J. Electrical Systems 20-11s (2024): 4135-4144

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Analysing Fault Detection Mechanisms In Photovoltaic Systems: A Review Of Current Technologies

Journal of Electrical Systems

Abstract—when failures in the components of a photovoltaic (PV) system, such as the PV module, controller, inverter, load, or cables, go undetected or unaddressed, they can severely compromise the overall efficiency, safety, and reliability of the PV power plant. Furthermore, unresolved faults like arc, ground, and line-to-line issues can potentially lead to fires. Therefore, diagnosing faults in PV systems (PVS) is essential to ensuring the reliability, safety, and efficiency of these power plants. Numerous diagnostic techniques and methods have been developed to address component failures in PVS. As PV technology continues to advance, increasingly sophisticated and intelligent diagnostic methods are being researched and introduced. However, there is still an urgent need for a comprehensive, systematic review, analysis, and conclusion. This paper discusses the types, causes, and consequences of PVS faults and examines the diagnostic methods presented in existing research, with particular focus on PV array failures. The paper also highlights the need to optimize different diagnostic methods according to various priorities, considering their limitations, feasibility, complexity, and cost-effectiveness. Lastly, the paper identifies challenges and offers recommendations for future research.

Keywords—*PVS, monitoring system, PV fault types, PV diagnosis, review.*

I.Introduction

In today's world, the on-going consumption of global fossil resources and the environmental risks posed by their use have become significant challenges to human existence. As a result, renewable energy has emerged as a promising solution to manage the energy crisis. Among renewable energy sources, photovoltaic (PV) power generation stands out as one of the most important. Figure 1 shows the most recent global annual PV installed capacity from 2015 to 2024.

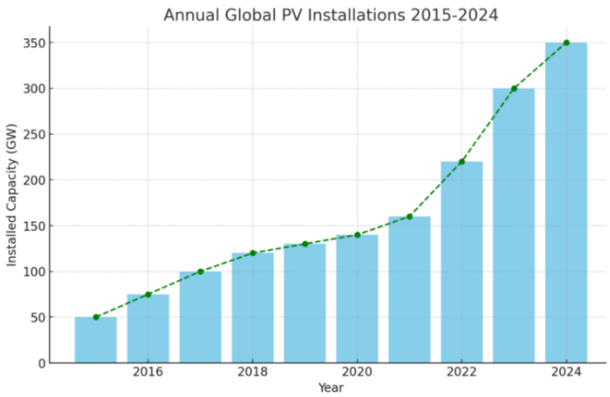

Fig.1.Global PV installed capacity from 2015 to 2024

Renewable energy sources, such as solar energy, are relatively inexpensive and inexhaustible, but the main challenge lies in overcoming the technological barriers and costs related to the development and utilization of these resources. To increase the efficiency and cost-effectiveness of PV power generation, researchers have devised numerous strategies, including enhancing the materials used in PV modules to improve their conversion rates. From the first generation of silicon-based PV modules to the second generation of multi-component film modules and now the third generation of new material PV modules, research has made significant advancements in boosting their efficiency.

Additionally, identifying faults in PV systems (PVS) quickly and performing appropriate diagnosis and repairs can help minimize energy and economic losses[1]. While various faults can occur in PV arrays (PVA), such as line-to-line faults (LLF), ground faults (GF), and arc faults (AF), hot spot faults (HSF) are also a critical concern. If not detected promptly, an HSF can cause permanent damage to PV cells. Moreover, if faults like LLF, AF, HSF, and GF are not resolved quickly, they could lead to dangerous fires. Efforts have been made to mitigate this risk, and fire prevention methods have been developed. For example, one study implemented an early fire warning system for PV power stations using an end-cloud architecture and imaging techniques. It is essential to distinguish between PV fault diagnosis and PV fault detection. Diagnosis involves determining the type and location of the fault, while detection verifies the presence of a fault based on differences between measured and expected data. One study examined the mechanism and characteristics of DC arc faults and provided an overview of detection and location methods for DC arc faults in PV systems. Another comprehensive

