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PV Fault Diagnosis, Including Signal Acquisition, Signal Processing, and Fault Analysis

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Abstract

The adoption of photovoltaic (PV) systems in modern electrical grids has expanded rapidly due to their economic and environmental benefits. However, these systems are prone to faults—such as partial shading, open circuit, line-to-line, and short circuit—that can significantly reduce energy output and reliability. Timely and accurate fault detection and diagnosis (FDD) are essential for minimizing energy loss, maintenance costs, and system downtime. This paper proposes a Fuzzy Logic Control (FLC)—based approach to detect and classify common DC-side PV faults under dynamic environmental conditions. Three PV configurations—series-parallel (SP), Total Cross-Tied (TCT), and a Hybrid SP-TCT—are modeled in MATLAB/Simulink to simulate fault scenarios. Unlike earlier studies that typically focus on single faults or fail to distinguish between temporary and permanent ones, this research addresses both issues by using a multi-fault detection framework. The FLC model utilizes three key electrical indicators—voltage, current, and power—with threshold values to classify faults as transient or permanent. To ensure robustness, the approach is tested under varying levels of solar irradiance and temperature. Validation is conducted through both simulation and experimental setups using a real PV array. To improve fault localization, wavelet feature extraction and fitness function analysis are incorporated, enhancing the detection of complex fault types such as open circuits and short circuits. Comparative evaluation with existing methods demonstrates the proposed FLC-based system's superiority in terms of accuracy, adaptability, and real-time capability. The proposed method enables faster and more precise fault classification, supporting improved operational efficiency in PV systems. These findings contribute to the advancement of intelligent FDD systems, particularly in smart grid and large-scale solar applications.

Keywords

PV System, Multi-Fault Situations, Feature Computation, Transient Faults, Artificial Intelligence, Fault Detection and Categorization

1. Introduction

This template, created in MS Word 2007, provides authors with most of the formatting specifications needed for preparing electronic versions of their papers. All standard paper components have been specified for three reasons: 1) ease of use when formatting individual papers, 2) automatic compliance to electronic requirements that facilitate the concurrent or later production of electronic products, and 3) conformity of style throughout a journal paper. Margins, column widths, line spacing, and type styles are built-in; examples of the type styles are provided throughout this document and are identified in italic type, within parentheses, following the example. Some components, such as multi-leveled equations, graphics, and tables are not prescribed, although the various table text styles are provided. The formatter will need to create these components, incorporating the applicable criteria that follow.

Solar energy is one of the most abundant forms of energy that can be found around the globe. Because of their rapid technical improvement and cost-effective operation, photovoltaic (PV) modules are among the solar systems installed and utilized the most often [1]. In recent years, photovoltaic (PV) systems have been installed in many locations, including residential, commercial, and industrial [2] [3]. With the aid of renewable energy sources and energy storage, it will be possible to safely and completely satisfy the world's need for power by the year 2050. According to estimates, anywhere between 7.3 and 9.7 billion people live on our planet. By the year 2050, the worldwide demand for energy from the power industry will have increased to more than 48,800 TWh, up from 24,310 TWh in 2015. As can be seen in **Figure 1**, the contribution of nuclear energy to the production of power over the globe in the year 2050 will be just around 0.3%. In addition, photovoltaic (PV) solar power achieved 1% in 2015 and is anticipated to reach 69% of world production by the year 2050 (the installed solar PV system is projected to reach 4674 GW) [4] [5]. The countries that produce the most photovoltaic solar energy are shown in **Figure 1**. The annual worldwide output of solar photovoltaic (PV) sources rose at a practically constant rate from 2020 until it reached 100 GW (this figure accounts for both on-grid and off-grid PV systems). Compared to the worldwide generation in 2008, which was 15 GW, the increase in total generation was almost 25%, bringing it to over 700 GW. In 2008, the generation was measured in gigawatts (GW). This is the consequence of various variables, including strong demand in developing markets or Europe, a significant decline in the going rate, and making up for China's tremendous market degradation, affecting the rest of the world [6]. Specifically, the high demand in emerging markets or Europe has significantly dropped the going rate. In addition, the lifetime of a PV module, which is predicted to be anywhere from 25 to 30 years, depending on the installation conditions [7], is adequate for improved economics.

However, as photovoltaic (PV) systems continue to grow in the modern world, they are running into several problems during their actual operation. These problems include the aging and degradation of components due to faults in PV modules. Because of these potential problems, the output of the PV systems may decrease. Researchers have documented, uncovered, and proposed many answers to these problems [8]. The operating parameters of PV modules and their output energy are influenced by several factors, such as solar irradiation, module temperature, and other factors, which may accelerate their degradation. This may cause PV modules to become less effective over time. This raises a problem that has to be solved as soon as possible. The deterioration rate linked with the PV module has to be checked and consistently considered to accurately determine the amount of power lost due to faulty modules. Numerous methods, such as taking thermal camera photos and analyzing the performance of the I-V curves of each string, are frequently used to make predictions regarding the decline in the amount of power that can be generated by photovoltaic (PV) systems [9] [10]. In addition, Colli A [11] also provides information that describes how the Photovoltaics Science Applications and Technology project (PSAT) explores different defects, such as the degrading fault, in connection to how their consequences manifest throughout the module's lifespan. According to the results, an energy loss between 0 and 20% can be categorized as module degeneration in the long run. In addition, Fiorentini L [12] offers analytical research that uses data acquired from 12 PV modules to consider mono- and multi-crystalline-silicon (c-si) kinds. This study was conducted. It has been shown that most PV modules experience a power loss of around 0.5% per year due to a drop in circuit current brought on by aging and degradation. This loss is because aging and deterioration cause the circuit current to decrease. Another study [13] examined the performance of solar panels after they had been in operation for 11 years using several PV modules installed in a desert environment. Along with the degradation problem, it is essential to predict the energy yield of the PV system under the real-time variation of the previously mentioned factors [14].

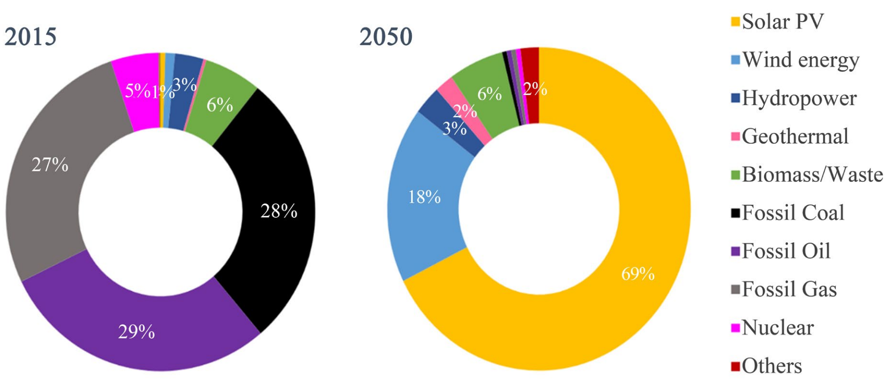

Figure 1. Electricity production from renewable sources in 2015 and 2050. http://www.leonardo-energy.info

Additionally, these variations should be considered when planning the operation of PV systems and researching how they function. To provide additional information, the operation of a photovoltaic (PV) system is analyzed while it is subjected to standard temperatures, and the expected losses are listed. These losses consist of 8% from dust and shadows, 5% from wire and DC/AC inverters, 6% from maintenance downtime, 5% from orientation, 50% from PV modules, and 8% from thermal losses. Consequently, it is estimated that photovoltaic modules have a conversion efficiency of approximately 16% [15] when they transform the solar energy input into the electricity output. In addition, the high cost of monitoring required in a natural PV system makes it more challenging to identify the problem type correctly. In other words, when less data is created, it becomes more complex and less accurate for system users to discover different problems. The photovoltaic (PV) system's components, such as PV cells, modules, inverters, and Maximum Power Point Tracking (MPPT) devices, may be correctly simulated or imitated to predict the characteristics of the system under a variety of operating modes and environmental conditions [16] [17].

