are fuzzy models

designed from neural networks and fuzzy logic [99]. Therefore, it has the advantage of a learning ability of neural networks and a logical ability of fuzzy logic. In [100], a multi-class adaptive neurofuzzy classifier (MC-NFC) has been developed for PV array fault detection and classification. An experiment data was collected for the training and validation of the model. It was reported that the proposed model can discriminate among five PV array faults. Although the model has the ability to detect multiple faults, it could suffer from implementational complexity. Using MC-NFC, [101] proposed a classifier for PV array faults diagnosis. Partial shading, increased series resistance, and short-circuit faults were considered. The proposed classifier was implemented in a DS1104 platform to validate its ability to detect and classify faults in real time. Like [100], correlation coefficient and root mean square were utilized as metrics to measure performance. In general, it is difficult formulating suitable rules for fuzzy inference systems. In [102], SVM was combined with a k-nearest neighbour (k-NN) for short-circuit fault detection in a PV generator. The SVM was deployed as classifier whilst the k-NN was utilized for optimization. The proposed hybrid algorithm was tested using a PV generator database. Classification accuracies recorded for various test cases were between 68 and 75.8%, which may be considered low in the context of fault management.

7. Performance Evaluation and Comparison of Advanced FDD Techniques

In order to evaluate the performance and to compare the various advanced FDD techniques for PV arrays, this paper has proposed a single evaluation metric referred to as Fault Management Score (FM score). This metric seeks to measure an FDD technique's capability to manage the four major PV array faults. To avoid biases as much as possible, some performance evaluation criteria are needed. As a result, FDD technique screening criterion, evaluation criteria, and a scoring scheme were followed in the evaluation. Details of these criteria are presented below. The authors of this paper hope that this assessment will not only help researchers to see where attention should be focused but also help PV practitioners in their choice of FDD technique.

7.1. FDD Technique Screening Criterion. This criterion considers the legibility of a research paper, reporting of an FDD technique, for inclusion in the performance evaluation. During this study, it was noticed that many FDD techniques have been published. While some of the techniques solely concentrate on one PV array fault, others consider multiple PV array faults and, in some cases, inverter and MPPT faults. Hence, it was not feasible to evaluate most of the FDD techniques against any specific fault, say LLF. To overcome this challenge, FDD techniques were evaluated in consideration of four major PV array faults, namely, LLF, GF, AF, and HSF. Hence, the requirement was that a study included in the performance evaluation should address at least one of the four major faults. In total, forty (40) papers were screened for the performance evaluation and comparison.

7.2. Evaluation Criteria. This paper evaluates FDD techniques based on four criteria, which are important functionalities required of an FMS for a PV array fault. Details of each criterion are as follows:

7.2.1. Criterion 1: Fault Detection and Classification Capability. This criterion measures the capability of an FDD technique to detect and classify (diagnose) faults. Fault detection and classification are very important steps in the management of PV array faults, so they are the basic requirements in any FDD technique. A fault will remain hidden forever if it goes undetected with its attendant consequence.

7.2.2. Criterion 2: Real-Time Detection. This criterion measures the capability of an FDD technique to detect fault existence in the actual time during which the fault occurs. Generally, in electrical installations, fault current rapidly propagates to the healthy sections which can result in further damages. Therefore, it is important to consider the real-time detection ability in the performance evaluation of FDD techniques.

7.2.3. Criterion 3: Fault Localization. This criterion measures the capability of the FDD technique to locate the faulty component of the array. Localization serves two important purposes. First, it helps to isolate only the affected PV module or string. In the absence of localization, the common practice has been to isolate the entire PV array upon the detection of a fault, which does not augur well for the reliability of power supply. Next, localization saves time and labour which otherwise would have gone into fault tracing by the maintenance team.

7.2.4. Criterion 4: Fault Isolation. Another important functionality required of any FMS is isolation. The role of this functionality is to isolate and impede fault propagation. The decision to isolate should be triggered by the information obtained after detection and classification. Criterion 4, therefore, seeks to determine an FDD technique's ability to generate a useful signal to trigger isolation.

7.3. Scoring Scheme. Based on the four evaluation criteria, a score is assigned for each FDD technique evaluated. Criterion 2, 3, and 4 were each assigned a maximum score of one, while criterion 1 was assigned a maximum score of four. An FDD technique that fully satisfies all criteria scores a total of seven points. Total raw score for a given FDD technique is an unweighted sum of the individual scores obtained with respect to each criterion. Total raw scores are converted into percentages as FM scores for individual FDD techniques.