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study analysed the causes and effects of four major faults (LLF, GF, AF, HSF) and their corresponding traditional and advanced fault diagnosis technologies. PVA fault diagnosis is explained using both conventional diagnostic methods and intelligent algorithms. The latter is categorized not by fault type but rather by the diagnosis method. This paper reviews various electrical methods used to diagnose faults in PVS and briefly introduces non-electrical methods. Eight fault diagnosis methods are divided into four categories, and their practical applications, diagnostic accuracy, diversity, complexity, advantages, and disadvantages are thoroughly compared and analysed[2]. The paper mainly focuses on the components of PVS and the causes and impacts of seven significant faults: PV module, inverter, junction box, by-pass diode faults, GF, LLF, and AF. Additionally, it provides recommendations for future advancements in PV fault diagnosis technology. The structure of this paper is as follows: Section II presents a detailed overview of PVS fault diagnosis methods, and Section III explores the potential faults that may occur on the DC and AC sides of PVS. Section IV reviews and discusses fault diagnosis methods proposed for PVS, while Section V summarizes various PV fault diagnosis technologies. Lastly, Section VI outlines challenges, offers recommendations, and discusses future trends in PV fault diagnosis technology.

II. Review Screening Methods

This paper adopts a methodical research approach to deliver a thorough analysis of PVS fault diagnosis techniques, examining diagnostic technologies, their performance benefits, and diagnostic directions. The exhaustive literature review was guided by four key terms: PVS, monitoring system, PV fault types, and PV diagnosis. The review was conducted using three major search engines. References related to junction box and by-pass diode faults, ground faults (GF), line-line faults (LLF), and arc faults (AF) were carefully selected. Additionally, the paper offers recommendations for the advancement of PV fault diagnosis technology. A total of 103 articles were chosen based on citation counts and journal impact factors. To provide clarity on the reference review and selection process, a detailed diagram is presented in Fig. 2, offering a comprehensive overview of the review methodology. Furthermore, statistical data regarding research in this domain from the past seven years (2016–February 2023) were gathered from platforms such as Science Direct, Web of Science, and Google Scholar.

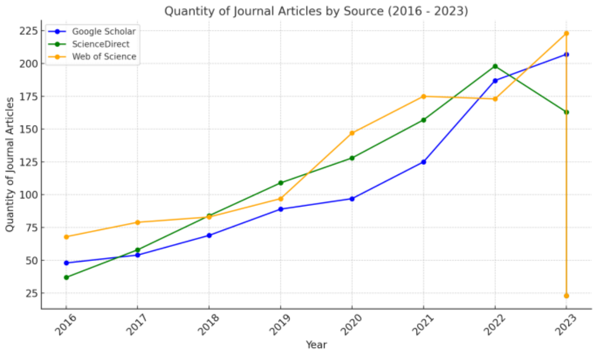

Fig.2 Research statistics on related references.

III. Types of Faults

Photovoltaic systems (PVS) can be categorized into three main configurations: standalone, grid-connected, and distributed PV power generation systems[3]. These systems consist of various components such as PV modules, controllers, inverters, loads, and cables. The PV modules generate electricity, which is then directed to the controller and distributed either to the load or the battery, depending on the system setup. The method of transmission varies—for instance, direct current (DC) can be supplied directly to DC loads, while an inverter is used to convert DC to alternating current (AC) for AC loads. In cases where local energy demand is low, surplus power can be stored in a battery for use during periods of reduced PV generation. A diagram illustrating this process is presented in Fig. 3.

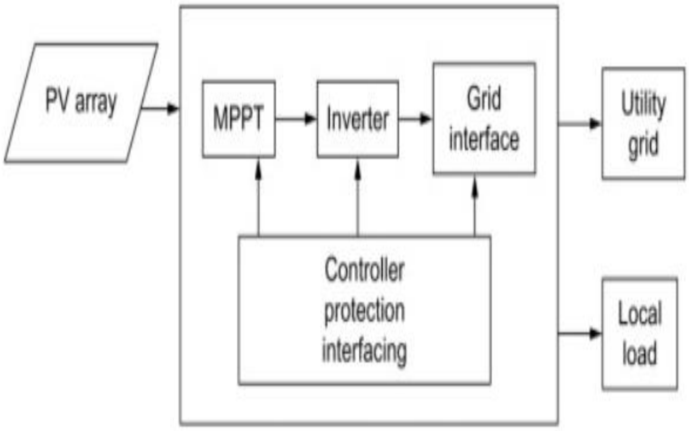

Fig.3.Photovoltaic system

However, PVS are susceptible to faults, which can severely affect their efficiency and power quality, sometimes even leading to fires. Faults within PV modules can be either permanent or temporary. Permanent faults include issues such as ethylene-vinyl acetate (EVA) discoloration, delamination, hot spots, potential-induced degradation (PID), and light-induced degradation (LID). In contrast, temporary faults generally result from external factors like shading or soiling, and they can often be resolved by simply removing the obstruction. Moreover, the diverse nature of faults in PVS can make diagnosing them a complex task. Fig. 4 illustrates examples of common PVS failures