This can be accomplished by accurately simulating or mimicking the devices' internal workings. In recent years, many research studies have been carried out to provide these specific models. The goal of these studies is not only to provide a variety of PV simulation models but also to acquire the corresponding optimum electrical characteristics of PV modules [18] [19]. On the DC side of PV systems running in practical applications, mismatch errors that occur on the DC side may be classified into two categories: permanent faults and transient faults. The PV modules in large centrally located arrays of photovoltaic cells might be momentarily hindered by non-uniform shadowing during the daytime [20] [21]. This phenomenon is induced by passing clouds. This fault category unequally influences the system's performance, which might lead to issues with local hot spots [22]. The hot spot problem has been discussed in several published papers, notably regarding c-Si PV solar cells. The occurrence of hot spots in PV modules of the c-Si type is expected when the flowing current of the PV module is higher than the short-circuit current (Ic) [23]. In photovoltaic applications, two typical problems that might result in the formation of hotspots are partial shadowing, often known as PS and PV cell parallel pathways. Using the infrared (IR) thermal approach [2] [24]-[26], it is possible to swiftly localize the hot spots found on the surfaces of PV module modules. These hot spots produce infrared light. Several studies were conducted to investigate the PS in addition to other faults and their effects on the performance of the PV system. In literature [27], the PS is examined as an actual fault condition, and it is advised that it should not be differentiated from the other flaws that impacted the PV modules. The research on the performance of the shunt bypass diode under the impacts of shadow shows a significant amount of distortion in I-V curves under various ambient conditions. The second kind of defect is known as a permanent fault because it has an impact that lasts for an extended period on the PV modules. Examples include open and short circuits, significantly decreasing system productivity and reliability while causing more severe long-term damage to PV arrays [28] [29]. As a direct consequence of these recurring flaws, large-scale PY plants risk experiencing catastrophic fires. In addition, if the electrical voltage is increased between the two PV system faulty sites, the amount of current flowing in the opposite direction may increase. However, the lower fault current caused by the low voltage difference makes it difficult to detect these faults, such as the Line-to-Line fault (LLF), using traditional fault detection techniques and protection devices [30]. This is because the LLF occurs when a fault between two lines occurs. After a system irregularity has been identified, correctly classifying the problem or carrying out a fault diagnostic can increase the system's availability by reducing the time spent on maintenance.

Aim and Objectives

The primary objective of the research for the thesis is to put into action an efficient FDD strategy built on Al methods. This strategy should be able to categorize the numerous mistakes that may arise in PV systems. The following is a list of the seven most essential objectives for the work on the thesis:

i. Carry out a number of simulations, considering a wide range of fault classes, to anticipate how the PV system will function in the event of possible problems. The proposed research considers a variety of PS patterns and rates, the fault resistance in the case of SC and LL fault conditions, and the OC and SC faults that occurred on the individual PV module and need to be investigated and recognized. These are only some of the significant elements that are taken into account.
ii. To develop an effective PV simulation model that can accurately predict the PV system's behavior under both normal and abnormal conditions.
iii. To conduct a variety of theoretical and practical tests on flaws while considering the many different conditions of the surrounding atmosphere. In other words, conducting theoretical examinations of the proposed methods cannot guarantee that they will be successful when put into practice.
iv. Based on the AL approaches, differentiate between and then classify the many types of errors, whether temporary or permanent. To accomplish this goal, it is necessary to investigate and assess a variety of fault classes originating from both kinds. In addition to considering the component efficiency of the PV system, the approach that is used to solve the problem should also consider the fluctuation in solar irradiation and temperature. Therefore, there is an immediate requirement for a creative strategy that can withstand these challenges while being practical.
v. To provide an innovative method for identifying flaws in the PV system so that it may be repaired. It is necessary to include detection and localization to reduce the amount of money spent on framework maintenance in actual applications. The robustness of the solution and its speed can be ensured, and the strategy provided may be applied in a wide range of situations regarding the amount of solar irradiation and the temperature.
vi. To develop a system based on deep learning that can accurately diagnose

common issues in settings with low illumination levels. The research that has been done on photovoltaic (PV) defects has produced several different methods of classifying them to manage their definitions better and the factors that generate them. The FDD approaches need to fulfil several requirements, such as high classification accuracy, ability to be applied, and fast calculation time. This is a significant challenge, especially considering the surrounding surroundings' unclear nature.

vii. To devise an innovative categorization scheme for the many single- and multiple-fault types that may occur. To put a reliable FDD approach to good use in actual practice, it is necessary to consider the frequency of single- and simultaneous multi-faults on PV systems. Finding a solution to this issue is essential to enhance the PV systems' efficiency.

2. I-V Curve Scanning Method for PV Modules Based on Fault Diagnosis

The I-V curve of photovoltaic modules, which is a curve made up of output data of photovoltaic modules under different voltages and currents, is the best indicator of the output characteristics of photovoltaic modules since it is both exact and immediate in its reflection of such qualities. Because it offers a wealth of information regarding the operational aspects of photovoltaic modules, it has seen extensive use in photovoltaic module defect detection. This is because the field relies heavily on this information. Because of this, it is exceptionally well suited for the identification of issue features. A portable module I-V curve scanner and a string I-V curve scanner are the most frequent methods for acquiring the I-V curve of a photovoltaic system. However, because both methods are offline, they cannot be used to promote distributed solar energy throughout the nation. Both the I-V curve scanning method of PV modules based on electronic load and the I-V curve scanning method of PV modules based on DC-DC converters are the primary focuses of this study. The primary objective of this research is to develop a methodology that can identify faults in PV modules online.

2.1. Principle of Electronic Load Method

In the electronic load method, transistors are used to load photovoltaic modules. These transistors are typically MOSFETs or IGBTs, and the voltage between the drain and source is modulated by gate voltage in both types of transistors. This allows the electronic load method to rapidly scan the I-V characteristics of photovoltaic modules, thereby reducing the lost power. By adjusting the gate voltage, MOSFETs, the most popular electronic load, can regulate the drain current. When functioning as an electronic load, the MOS transistor is required to operate in the variable resistance region. The conditions necessary for the MOS transistor to function correctly in the region of variable resistance are outlined in Equation (1).

$$V_{\mathrm{DS}} < V_{\mathrm{GS}} - V_{\mathrm{th}} \quad (1)$$

where, V_{DS} is the drain-source voltage, V_{GS} is the gate-to-source voltage; V_{th} is the threshold voltage. The characteristics can be represented by formulas 2.11 and 2.12.

In the variable resistance region:

$$I_D = K_N\left(2\left(V_{\mathrm{GS}} - V_{\mathrm{th}}\right)V_{\mathrm{DS}} - V_{\mathrm{DS}}^2\right) \tag{2}$$

In the saturation zone:

$$I_D = K_N\left(V_{\mathrm{GS}} - V_{\mathrm{th}}\right)^2 \tag{3}$$

where, K_N is a device constant. Equation (3) shows when the MOSFET operates in the saturation region. I_D Only with V_{GS} relate.