The scoring details for the proposed criteria are as follows. For criterion 1, a technique capable of detecting and classifying a fault into one of the four fault types scores one point. For instance, a technique capable of detecting and classifying LLF scores one point. Accordingly, a technique capable of detecting and classifying all the four PV array fault scores a maximum of four points. A technique capable of detecting a fault but unable to reveal the identity of a fault through its classification receives a score of one-half. Such techniques usually render an output status of either healthy

or faulty without any hint of the possible fault type. For criterion 2, an FDD technique capable of real-time fault detection scores one, otherwise, a score of zero is assigned. An FDD technique capable of localizing fault is given a score of one and zero for otherwise with respect to criterion 3. For criterion 4, an FDD technique with the ability to trigger isolation scores one point and a zero for otherwise.

7.4. Result and Discussion of Performance Evaluation of FDD Techniques. Table 1 presents the results of a performance evaluation of forty (40) advanced FDD techniques. From the table, under criterion 1, the maximum score recorded was three out of a possible four as none of the FDD techniques examined fully satisfied the criterion. This means that there is no single FDD technique capable of detecting and diagnosing all four fault cases considered in this review. For criteria 2 and 4, it was noticed that all FDD techniques successfully passed. This underscores the importance of such functionalities in a PV array FDD techniques. In contrast, it was noticed that most FDD techniques do not have the ability to localize fault as can be seen under criterion 3. Overall, only 12.5 percent of all techniques considered had the capability localize faults. A possible reason for this trend might be that researchers in this area assume that PV array installations are still at a level which permits manual fault tracing or that there are presently no effective techniques for doing so. However, as PV power plant size continues to grow, localization will be much more important. One FDD technique from the CBT category emerged as an overall best technique for managing the four PV array faults considered in this paper.

7.5. Limitations of Performance Evaluation. Although the performance evaluation conducted in this paper is based on important criteria drawn from a fault management perspective, the authors wish to admit certain limitations. First, it is required of any effective FDD technique to have the capability to deal with multiple PV array faults in a highly accurate manner. The performance evaluation did not take the accuracy of the individual FDD techniques into account because some of the papers reviewed in this study did not report detection and classification accuracy. Thus, a technique reported to be more capable of managing the four major faults might not necessarily be accurate. Next, it was noticed that in some FDD techniques, efforts have been made to detect blind spot faults; however, our scoring system did not take this into account because blind-spot fault does not apply to all the four major faults considered.

8. PV Array Fault Management Future Trends and Recommendations

From the collection of studies reviewed in this paper, PV array fault management future trends and recommendations emanate as follows.

- (i) Climate change concerns and dwindling fossil resources will continue to drive the demand for solar PV energy. As a result of this, installation of many large stand-alone and grid-connected PV power

plants will be witnessed globally. For large PV power plants, an important requirement in its fault management is fault localization. Fault localization helps to isolate only the faulty section of the PV plant, which ensures the reliability of power supply and speedy repairs or replacement of affected components. As it has already been demonstrated in this review, most of the PV array FDD techniques do not offer localization. In the coming years, PV array fault detection and diagnosis research will focus more on localization. Machine learning techniques and TDR techniques are very promising areas to explore

- (ii) In the context of fault isolation, an intelligent and fast protection scheme is important for solar PV power systems. The design of fast operation and low-loss switches can enhance the performance of fault isolation schemes [54]. A DC isolation (interruption) based on solid-state devices is very promising. Some research efforts have been dedicated to the realization of such devices in the context of DC microgrids, but not much is seen for PV array fault isolation. Hence, research is needed in this regard
- (iii) In the reviews, it was observed that ML-based fault detection and diagnosis-based techniques have attracted a significant research attention, and it is expected to continue in the coming years. In general, the performance of an ML algorithm largely depends on the quality of the training data it trains with. Again, in the review, it was noticed that input features fed into the ML algorithms, particularly ANNs, were raw sensor-acquired data such as temperature, irradiance, MPP voltage, and current. During training, the ML algorithm learns its own unique features for detection and classification in its hidden layers. To do so effectively, the ML models should have more hidden layers. However, deep NNs have a problem of computational complexity. To reduce this burden, convolutional neural networks (CNNs) and Long Short-Term Memory (LSTM) networks should be considered. This computational complexity reduction is due to the ability of CNN and LSTM networks to share parameters. Moreover, these networks are capable of automatically mining good features from raw datasets. To use such networks, it is required that such sensor-acquired data should be captured as a sequence data. LSTMs can be fed with such sequence data; however, because CNNs work on images, such sequences must be fused together in a process called data fusion in order to form a 2D matrix
- (iv) In real-world applications, monitoring of PV power system installations for control, fault detection, and diagnosis is generally executed from remote locations due to the harsh environmental conditions in which they are installed. Such remote monitoring requires

TABLE 1: Performance evaluation results for the FDD techniques.