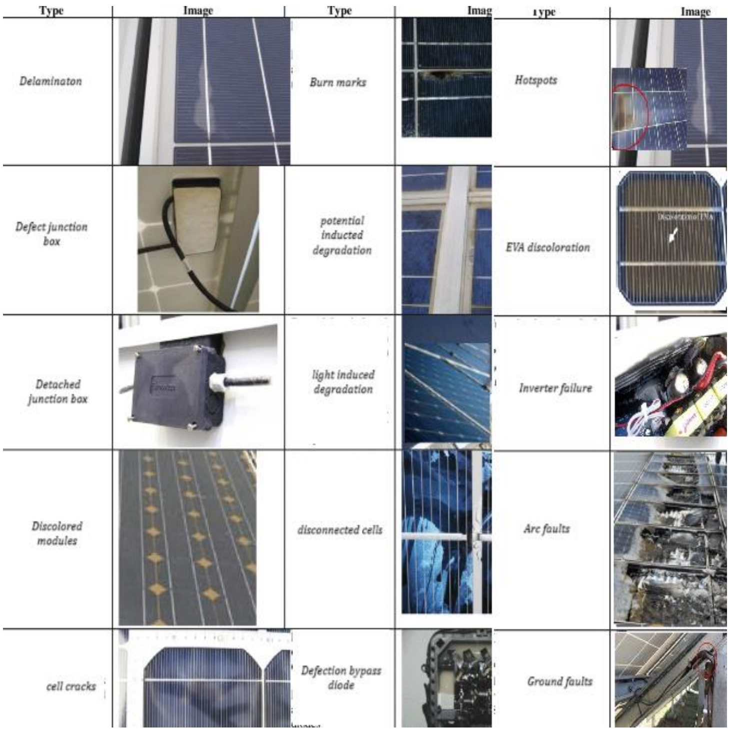

Fig.4.PVS failures.

EVA Discoloration

EVA (ethylene-vinyl acetate) discoloration in PV modules is primarily caused by high temperatures, high humidity, and an unstable additive formula used in the manufacturing process. This leads to several issues, such as a shorter lifespan for the PV modules, reduced efficiency, and the stratification of materials. The discoloration accelerates the degradation of PV modules, and unfortunately, the damage caused by this issue is permanent and cannot be reversed.

Delamination

Delamination occurs when there are foreign objects on the surface of materials like EVA, glass, or backplanes. Additionally, a small flux combined with prolonged exposure to high temperatures can trigger delamination. The composition of EVA (such as ethylene and vinyl acetate) may also lead to insolubility at room temperature, causing delamination. Low film application temperature or short film application time can further aggravate the issue. Small areas of delamination may affect the performance of high-power battery modules, while large areas of delamination can lead to complete failure, resulting in the scrapping of the entire module. The losses caused by delamination are permanent and irreversible.

Hot Spots(HS)
Hot spots in PV modules are often caused by the mixing of defective batteries, virtual welding of the electrode solder lug, or the evolution of cracks into breaks. Additionally, shadows that partially obscure the battery can lead to the formation of hot spots. Hot spots reduce the output power of PV modules and shorten their lifespan. If not addressed, they can burn components and even cause fires. Many types of occlusions that cause hot spots can be reversed, though some may lead to permanent damage.

Potential-Induced Degradation(PID)
PID is caused by environmental factors like humidity or contamination on the module surface with conductive, acidic, alkaline, or ionic substances. This results in the attenuation of the module's power due to the generation of leakage currents, which ultimately shortens the lifespan of the PV modules. However, this fault can be repaired by adding a PID repair device in parallel with the inverter's DC input.

Light-Induced Degradation(LID)
LID is another degradation process that affects PV modules, typically due to impurities and defects within the battery cells. High-temperature environments exacerbate this phenomenon. LID causes a reduction in the power output of the PV modules and shortens their operational life. Fortunately, LID can be repaired within a certain time frame, although it still poses a significant challenge to the longevity of PV modules.

Shading and Soiling
Shading and soiling, such as gas buildup, dust, or other obstructions, can significantly reduce the efficiency of PV modules. These blockages may also lead to the development of hot spots, further compromising the module's performance. However, this type of fault is considered temporary and can be resolved by removing the obstruction to restore the module's normal operation.