The principle that photovoltaic modules use MOSFETs as electronic loads is shown in **Figure 2**. This method measures based on the current slope instead of the traditional voltage slope. MOSFETs can provide approximately linear measurement points as a scanning method for PV modules for electronic loads. From Equation (2), we can see I_D follow V_{GS} approximately linear change. However, for PV modules, the voltage V_{pv} is in the power and current source regions, and the I-V curve is almost flat, making V_{pv} sensitive to small changes. The measuring point rushes in the power and current source regions. This limitation is mainly achieved by control circuitry. In this project, a low-frequency sweep signal is used to control and change the gate voltage of the MOSFET to track the entire range of PV module characteristics.

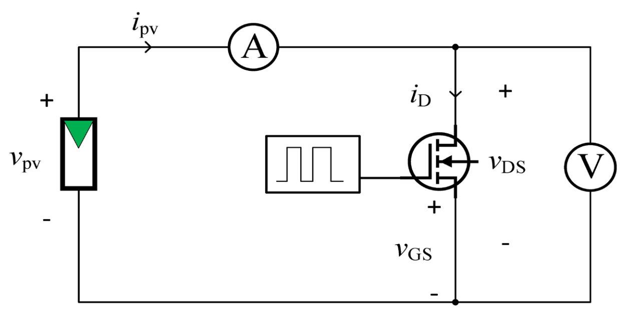

Figure 2. The MOSFET is an electronic load to obtain the I-V curve schematic.

In practical applications, multiple MOSFETs are used parallel to increase the output current. The disadvantage of this method is that all power is dissipated on the MOSFET, resulting in the device's temperature exceeding the tolerance range. The heat sink is required to dissipate heat, resulting in large device size and weight.

2.2. Physical Simulation of the Electronic Load Method

Simscape tools in MATLAB-Simulink were used to verify the electronic loading method's application in photovoltaic modules. Simscape's tools and language for creating physical system models in the Simulink environment can be used to model and simulate without converting equations of motion. The parameters of photovoltaic modules are shown in **Table 1**.

Table 1. Parameters of PV module manufacturers.

Parameter	$P_{m,ref}$/W	$V_{OC,ref}$/V	$I_{SC,ref}$/A	$V_{m,ref}$/V	$I_{m,ref}$/A
Value	250	37.92	8.62	30.96	8.07

To realize the fault diagnosis at the component level, it is possible to judge the fault, such as the blocking of the module, and when the module physics simulation is carried out, the 60 photovoltaic cells are divided into three parts, each part is composed of 20 photovoltaic cells, and the bypass diodes are connected in parallel in each part of the photovoltaic cells. The simulation is STC (Radiation intensity S_{ref} = 1000 W/m^2, T_{ref} = 25˚C). For reference, a simulation model based on a MOSFET-based parallel connection of one PV module is established in the Simscape simulation model.

The electronic load is implemented in parallel with multiple MOSFETs to solve when the I-V curve is almost flat, make V_{pv} to V_{GS} Small changes in sensitive issues, V_{GS} a low-frequency control signal is generated for scanning using a wire-controlled voltage source. It can be seen from **Figure 3** that the MOSFET gate-source control voltage adopts a segmented linear low-frequency signal to ensure that the MOSFET works in the variable resistance region. The given control voltage moves the photovoltaic module from the short circuit point to the open circuit, and the I-V curve of the photovoltaic module is drawn using voltage and current measurement.

3. Different Types of Methods for PV Array Fault Simulation and Analysis

When defects in the solar array occur, such as an open circuit, a short circuit, a shadow, or a hot spot, the I-V curve of the photovoltaic array will vary dramatically, particularly in the location of the open circuit voltage, the short circuit current, the maximum power point, and so on. I-V curves corresponding to the normal operation and fault of the PV array can be effectively obtained, so as to provide important data support for the subsequent extraction of the fault characteristics of the PV array, the establishment of fault diagnosis models, and the realization of information fusion. This is made possible through the combination of the I-V curve scanning method described in Section 2 with the method described in this section.

3.1. Current Fault Detection Methods

Monitoring systems (MS) are essential for controlling, supervising, and performing fault detection on photovoltaic plants; consequently, many systems have been recently proposed with the intention of performing a real-time monitoring of photovoltaic plants (PVP); in this context, the common reference documents are the standard IEC 61724 [31], titled: Photovoltaic system performance monitoring—Guidelines for measurement, data exchange and analysis, as well as the guidelines of the European Joint Research Centre in IEC 61724. [31]-[35] outlines in further detail the necessary degrees of precision as well as the techniques for validating the data. Prior to the development of a particular project, one should give the reason for the monitoring a lot of careful thought.

Several FDD methods have been proposed in the published research; the primary characteristics that can be used to characterize such methods are the following: the ability to quickly detect malfunctions; the input data required, which include climatic and electrical data; and selectivity, or the capacity to differentiate between various types of faults. They are able to be placed into one of two primary categories [8]:—Visual and thermal methods [13] [36], which can be used for detecting discoloration, browning, surface soiling, hot spot, breaking, and delamination; and—Electrical methods, which can be used for detecting and diagnosing faulty PVM, strings and arrays, including arc fault, grounding fault, diode's fault, and other types of faults.

3.1.1. Methods Based on Statistical Signal and Processing Approaches (SSPA)

Methods for signal processing are primarily cantered on the examination of waveform signals. For instance, Time Domain Reflectometry (TDR), Speared Spectrum TDR (SSTDR), and Earth Capacitance Measurement (ECM) are utilised in order to discover and localise malfunctioning PV modules. The TDR approach is used in the study referenced in [37], which aims to pinpoint the location of a failing PVM inside a PVA. The authors emphasised that the approach may be used for defect detection and localization; nevertheless, the method is readily impacted by the installation circumstances, such as modules mounting, dc wiring, or PVA components materials. This was mentioned in the previous sentence. Electrical techniques [38] [39] based on the ECM and TDR can determine which PVM in a string is detached from the rest of the string. According to the authors, the ECM may be used to identify the disconnection locations between the PVM in the string without the impacts of the change in irradiance, and the TDR can detect the position of the deterioration, such as an increase in the Rs between the PVs. Both of these detection methods are independent of the effects that the change in irradiance has on the string. The study that was done by Takashim *et al.* [40] demonstrated that the ECM approach could be used not only to a PV string consisting of crystalline Si PVM but also to a string consisting of amorphous-Silicon (a-Si) PVM. This was shown by the fact that the ECM method was able to be applied to both of these types of PV strings.

3.1.2. Methods Based on the I-V Characteristic Analysis (I-VCA)

FDi of PVA based I-V characteristic was originally presented in [41], which also proposes a method for the identification of PVA flaws. FDi was based on the I-V characteristic of PVA. It involves contrasting the observed electrical parameters with those predicted based on the I-V characteristics. The investigation of the faulty disconnection in PVA focuses on PVNode and shadow programmes as the two most important components of the approach. The usefulness of the approach to identify certain PVA defects was proved by the experimental testing that was done. The existence of defects cannot always be determined by analysing the form of the I-V characteristic of PVA. For instance, the partial shadow of one or two cells in a string cannot be determined by the development of a peak in the I-V characteristic. Because of this, Miwa *et al.* [42] have presented a technique that is based on the study of the (dI/dV)-V characteristic in order to automatically assess the output drop of PVS that is induced by various loss causes. It has been established that the presence of a peak in the (-dI/dV)-V characteristic may successfully identify a decline in the power output of a PVS.