Study reference	Approach	Fault detection & classification capability	Evaluation Criteria			Total raw score	Evaluation metric FM score (%)
			Real-time detection	Fault localization	Fault isolation		
[58]	CBT	0.5	1	0	1	2.5	35.71
[59]	CBT	1	1	1	1	4	57.14
[60]	CBT	1	1	0	1	3	42.86
[63]	CBT	1	1	0	1	3	42.86
[64]	CBT	2	1	0	1	4	57.14
[65]	CBT	2	1	0	1	4	57.14
[66]	CBT	1	1	0	1	3	42.86
[17]	CBT	3	1	0	1	5	71.43
[67]	CBT	1	1	0	0	3	42.86
[68]	CBT	1	1	0	1	3	42.86
[69]	SSPBT	1	1	0	1	3	42.86
[71]	SSPBT	1	1	0	1	3	42.86
[37]	SSPBT	0.5	1	0	1	2.5	35.71
[3]	SSPBT	2	1	0	1	4	57.14
[22]	SSPBT	1	1	0	1	3	42.86
[73]	SSPBT	1	1	0	1	3	42.86
[74]	SSPBT	1	1	0	1	3	42.86
[75]	SSPBT	2	1	0	1	4	57.14
[19]	SSPBT	2	1	0	1	4	57.14
[76]	SSPBT	2	1	0	1	4	57.14
[79]	RBT	1	1	1	1	4	57.14
[82]	RBT	1	1	1	1	4	57.14
[83]	RBT	1	1	0	1	3	42.86
[81]	RBT	1	1	1	1	4	57.14
[87]	MLBT	1	1	1	1	4	57.14
[88]	MLBT	1	1	0	1	3	42.86
[2]	MLBT	2	1	0	1	4	57.14
[93]	MLBT	2	1	0	1	4	57.14
[89]	MLBT	1	1	0	1	3	42.86
[94]	MLBT	2	1	0	1	4	57.14
[95]	MLBT	1	1	0	1	3	42.86
[96]	MLBT	2	1	0	1	4	57.14
[13]	MLBT	2	1	0	1	4	57.14
[97]	MLBT	1	1	0	1	3	42.86
[98]	MLBT	1	1	0	1	3	42.86
[31]	OT	1	1	0	1	3	42.86
[27]	OT	1	1	0	1	3	42.86
[100]	OT	2	1	0	1	4	57.14
[101]	OT	2	1	0	1	4	57.14
[102]	OT	1	1	0	1	3	42.86

a reliable communication medium between plant and monitoring station. Over the years, cable wiring has been used to exchange information between power plants and monitoring stations. For long distances, attenuation and delay in signal propagation can prevent real-time monitoring. Recently, Internet of

Things (IoT) [103], which is an information-sharing environment where objects in everyday life are connected to wired and wireless networks, has been introduced. In the coming years, fault detection and diagnosis techniques should incorporate IoT for remote monitoring and sensing of data

- (v) It was observed in the review that no single fault detection and diagnosis has the capability to detect and diagnose all the four fault cases considered in this paper. Towards a goal of developing an all-in-one fault detection and diagnosis models, future research is expected to give much attention to hybrid techniques, where two or more techniques will be combined to develop a more comprehensive FDD technique

9. Conclusion

This paper has presented a review on four major PV array fault types along with their detection and diagnosis techniques. Specifically, GF, LLF, AF, and HSF have been discussed. In each case, fault description/definition and possible causes have been presented, followed by a review of conventional protection techniques available for fault detection and classification along with their limitations. Besides, a review of advanced FDD techniques has also been presented. Moreover, performance evaluation of these advanced techniques has been conducted to guide PV system operators in their choice of FDD techniques. Finally, in consideration of the papers reviewed, future trends of PV array fault management systems have been identified along with recommendations. It is hoped that this review can help develop essential guidelines for the design of future PV array FDD techniques.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

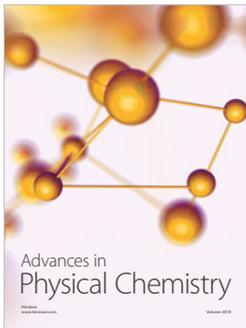
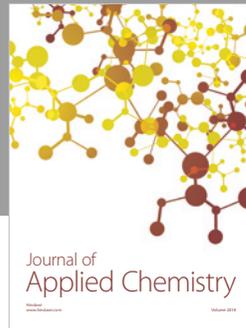
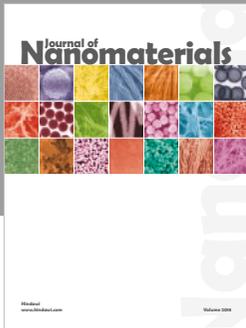
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