Inverter Failure Modes
Inverter failures can occur due to a variety of reasons, including over-voltage, over-current, and over-temperature. Harmonic current and high temperatures, as well as rapid charging and discharging cycles, can also contribute to inverter failures. Additionally, the failure of the fan’s power supply or foreign objects entering the fan can cause significant energy loss in the PV system. Depending on where the failure occurs, inverters may experience recoverable or non-recoverable failures.

Bypass Diode Failures
Bypass diodes in PV modules can fail due to excessively high reverse voltage, or when the junction temperature exceeds its range. This failure can lead to abnormal appearances, such as the peeling of packaging materials or the melting of backplanes. It may also cause deformation or melting of the junction box, which poses a fire hazard. Thermal breakdown in the bypass diode can be recovered, but electrical breakdown is irreversible.

Junction Box Failures
Junction box failures in PV modules often stem from poor welding and sealing processes during component assembly. These failures can also be triggered by shadow occlusion, cracks, or lightning strikes. As a result, the efficiency and reliability of the PV system are compromised, and the system becomes vulnerable to damage and fire. In such cases, the junction box must be disassembled and repaired to restore functionality.

Ground Faults
Ground faults occur when the insulation of cables is damaged, often due to aging, corrosion, or animal bites. These faults can also arise within the PV module itself, resulting in an unexpected short circuit between a conductor and the ground. Ground faults can cause the power supply switch to burn out, lead to inverter failure, and may result in fires. Ground faults are divided into recoverable and non-recoverable categories; recoverable faults are usually automatically eliminated by the system.

Line-Line Faults
Line-line faults occur when the insulation of cables is compromised, either due to aging, corrosion, or damage from animals. These faults reduce the overall efficiency and reliability of the PV system and can cause significant damage, including fires. While line-line faults are recoverable, the recovery process takes time.

Arc Faults
Arc faults are caused by loose terminal blocks or the aging and rupture of insulation on wiring. Arc faults can lead to dangerous fires. Although the system can recover from such faults, the process takes time, and the potential damage from fires can be severe if not addressed quickly.

IV. FAULT DIAGNOSIS METHODS

Various methods exist for diagnosing faults in photovoltaic (PV) systems, each based on distinct principles. This section primarily focuses on electrical methods for fault diagnosis in PV systems (PVS). Conventional electrical approaches can be categorized into four main types:
Statistical and Signal Processing Approaches (SSPA)
I-V Characteristic Analysis (IVCA)
Artificial Intelligence Technology (AIT)
Circuit Structure Method (CSM)

A. Statistical Signal and Processing

The core of Statistical Signal and Processing Approaches (SSPA) lies in the analysis of waveform signals. Three prominent methods in this category include Time Domain Reflectometry (TDR), Earth Capacitance Measurement (ECM), and Spread Spectrum Time Domain Reflectometry (SSTDR), illustrated in Figure 5.

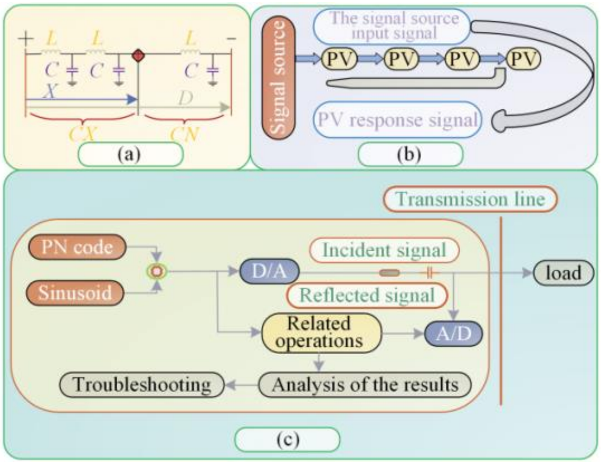

Fig. 5. Three SSPA models. (a) ECM model diagram. (b) Time domain reflectometry model. (c) SSTDR model diagram.

Earth Capacitance Measurement (ECM) is particularly effective for identifying disconnection points along transmission lines, which can be modelled as distributed parameter circuits. When a fault occurs, ECM utilizes the ratio of the grounding capacitance at the fault point (CXC_XCX) to the total capacitance of the line (CDC_DCD) to compute the distance (XXX) from the starting point to the fault, as depicted in Figure 5(a).

Time Domain Reflectometry (TDR) functions on the principle that any change in impedance along a transmission path will reflect a portion of the transmitted signal back. By measuring the voltage of the reflected wave, TDR calculates impedance changes. The time interval between the reflection point and the signal output point provides the location of the impedance change within the transmission path.