In literature [43], research was conducted on the five most prevalent forms of defects in PVA, which were mismatch, DF, connection, PVMF, and GF. For the purposes of this investigation, a model built on Matlab and Simulink is being constructed. The findings of the simulation reveal that the model that was built can simulate the various problems that were evaluated. Daliento *et al.* [44] devised a unique way to identify problems based on simple electrical measurements. This method was published. The authors performed an analysis of both the first and second derivations of the I-V curve in an effort to identify any potential flaws in RS and BpD. Despite the approach's restricted application, it is simulated and confirmed by experimentation. However, the method is not widely applicable. Hu *et al.* [45] provide an online PVA FDi that is both cost-effective and has voltage sensor placements that have been optimised. The authors said that the created approach has the potential to boost production while simultaneously decreasing the amount of money spent on both initial investment and ongoing maintenance. This would be accomplished by cutting down on the total number of sensors and honing in on an efficient FDI strategy. The work that Rezgui and colleagues [46] have done demonstrates a newly developed method for fault identification in PVM. The developed technique is able to represent the PVM in both normal and malfunctioning states. It is also able to determine the sort of defect that impacts the SC, OC, impedance, and reversed polarity of the power supplied by the PVA.

The optimization techniques are used to automatically alter the network topology and the hyperparameters to resolve the issues described above. In the paper [47], the Bayesian optimization algorithm (BOA) is used to accomplish the hyperparameter optimization of the semi-supervised ladder network (SSLN) to detect a variety of defects. These faults include line-line faults, open-circuit faults, and partial shading faults. Unfortunately, the iterative optimization process becomes significantly more expensive because of these methods increasing computational demands. In addition to this, the fault diagnostic techniques that were discussed before only cover a single defect type. It is not considered whether there are concurrent faults, such as the partial shading with the bypass diode open-circuit fault (PSBO) or the partial shading with the bypass diode short-circuit fault (PSSC), etc. On the other hand, there was no research done on the likelihood that many defects may happen at the same time in PV systems.

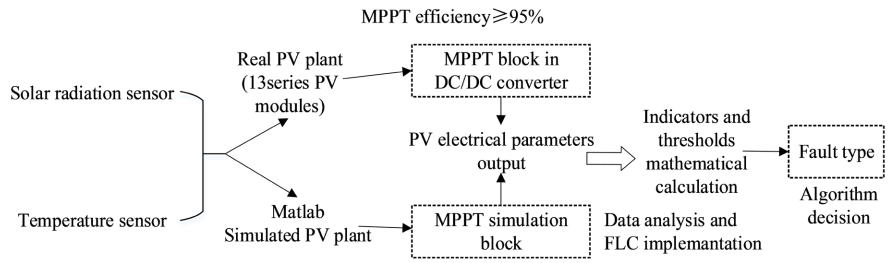

Figure 3. The setup of the FDD method in the PV array.

The dependability of photovoltaic (PV) systems has garnered increasing attention as a result of the many short-term and long-term PV failures that have occurred. In addition, further effort has to be done to help photovoltaic (PV) systems with high operating efficiency, which boosts the need for FDD methods and increases the amount of electricity that is generated. To be more specific, the simultaneous development of a large number of PV faults makes it far more difficult to recognise and differentiate between the various kinds of defects. According to [48] [49], a few research works have recently studied this topic. However, previous works had some drawbacks, including the following: 1) they assumed that shunt bypass diodes connected to the PV modules would operate normally during PS fault conditions; 2) some hard shading conditions, such as birds swooping or leaves fluttering, were not discussed or detected; and 3) simultaneous PV fault conditions, such as SC with PS conditions, had been observed. This research work seeks to address these shortcomings.

The most up-to-date FDD approaches for the PV system are discussed, along with a comparative study that is based on a number of criteria, such as the methodology that was utilised, the fault types that were examined, the classification accuracy, and so on. In Section 3.2, you'll read about the first way, which is based on applying the FLC method to the FDD problem, and you'll see how it works. In order to anticipate the real-time operational performance under usual and atypical operating circumstances in the case of changing atmospheric conditions, first a modelling of a real PV array has to be constructed. This allows for the prediction of the real-time operational performance. In addition, instead of modelling and distinguishing long-lasting PV failures like OC and SC fault instances, a variety of transitory PV faults, such as PS with/without bypass diode connection, snowfall, leaf or bird fall, and PS with/without bypass diode connection, are modelled and discriminated. In order to classify the PV faults discussed in previous sections, there are a few different approaches that may be used to identify the myriad of problems that can arise on both the DC and AC sides of the photovoltaic system. This section covers the methods that are used in the process of determining the different PV faults, and it does so by separating them into two primary classifications: traditional methods and Al approaches. The detection procedure in traditional methods, such as voltage and current measurements, power loss analysis, statistical analysis, and so on, often makes use of mathematical approaches, and Al models are used to increase classification accuracy. Recently, a variety of FDD strategies based on the application of different Al approaches, such as FLC, PNN, CNN, and others, have been presented for the second group. These strategies have been developed relatively recently. In this section, we will focus on many approaches that are quite similar to those that will be used in the subsequent chapters for the purpose of fault localization and classification. While another category, such as detection, diagnosis, localization, and supervision, can be used to differentiate between the various FDD approaches according to their capacity to address the various PV faults, this is not the only category that can be used. Readers who are interested can look at [28] for additional information that may be of use to them. The simultaneous study of seven electrical characteristics' changes under various temporary and permanent PV faults. The study's main findings supported the idea that, of all the PS conditions examined, the TCT configuration had almost the maximum generated power for the PS condition.

3.2. The Fault Detection Based on FLC Classification Method

In this sub-section, we provide a novel technique for identifying and categorising the different failure scenarios while taking into account the Sugeno FLC type. The Open Circuit Voltage Ratio (OCR), Current Ratio (IR), and Voltage Ratio (VR) are the three ratios that the suggested FDD technique uses to analyse the performance of the PV array. The ratios are calculated mathematically while taking into consideration the actual properties of the PV array in both healthy and various defective conditions.

Table 2. The various chosen fault cases.

Fault type	Symbol
Normal operation	F0
PS effect without bypass failure	Fl
PS effect with bypass failure	F2
Two modules SC in PV array	F3
Four modules SC in PV array	F4
Two OC modules	F5
Four OC modules	F6
Snow falling	F7
Bird or tree leaves dropping	F8

The suggested technique's complete setup is shown in **Figure 5**, where the simulation model developed on the MATLAB Simulink platform is used to apply the FDD method in order to forecast the performance of a PV array under varying environmental circumstances as detected by solar irradiance and temperature sensors. In addition, these data represent the inputs of the real PV system using a solar PV array with a rating of 3.2 kW, mounted on the roof at North China Electric Power University, Beijing, China. Then, the selected electrical parameters and indicators are collected from the MPPT blocks of the experimental and simulated platforms to be used for the FLC implementation using the laboratory compute. In the end, the FLC output represents the correct PV fault class which can help the operators with any further decisions. We select eight fault cases in this work, as shown in Table 2. Comparative Analysis of Proposed FLC + Wavelet Method with Existing AI/ML Approaches for PV Fault Diagnosis are shown in Table 3.

Table 3. Comparative analysis of proposed FLC + Wavelet Method with existing AI/ML approaches for PV fault diagnosis.

Feature	Proposed FLC + Wavelet Approach	CNN-Based Methods	SVM-Based Methods	ANN-Based Methods
Fault Types Handled	Multiple simultaneous faults (OC, SC, PS, hot spot, LLF)	Mostly single or limited concurrent faults	Mainly single faults	Mostly single faults
Transient vs Permanent Fault Detection	Yes, both distinguished accurately	Partial (needs retraining)	Limited	Limited
Real PV Experimental Validation	Yes (Roof-top 3.2 kW system at North China Electric Power University)	Limited or simulated datasets mostly	Mostly simulation-based validation	Primarily simulations
Handling Dynamic Environment (irradiance/temperature changes)	Robust performance under varying conditions	Sensitive to environmental changes, needs more retraining	Moderate sensitivity	High sensitivity
Complex Fault Localization	Achieved using wavelet feature extraction and fitness function analysis	Possible but computationally expensive	Very limited localization ability	Limited localization
Classification Accuracy	~99% (simulation & experimental)	~97% - 98% (mostly simulation)	~93% - 95% (depends on data balance)	~90% - 95% (depends on tuning)
Computation Complexity	Low to moderate (real-time capable)	High (deep learning models)	Moderate	Moderate
Ease of Implementation in Practical Systems	High (threshold-based + FLC rules)	Medium to Low (needs GPU, complex tuning)	Medium (needs model tuning)	Medium
Interpretability	High (fuzzy rules are human-readable)	Low (black-box deep learning)	Moderate	Moderate
Suitability for Large PV Arrays	Very suitable	Requires extensive retraining and data augmentation	Limited scalability	Limited scalability

3.3. PV Array Fault Simulation and Analysis

In this paper, a 5 × 3 PV array as shown in Figure 6 is established in MATLAB/Simulink, which consists of three strings, each of which includes 5 PV modules in series. On the basis of this photovoltaic array, the common faults (open circuit, short circuit, shadow, hot spot) of the photovoltaic array are simulated and analyzed. In this paper, the idealized I-V curve scanning of the photovoltaic array shown in

Figure 3 is carried out by the controllable voltage source method described in Section 2.

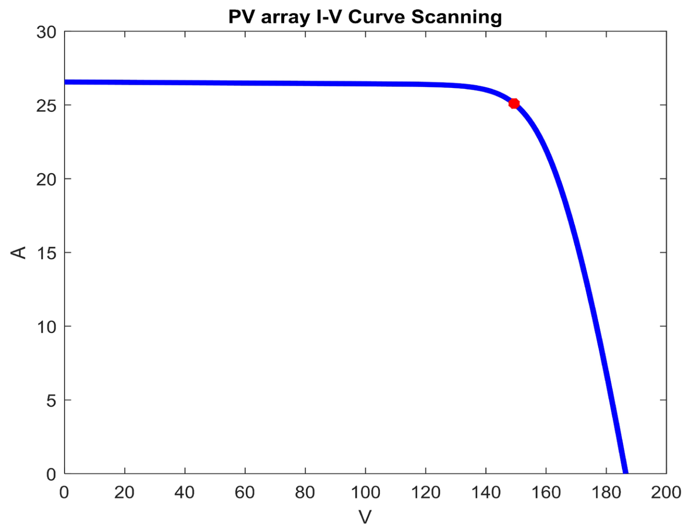

Figure 4. PV array I-V curve (irradiance 1000 W/m^2, temperature 25˚C).

Based on the I-V curve scanning method of photovoltaic array shown in Figure 4, the I-V and p-V curves of photovoltaic array when common faults such as open circuit, short circuit, shadow, and hot spot are simulated respectively.

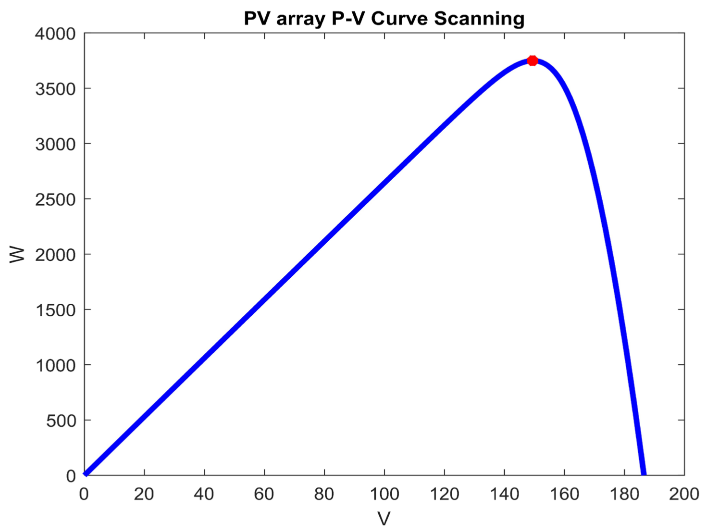

Figure 5. PV array P-V curve (irradiance 1000 W/m^2, temperature 25˚C).

The simulation of the PV array open circuit fault is shown in Figure 5, and the PV module in column 1 is disconnected from the PV array by the switch module to simulate the PV array break fault. Combined with the above photovoltaic array I-V curve scanning method, the I-V AND P-V curves of the photovoltaic array at this time can be obtained, and compare with the I-V and P-V curves under normal operation shown in Figure 4, as shown in Figure 6.

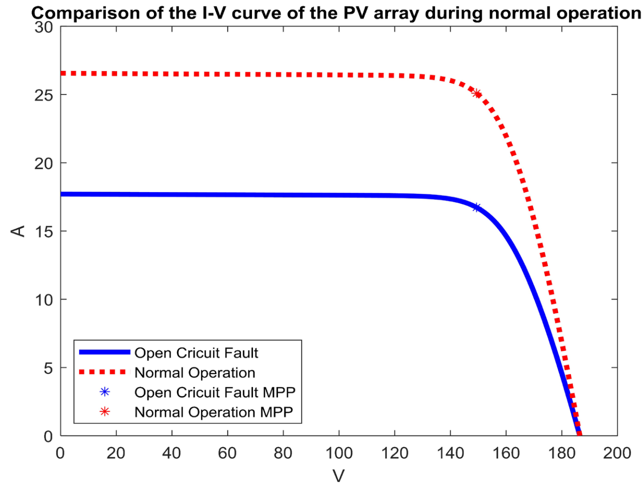

Figure 6. Comparison of the I-V curve of the PV array during normal operation with an open circuit fault.

It can be seen in **Figure 6** that the I-V curve of the photovoltaic array with open circuit fault, the open circuit voltage point and the maximum power point of the P-V curve are quite different from those under normal operation. As shown in **Figure 7**, the simulation of the PV array short-circuit fault is the short-circuit fault of the PV array is simulated by using the short circuit connection between the PV modules in the first column.

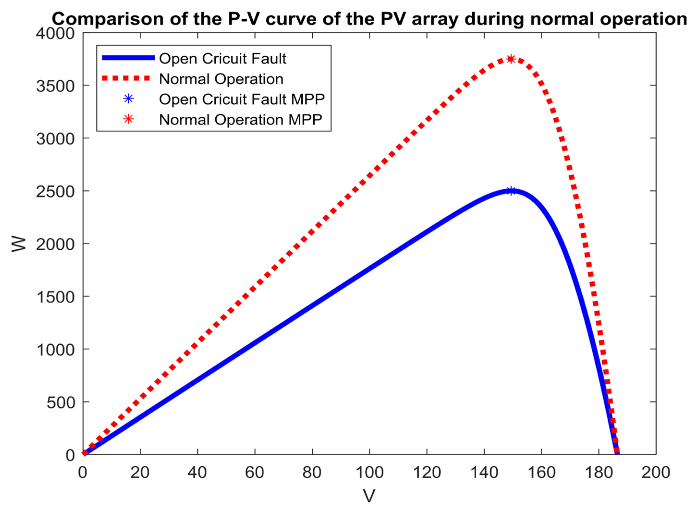

Figure 7. Comparison of the P-V curve of the PV array during normal operation with an open circuit fault.