Spread Spectrum Time Domain Reflec tometry (SSTDR) enhances this process by generating a pseudo-random sequence through a signal generator. This sequence is modulated to achieve spread spectrum characteristics and transmitted as a test signal. When the signal encounters a fault, an impedance mismatch occurs, reflecting the signal back to the sending end. By correlating this reflected signal with a local reference, the delay can be determined through peak detection, allowing for the calculation of the distance to the fault.TDR and ECM have been extensively reviewed in literature, and both methods have been tested for locating faults in PV module strings in outdoor settings. Notably, ECM is effective for detecting series module disconnections, independent of variations in irradiance, while TDR is useful for periodic inspections to identify system degradation [4]. Previous studies have highlighted TDR's capability to detect and locate common fault conditions such as circuit interruptions and insulation defects. The complexity of testing PVS with reflectometry has increased due to the incorporation of communication signals for rapid shutdown, which may interfere with TDR signals. In this context, SSTDR presents an alternative that does not depend on the amplitude of the fault current. Unlike TDR, SSTDR focuses on the impedance changes due to ground faults in PVS, making it more resilient to noise and effective even in the absence of solar radiation. Recent research indicates that SSTDR can predict potential arc faults by monitoring impedance changes without considering the inverter's operational state. SSTDR can also assess the aging or degradation of MOSFETs in live PV inverters, allowing for the detection of issues related to power semiconductor devices without disrupting normal circuit operation. Furthermore, a method proposed for fault location diagnosis using SSTDR correlates incident and reflected signals to ascertain the distance to the fault. Investigations into SSTDR's application for detecting disconnections in extensive PV strings highlight the importance of parameters such as resolution, frequency, and attenuation[5]. Proper adjustment of these factors can enable accurate identification of faults. Additionally, SSTDR has been evaluated for its effectiveness in locating damaged PV cells and modules, revealing that bus damage becomes evident only when an inter-cell bus bar is completely severed. However, despite its effectiveness, studies have pointed out limitations of SSTDR in diagnosing faults in multiple PVS. Notably, its performance is influenced by environmental conditions like temperature and humidity. The precision of SSTDR in fault detection is significantly affected by the baseline count, prompting the development of methods to determine the necessary number of baselines for accurate detection under various climatic conditions.

B. I-V Characteristic Analysis

The I-V Characteristic Analysis (IVCA) method leverages the unique output curve characteristics of photovoltaic (PV) modules to analyse and identify faults based on indicators such as voltage, current, and maximum power point. These indicators can vary significantly based on location and environmental conditions. The I-V curve during a fault condition is illustrated in Figure 6.Traditionally, the acquisition of the I-V curve has relied on handheld tools, but technological advancements have introduced alternative methods. These include portable systems utilizing capacitive load tracking to analyse the I-V curve of PV strings, as well as deep learning applications for automatic tracking.

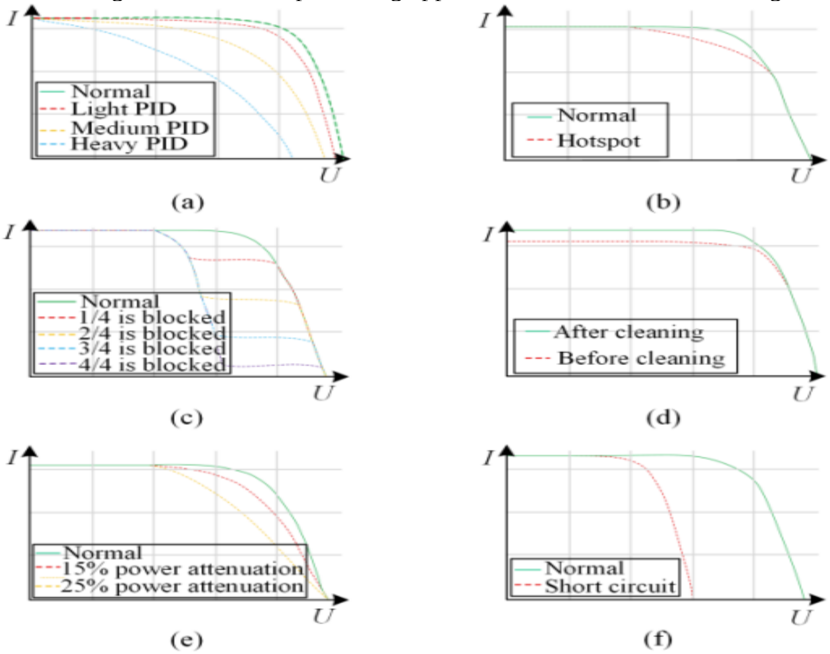

Fig. 6. I-V curve in a fault condition. (a) PID fault I-V curve characteristics. (b) Hotspot fault I-V curve characteristics. (c) Masking fault I-V curve characteristics. (d) Pollution fault I-V curve characteristics. (e) Aging fault I-V curve characteristics. (f) Bypass diode short circuit fault I-V curve characteristics.