Combined with the above photovoltaic array I-V curve scanning method, the I-V and P-V curves of the photovoltaic array at this time can be obtained and compared with the I-V and P-V curves during normal operation. From **Figure 8** can be seen that the I-V curve of the photovoltaic array with short-circuit fault, the short-circuit current point and the maximum power point of the P-V curve are obviously different from the normal operation.

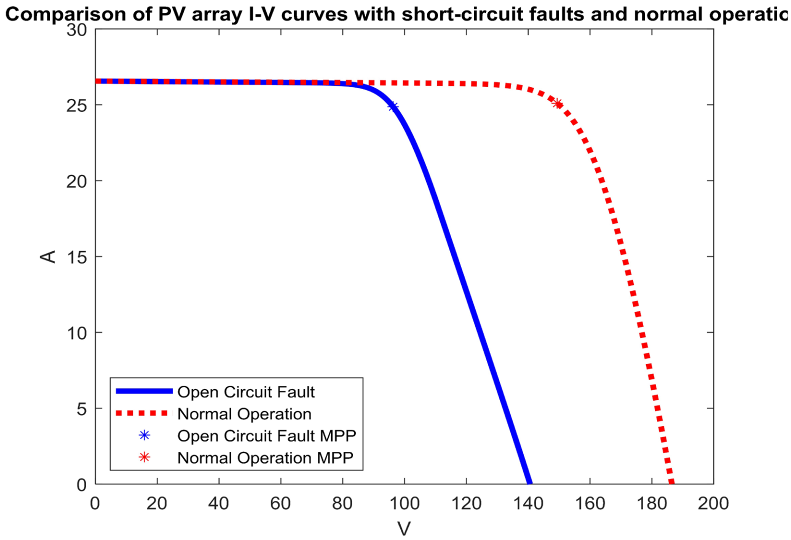

Figure 8. Comparison of PV array I-V curves with short-circuit faults and normal operation.

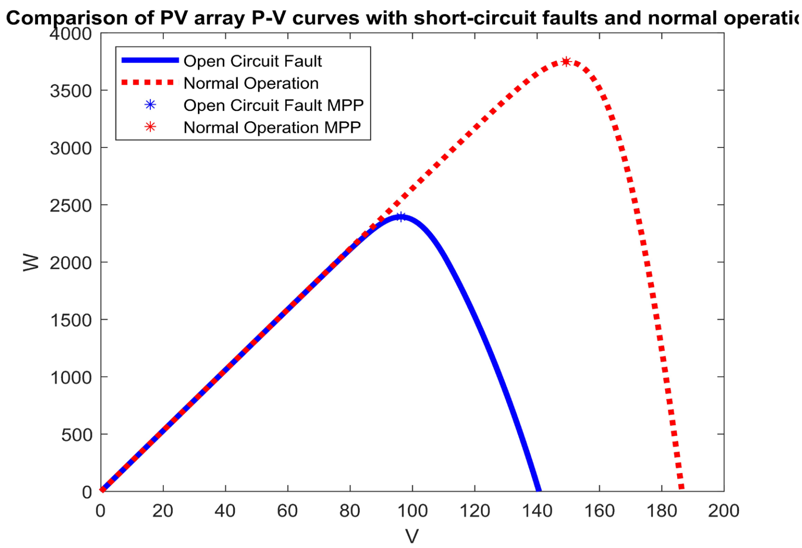

Figure 9. PV array shadow fault simulation.

The simulation of the shadow fault of the PV array is shown in Figure 9, and the shadow fault of the PV array is simulated by changing the light intensity of the PV module in the second column part. At this time, the I-V and P-V curves of the photovoltaic array at this time can be obtained by the above-mentioned photovoltaic array I-V curve scanning method and compared with the I-V and P-V curves during normal operation, respectively, and the I-V curve and P-V curve comparison chart. The maximum power point of the I-V curve and P-V curve of the photovoltaic array with shadow fault is quite different from the normal operation, and there is an obvious step phenomenon in the curve. The simulation of the thermal spot fault of the photovoltaic array, and the hot spot failure of the photovoltaic array is simulated by changing the light intensity and temperature of the photovoltaic module in the third column part.

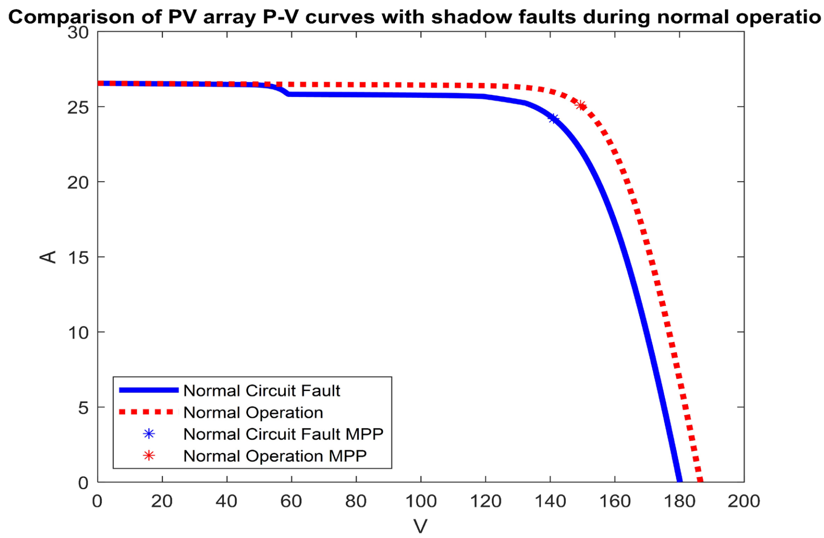

Figure 10. Comparison of I-V curves of PV arrays with hot spot faults during normal operation.

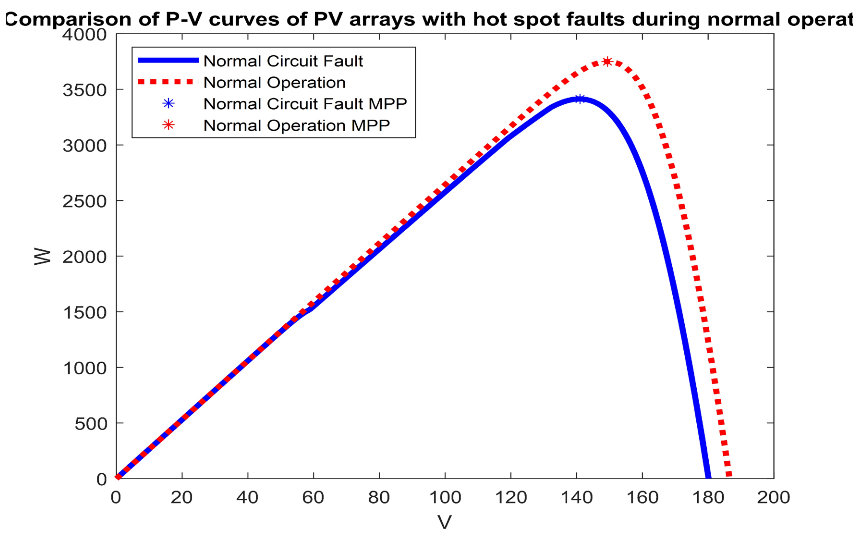

Figure 11. Comparison of P-V curves of PV arrays with hot spot faults during normal operation.