Fault Conditions Illustrated in I-V Curves

The variations in I-V curves under different fault conditions are characterized as follows:

PID Fault Shows specific I-V curve characteristics associated with potential-induced degradation. Hotspot Fault Indicates localized overheating, affecting performance. Masking Fault Results from obstructions or shading, impacting output. Pollution Fault Reflects performance degradation due to dirt or other contaminants. Aging Fault: Represents degradation over time due to wear and environmental factors. Bypass Diode Short Circuit Fault Displays characteristics related to short circuits within bypass diodes.

Research has explored the relationship between I-V characteristics and various fault factors, including the effects of irradiance and shadow coverage on these characteristics. For instance, one study introduces an efficient prediction model that can forecast the I-V curve of PV modules at any given irradiance and temperature, addressing uncertainties caused by environmental variations. This model employs a long short-term memory (LSTM) architecture to predict solar radiation and temperature conditions impacting PV module performance. Another approach investigates an online methodology for diagnosing cracks in PV modules through the analysis of I-V curves. This method capitalizes on the inconsistent reverse bias characteristics of pyrolysis PV modules, utilizing derivative techniques for fault diagnosis. A rapid diagnostic method has also been proposed, which involves comparing I-V curves obtained from component optimizers with analysed curves to identify hotspots in PV modules. Further advancements include an online diagnostic technique focused on current mismatch faults in PV strings, which utilizes the I-V curve to quickly and accurately detect inflection points and step characteristics that occur during mismatch scenarios. Given that potential-induced degradation (PID) can mimic other fault characteristics, existing diagnostic methods for PID can be complex and time-consuming. One study assesses the severity of PID faults by detecting open-circuit voltages at varying irradiation intensities. Another method integrates multiple fault diagnosis techniques into a step diagnosis approach. This method obtains open-circuit voltages at high and low irradiances, denoted as V_{oc1} and V_{oc2} .If the condition $\frac{V_{oc1}}{V_{oc2}} \geq 1.1$ is met, it indicates the presence of PID. In the absence of a step, an aging threshold is used to determine if an aging failure has occurred. A novel technique has been developed for estimating PV module degradation by extracting the I-V curve under specific conditions prior to inverter activation allowing for uninterrupted operation without additional circuitry or data requirements. Empirical studies show that variations in I−V curve can effectively diagnose degradation within PV systems, as abnormal sub arrays demonstrate significant variance compared to normal arrays, regardless of weather influences. Finally, a hybrid diagnostic model combining artificial bee colony optimization and semi-supervised extreme learning machines (ABC-SSELM) has been proposed. This model accounts for dust impacts and requires minimal labelled data while maintaining high diagnostic accuracy.

Neural Network Methods (NNM)

Neural Network Methods have been extensively studied for fault diagnosis in photovoltaic systems. Research by [6] demonstrated the application of Back Propagation (BP) Neural Networks in detecting faults based on operational data from PV arrays. Their findings indicate that BP networks can achieve high accuracy in real-time monitoring, especially when enhanced with dropout techniques to prevent overfitting.

RBF Neural Networks have also gained traction, particularly for their efficiency in handling non-linear problems. Recent work by [7] focused on the integration of RBF with evolutionary algorithms, which optimized the network structure and parameters. This study reported significant reductions in environmental impacts due to improved system performance under variable weather conditions.Long Short-Term Memory (LSTM) networks have emerged as powerful tools for fault prediction and detection over time. [8] explored the use of LSTM networks in conjunction with external environmental variables, demonstrating their effectiveness in predicting failures before they occur. This proactive approach to fault management is crucial in minimizing downtime and maintenance costs. Additionally, recent advancements in **1**.**Probabilistic Neural Networks (PNN)** show their potential in reducing sample sizes required for accurate predictions. A study by [9] highlighted the use of PNNs to handle datasets with imbalanced fault conditions, enhancing detection rates for less common faults.