According to Figure 10 and Figure 11, the I-V curve and P-V curve of the photovoltaic array with hot spot fault have a certain step phenomenon, and their maximum power point and short circuit current point are quite different from normal operation.

4. Signal Processing and Diagnosis of PV Fault

4.1. Extraction of PV Module Fault Features

According to the 5 × 3 photovoltaic array built in MATLAB/Simulink, open circuit and short circuit faults under standard working conditions are simulated according to Section 3. It is specified that the first PV string current, the 2nd PV string current, the fault component voltage, the fault string normal component voltage, and the normal module voltage. When the module in row 1 of the first column of the string is open, the change characteristics of output current and voltage of the photovoltaic array when it is open are shown in Table 4 and Table 5.

Table 4. Current values under open faults.

	I_1 (A)	I_2 (A)
normal	0.6269	0.6269
Open	0	0.9366

Table 5. Voltage values under open-circuit faults.

	U_1 (V)	U_2 (V)	U_3 (V)
normal	37.61	37.61	37.61
Open	37.92	37.92	37.46

It can be seen from Table 3 and Table 4 that when an open circuit fault occurs, the fault string current is 0, the rest of the string current becomes larger, the fault component voltage and the fault string normal component voltage become larger, it is an open circuit voltage, and the normal component voltage decreases. According to the analysis, short circuit fault diagnosis and position identification can be carried out through the optimizer upload data, when the PV module is open, because the voltage of the faulty component and the normal module in the fault string is increased to the open circuit voltage, the current is 0, and the open circuit fault can only judge the fault PV string according to the feed data, and the accurate identification of the faulty module will be solved in the next chapter.

When the module of the first row of the first column of the string is short-circuited, the change characteristics of the output current and voltage of the photovoltaic array during the short circuit are shown in Table 6 and Table 7.

Table 6. Current values under short-circuit faults.

	I_1 (A)	I_2 (A)
normal	0.6269	0.6269
short circuit	0.3192	0.7731

Table 7. Voltage values under short-circuit faults.

	U_1 (V)	U_2 (V)	U_3 (V)
normal	37.61	37.61	37.61
short circuit	0	37.92	37.38

It can be seen from Table 6 and Table 7 that when a short circuit fault occurs, the fault string current decreases, the remaining string current becomes larger, the fault component voltage is 0, the normal component voltage of the fault string becomes larger, and the normal component voltage decreases. According to the analysis, short-circuit fault diagnosis and position identification can be carried out through the optimization data feed, and when the PV module is short-circuited, the short-circuit module current becomes smaller, and the voltage decreases to 0 is the short-circuit component.

4.2. Feature Layer Fusion Based on Wavelet Features

Shadow Fault Feature Extraction

As a common method in the field of artificial intelligence, wavelet transform has good practical results in fault feature extraction. According to the shadow fault simulated under standard working conditions and the corresponding I-V and P-V curves as shown in **Figures 10 - 11**. IN section 3, the shadow fault features were extracted by combining the wavelet transform correlation method. In this paper, db3 wavelets are used to decompose the I-V curves in normal operation and shadow faults. It's well known that each PV module is usually connected with a reversed shunt bypass diode, while the diode voltage has a negative value when the PV module output voltage has a positive value and vice versa. Additionally, the generated power and voltage decline lost in these diodes can be the main key to distinguish among the OC and SC faults in PV modules when they have the same module numbers, as shown in **Figure 13**. It is noticed that the decline in output power and voltage is larger during the OC fault cases.

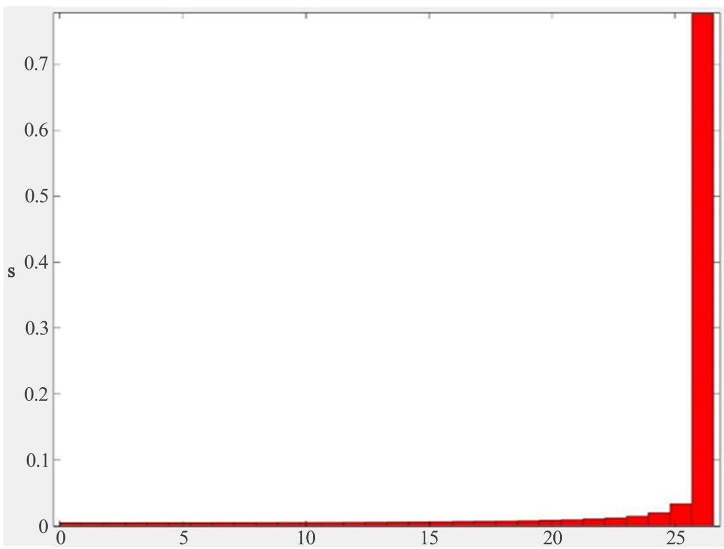

Figure 12. Wavelet transform histogram during normal operation.

It can be seen from **Figure 12** that the shadow fault can be further highlighted by the 5-layer decomposition of the I-V curve during normal operation and shadow fault by db3 wavelet, so the shadow characteristics of the photovoltaic array can be characterized by the information of the d1, d2, d3, d4, and d5 data. In order to further express the characteristics of shadow faults, db3 wavelets were used to decompose the P-V curves for normal operation and shadow faults, as shown in Figure 13, respectively. From the comparison of Figure 13, it can be seen that the knee point corresponding to the P-V curve in the presence of shadow fault shows abnormal fluctuations in the data of d1, d2, d3, d4, and d5, so the information of the d1, d2, d3, d4, d5 data shown in **Figures 4 - 7** is also used to characterize the shadow fault characteristics of the photovoltaic array, and the information of the d1, d2, d3, d4, d5 data shown in Figure 13 is combined to further highlight the difference between normal operation and shadow fault. The Performance metrics of the proposed integrated FLC, Wavelet, and CNN fault diagnosis system has been displayed in Table 8.

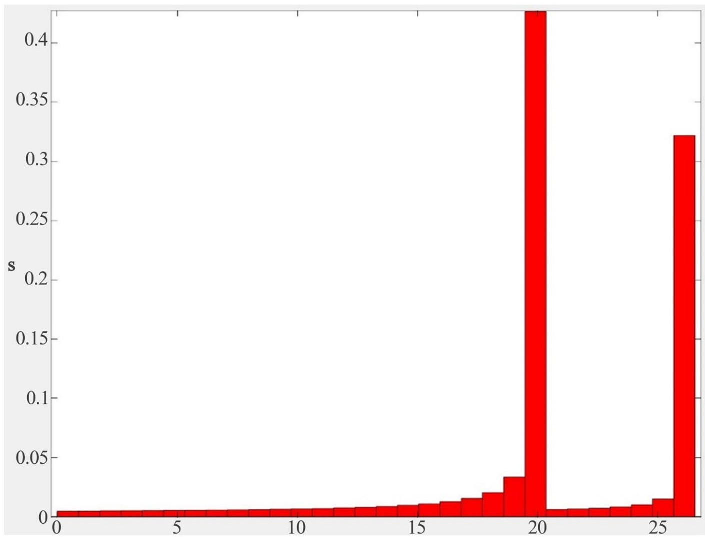

Figure 13. The result of a 5-layer decomposition of the P-V curve during normal operation.

Table 8. Performance metrics of the proposed integrated FLC, Wavelet, and CNN fault diagnosis system.

Metric	Simulation Results	Real PV Experimental Results
Accuracy	99.0%	97.0%
Precision	98.8%	96.5%
Recall (Sensitivity)	99.2%	96.8%
F1-Score	99.0%	96.6%
Specificity	98.7%	96.2%
Confusion Matrix Analysis	Low false positives and false negatives observed	Very few misclassifications under dynamic irradiance conditions

5. Conclusions

The installation of PV systems is fast expanding around the globe, however prior to 2010, the situation was not particularly comparable. As a consequence, these PV systems encounter a variety of component failures, including PV modules, inverters, wires, etc. Continuous inspection and testing of PV systems are essential for efficiently capturing solar energy and for dependable electricity production. Furthermore, since fault detection is crucial progress in enhancing diagnostic techniques is even more important. The PV systems will operate more effectively and the required maintenance will be more suitable if the diagnosis is correct. PV systems may generally be set up in a variety of ways. Three PV setups have been looked at in this thesis. Series-Parallel, or SP, Cross-tied total (TCT), hybrid SP-TCT topology, etc. Seven electrical properties have had their alterations under various temporary and permanent PV defects studied simultaneously. The major conclusions of the study supported the notion that, for the PS condition, the TCT configuration had almost the highest produced power among all PS conditions analysed. Additionally, TCT and hybrid SP-TCT configurations provide the highest output power under OC and fault conditions, respectively. The SP design, on the other hand, is the most effective for maximising power under LL failures.

Numerous temporary and permanent faults, including multiple faults, have been experienced with regard to the fault detection and diagnosis (FDD) task that can be applied to real-world practise. Initially, the proposed FDD method has been developed based on three chosen ratios to evaluate the performance of the PV array in order to implement the Sugeno fuzzy logic control (FLC). The suggested FLC method's effectiveness under unpredictable environmental circumstances has been assessed by simulation and experimental validations; the proposed FLC's average accuracy was about 99%. Additionally, the suggested approach could divide common faults into distinct classes with the aid of predetermined threshold settings. In comparison to previous approaches that may be used in large-scale PV arrays, the suggested method has been shown to be straightforward and accurate in classifying data. Additionally, it has been demonstrated through a number of theoretical and experimental tests to be easily applicable in a real situation.

The study then suggests a new wavelet features correlation methods-based approach for fault identification and localization of OC and SC faults that occurred on the PV modules. These PV faults have been simulated using an approach that aids in differentiating between the examined fault types and the healthy state. Due to the formulation's nonlinearity issue, a mathematical formula has been developed that increases the use of wavelet features correlation methods-based approach for minimising the optimisation function. In nine experimental instances, a non-uniform distribution and tri-levels of solar irradiance and temperature have been taken into consideration to address the challenge posed by the environmental condition uncertainties. In the end, the simulation results confirmed that wavelet features correlation methods-based strategy was better in terms of localization accuracy and computational complexity.

The convolutional neural network CNN model has been used in this thesis as a last step because of its enormous potential for automated feature extraction. To get the SDM's optimum solutions and effectively anticipate the properties of PV systems, the Improved Teaching-Learing Based Optimisation (ITLBO) method has been used. This has shown its viability, particularly in situations where genuine PV systems are not feasible. Based on simulated and real-world validations that took into account low irradiance levels, low mismatching line-to-line fault instances with zero fault resistance, and quick environmental condition changes, the implemented CNN approach has been successfully approved. According to the findings, the suggested CNN has a high classification accuracy, with average accuracy values of 98.6% for the simulation test and 97% for the experimental test, respectively. This improves the method's suitability for usage in massive PV arrays.

6. Future Work

As far as we are aware, the Three Sequential-PNN (TS-PNN) approach is suggested for use in the process of distinguishing between single- and multi-fault types. In the first step of this process, seven indicators are investigated at STC and in a range of different climates. These indications are the maximum power Pmax, the fill factor (FF), the series resistance, and V mpp. Ise Voc and Impp are also included. Due to the results of the study, these indications have been simplified in order to more accurately and easily predict the nonlinear behavior of the PV system. The next step is an examination of a number of different types of faults as well as single fault scenarios, such as OC, SC, PS, and degradation ageing. The 1.22 kW PV array, which has an average accuracy of 98.5 percent, is utilized to finally test the recommended method both conceptually and experimentally. In addition, a comparison technique employing two distinct ANN models, TS-ANN and 1-ANN, was put into practice and proved that the suggested method is easier and more accurate for identifying frequent errors. This will be shown by the fact that the presented method was the winner.

The Mixed Integer Linear Programming (MILP) optimization strategy is for localizing the OC and SC faults. This approach uses a mixture of integers and linear programming. The minimum value of the fitness function, which is calculated as the power difference between the estimated power and the measured one, is intended to obtain the exact fault patterns when three-level environmental factors are taken into consideration. This value is determined as the power difference between the estimated power and the measured one. In order to describe the faulty OC and SC components, simulated parallel and series switches are employed. With the help of an experimental photovoltaic array consisting of 13 modules, nine fault scenarios are investigated for the purpose of assessment. This is done while taking into consideration a variety of OC and SC fault locations as well as environmental conditions. In conclusion, a comparison with alternative fault localization approaches demonstrates that the suggested method has a higher detection accuracy and a shorter reaction time when it comes to identifying the fault situations that were researched.

Future plans include the implementation of the investigated fault detection techniques using a double diode model to build a simulation PV model and the application of effective optimization techniques to obtain the necessary electrical parameters, which will improve the FDD accuracy when using historical weather data.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Abbreviation

PV	Photovoltaic
FDD	Fault Detection and Diagnosis
FLC	Fuzzy Logic Control
SP	Series-Parallel
TCT	Total Cross-Tied
PSAT	Photovoltaics Science Applications and Technology Project
I-V curves	Current-Voltage Curves
MPPT	Maximum Power Point Tracking
DC	Direct Current
AC	Alternative Current
IR	Infrared
PS	Partial Shadowing
LLF	Line-to-Line Fault
SC	Short Circuit
OC	Open Circuit
MOSFET	Metal-Oxide-Semiconductor Field-Effect Transistor
IGBT	Insulated-Gate Bipolar Transistor
MS	Monitoring Systems
PVP	Photovoltaic Plants
DD	Detecting Discoloration
SS	Surface Soiling
HS	Hot Spot
PVM	Photovoltaic Module
SSPA	Statistical Signal and Processing Approaches
TDR	Time Domain Reflectometry
SSTDR	Speared Spectrum DTR
ECM	Earth Capacitance Measurement
PVA	Photovoltaic Array
PVMF	Photovoltaic Module Frame
BOA	Bayesian Optimization Algorithm
SSLN	Semi-Supervised Ladder Network
PSBO	Partial Shading with the Bypass Diode Open-Circuit Fault
PSSC	Partial Shading with the Bypass Diode Short-Circuit Fault
OCR	Circuit Voltage Ratio
IR	Current Ratio
VR	Voltage Ratio
ITLBO	Improved Teaching-Learning Based Optimization
STC	Standard Test Conditions
FLC	Fuzzy Logic Control
MILP	Mixed Integer Linear Programming