2. Support Vector Machine Methods (SVM)

Support Vector Machine Methods have shown significant promise in fault diagnosis, with research indicating their robustness in various applications. The hybridization of SVM with other machine learning techniques has been a prominent area of study. [10] presented a KNN-SVM model that improves classification rates through enhanced distance metrics, providing better accuracy in distinguishing between normal and faulty operational data. Genetic Algorithm-Optimized SVM (GA-VCM) methods have also been explored for parameter optimization. [11] utilized a genetic algorithm to fine-tune SVM parameters, reporting improved diagnostic performance compared to traditional SVM methods. This optimization strategy not only enhanced detection rates but also reduced computational time. Moreover, advancements in **Particle Swarm Optimization-SVM (PSO-VCM)** have shown the potential for adaptive learning. Research by [12] demonstrated the use of PSO to dynamically adjust core parameters based on real-time data, resulting in a more responsive fault diagnosis system capable of adapting to changing environmental conditions.

3.Fuzzy Control Algorithm Methods (FCAM)

Fuzzy Control Algorithm Methods have become increasingly relevant for managing uncertainty in fault diagnosis. The application of **Fuzzy C-Means (FCM)** has been widely investigated, with recent studies focusing on adaptive clustering techniques. **[13]** proposed a novel FM-FCM approach that integrates machine learning to improve the calculation of membership degrees, significantly enhancing fault classification accuracy.The 3-Sigma Fuzzy C-Means (3σ-FCM) technique has also evolved, with research by [14] highlighting its effectiveness in real-time fault detection. This method now utilizes streaming data analytics, allowing for immediate identification of faults based on real-time current measurements. Furthermore, **Generalized Kernel Fuzzy C-Means (GKFCM)** has been enhanced through the integration of noise reduction techniques. [15] explored the use of wavelet transforms to preprocess data, demonstrating that GKFCM can effectively mitigate the impact of noise, leading to improved diagnostic reliability.

4. Circuit Structure Method

Fault detection in photovoltaic (PV) systems is critical for maintaining efficiency and reducing system downtime. The **Circuit Structure Method (CSM)** has been one of the prominent approaches to identify faults in these systems, especially as PV installations expand into larger power plants. This method involves the placement of current and voltage sensors in various parts of the PV circuit to monitor system performance and detect anomalies. The collected data during potential fault conditions is then compared to baseline or standard data to assess whether a fault has occurred.

Sensor-Based Fault Detection

In early literature, sensor-based fault detection was recognized as an effective way to maintain PV system performance. For example, [16] emphasized the use of both current and voltage sensors to identify mismatch losses and other common fault types in PV modules. However, as PV systems expanded, it became evident that the scalability of sensor-based systems presented a significant challenge. Large-scale PV plants, which may consist of thousands of modules, require an extensive number of sensors, leading to prohibitive costs and increased complexity [17].Limitations of CSM in Large-Scale Systems Several studies have outlined the limitations of the Circuit Structure Method, particularly in large PV arrays. [18] discussed the computational burden created by the vast amount of data generated in large installations. The more modules and sensors involved, the more complex the data processing becomes. This was corroborated by [19] who highlighted the challenges in real-time monitoring when the system's size and data volume grow exponentially. Moreover, large-scale systems with multiple strings in series and parallel connections may lead to difficulty in pinpointing the exact location of a fault due to the interdependencies between modules.

Series-Parallel (SP) Array for Improved Fault Diagnosis

In an effort to overcome the shortcomings of the traditional CSM, researchers have proposed structural improvements to the PV array itself. One such approach is the **Series-Parallel (SP) Array** method, as highlighted in studies by [20]. This approach divides the array into multiple strings and components, enabling more localized fault detection. The SP array reduces the need for a large number of sensors by strategically placing current sensors on strings and voltage sensors on branches, enabling more efficient fault localization.

Research by [21] showed that the SP array method significantly improves fault detection accuracy. This method allows for identifying the faulty string through current measurements, followed by isolating the problematic branch and pinpointing the exact faulty module with voltage measurements. The efficiency of this method was demonstrated in medium-scale PV installations, although its performance in larger arrays is still being investigated.

These approaches provide alternative ways to detect faults without requiring direct electrical measurements, offering potential cost savings and practical advantages.

1) Infrared Image Analysis (IIAM)

Infrared Image Analysis has emerged as a key technique for diagnosing faults in PV systems. By detecting variations in temperature across PV modules, IIAM can identify defects that might not be detectable using traditional electrical methods. Faults such as hot spots, damaged cells, or connection issues generate localized heat, which is captured through thermal imaging.

Thermal Imaging for Fault Detection

Several studies have explored the efficacy of infrared imaging in detecting PV system faults. [22] demonstrated that infrared thermography can rapidly detect hot spots caused by faulty cells, interconnections, or shading effects. Their study showed that IIAM is particularly effective in identifying early-stage degradation in PV modules. Similarly, [23] found that infrared imaging can detect insulation faults, which manifest as temperature anomalies on the surface of the PV modules.[24] conducted extensive field tests and concluded that IIAM is advantageous because it is a non-contact method that can be performed without interrupting the operation of the PV system. This reduces system downtime and provides operators with a clear visual indication of faulty areas. Moreover, the portability of infrared cameras allows for inspections to be conducted on-site with ease.

Limitations of IIAM

Despite its benefits, IIAM has limitations. [25] noted that environmental conditions, such as ambient temperature and wind speed, can affect the accuracy of thermal imaging. If the temperature variation between faulty and healthy modules is small, detecting anomalies becomes challenging. [26] also pointed out that interpreting infrared images requires a certain level of expertise, as other factors, like dust and soiling, can also cause temperature variations that may be mistaken for faults.To address these challenges, recent research has focused on enhancing image processing algorithms to better distinguish between different types of faults. [27] proposed advanced machine learning techniques to automate the identification of fault patterns in thermal images, significantly improving fault detection accuracy and reducing false positives.

2) Mathematical Model Methods (MMM)

Mathematical Model Methods (MMM) provide a theoretical framework for diagnosing PV system faults by comparing real-time data from the system with predictions made by a mathematical model. These models are typically based on physical parameters, such as current-voltage (I-V) characteristics, irradiance, and temperature, and can simulate the expected performance of the system under different operating conditions.

Model-Based Fault Detection

In one of the early applications of MMM, [28] developed a model-based diagnostic tool that used simulated performance data to identify deviations in PV system behavior. By comparing the actual output to the expected output, the model could detect underperforming modules caused by issues like shading, degradation, or connection faults.[29] extended this approach by incorporating real-time monitoring data into their mathematical model. Their study showed that model-based methods could detect even small deviations from normal operation, allowing for the identification of partial shading or soiling that would otherwise go unnoticed by standard electrical methods. Additionally, [30] highlighted that model-based methods are scalable and can be applied to large systems without the need for additional hardware.

Enhanced Mathematical Models

Recent advances in MMM have focused on improving model accuracy and fault detection precision. proposed a hybrid approach that combined data-driven machine learning models with traditional physical models. This approach improved the ability to detect subtle faults, such as those related to temperature and irradiance changes. Furthermore, [31] developed a more sophisticated mathematical model that accounted for varying environmental factors, such as irradiance and temperature gradients across large arrays, which improved fault detection in systems with complex configurations.

Limitations of MMM

Despite the improvements, mathematical models are not without limitations. [32] pointed out that the accuracy of fault detection depends heavily on the quality of the input data and the assumptions used to create the model. For instance, sudden changes in weather conditions or sensor inaccuracies can lead to incorrect fault diagnoses. Additionally, [33] noted that developing highly accurate models requires significant computational power and expertise, making it less accessible for smaller PV installations or operators without technical resources.

Conclusion

Fault diagnosis in photovoltaic (PV) systems is a critical aspect of ensuring their reliability, performance, and safety. The increasing global deployment of PV systems emphasizes the need for robust diagnostic methods to maintain system efficiency and minimize energy losses. The review of various fault diagnosis techniques highlights several approaches, including model-based methods, artificial intelligence (AI) techniques, signal processing, and data-driven algorithms. Each method has its strengths and limitations, with AI-based approaches such as machine learning (ML) and deep learning (DL) gaining prominence due to their ability to handle large datasets and complex system behaviours. While traditional methods such as current-voltage (I-V) curve analysis and thermal imaging provide effective fault detection, they often require manual intervention and are limited by environmental conditions. AI and data-driven techniques, on the other hand, offer automated, real-time fault detection and diagnosis with improved accuracy, though they require extensive training data and computational resources. Despite advancements, challenges remain, particularly in the areas of data acquisition, computational cost, and the development of generalized models that can adapt to various system configurations and environmental conditions. Future research should focus on hybrid models combining multiple diagnostic approaches, enhancing the integration of Internet of Things (IoT) technologies for real-time monitoring, and improving the resilience of fault diagnosis methods to external disturbances.

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