RENEWABLE ENERGY ENGINEERING

Solar Photovoltaic Fault Diagnosis: A Comprehensive Survey of Conventional and Machine Learning Techniques

Faheem Ahmad Qureshi[1*], Zahoor ud Din[2]

[1]NADEC, Riyadh, Saudi Arabia
[2]COMSATS University Islamabad, Islamabad, Pakistan

Published November 2026

Abstract

Faults are the principal impediment to achieving elevated levels of efficiency, reliability, and longevity in photovoltaic (PV) systems. In this article, we reviewed solar PV fault diagnostics techniques and compared different fault signature interpretations based on three primary data sources: electrical measurements, environmental conditions, and thermal inspection images. Five overlapping diagnostic perspectives are discussed: measurement modalities (electrical and thermal), statistical methods, optimization-based methods, machine learning techniques. The different approaches are compared regarding: the extent to which faults can be detected; quality of the diagnostic evidence that is generated; what measurements are required for diagnostics; how the topology of the system affects diagnostics; ability to localize faults; under what conditions a diagnosis is validated; and at what time interval the data needs to be acquired. Overall, our evaluation shows there is no single optimal method for identifying faults of all types, primarily because of differences in datasets, definitions of faults, validation conditions and timing measures which make it difficult to make direct comparisons. Finally, we identify areas for future research; Hybrid Physical/Data-Driven Models, Digital Twins, Embedded Inference, Standardized Datasets, Learning with Limited Labels, Longitudinal Field Evaluations.

Keywords: solar photovoltaic (PV) fault diagnosis; machine learning; deep learning; infrared thermography; solar PV monitoring

1 Introduction

The production of electricity will always be particularly important to the development of all countries. All power plants must use either one of three traditional types of fuels (oil, coal, and/or natural gas), or nuclear materials that undergo an energy conversion process to convert fuel into electrical energy. Power generation does come with several positive aspects; however, it comes with one major negative aspect: the environmental pollution generated from the waste products. These waste products are causing severe damage to our environment through contamination of the soil, water, and air. Therefore, the extreme increase in pollutants is resulting in an extreme amount of environmental degradation. This can result in the loss of human life, wildlife, and natural ecosystems. [1].

To mitigate such issues, researchers are now considering the option to extract energy using renewable energy systems. Like in a region we have the option of geothermal site then we can utilize geothermal energy from it. If a region has tidal energy potential to extract tidal energy from it or higher irradiance of solar energy to be utilized as solar energy systems or have suitable sustainable speed of air to exploit wind energy from it, then utilizing these resources give us a green energy

solution thus cutting the CO2 emission. The major efforts to be considered in this regard are EU 20:20:20 programmed with the ambition of 20% more integration of renewable energy systems, 20% cutting short of CO2 emission and 20% depletion in the fossil fuel-based generation [2, 3]. Moreover, if we consider the techno-economic factors of power generation using the novel trends of renewable energy systems, we will observe that in addition to being environmentally friendly it is also cost effective [4, 5].

Solar energy is one of the most popular forms of renewable energy, largely because of the potential for its wide availability and suitability for installation on residential properties. Solar Photovoltaic Systems (SPVS) can convert solar radiation into electricity. The process by which SPV's capture energy from sunlight and converts it into a usable form consists of either Solar Thermal Systems or Solar Photo Voltaic (PV). This paper will focus upon Solar PV Systems. The term "solar photo voltaic" refers to any component or system capable of converting the energy present in the photons of light produced by the sun into electrical energy. PV Cells or a combination of multiple PV Cells is typically used to capture energy from sunlight.

Fault diagnosis for PV systems involves both faults due to electrical, environmental or degradation (aging) causes [6–16] and learning-based methods such as semi-supervised fault detection and classification based on a graph [17]. The feasibility of these methods depends on what measurements are used, whether there are fault labels associated with that measurement, the structure of the system being monitored and the setting in which they will be evaluated. Therefore, this survey does not attempt to assume that each fault detection method can identify all faults; instead, it focuses on comparing the diagnostic capability with the requirement for evidence.

The three independent functional modules reviewed here are: fault related observation acquisition, recovery/preprocessing of monitoring data, and diagnostic interpretation. Independent Component Analysis is included as part of the Signal Recovery module.

1.1 Problem statement

Solar photo-voltaic (PV) systems are susceptible to faults [6–12, 14, 15, 18], which are diagnosed and rectified accordingly. The most critical step to resolve any fault is the fault diagnosis. As the fault rectification procedures can only be effectively applied when nature and location of fault is known. Furthermore, transmission of recorded data and its analysis at the control center also call for an efficient and reliable communication system. [18, 19]

An evaluation of a diagnostic method should therefore consider the conditions under which measurement and communication take place. Incorrectly measured data or missing data can impact the creation of features and/or interpretation of anomalous behavior in power plants. Therefore, this review includes consideration of required sensors and available information as well as methods for learning/inference.

1.2 Review scope and comparative approach

This survey article reviews methods used to diagnose faults with respect to various faults for photovoltaic (PV) systems. Comparative analysis presents the measured quantities, the diagnostic function, the range of faults covered according to the references mentioned in this study, the type of system studied and the conditions under which each of these studies were validated. In cases where there is no information regarding the precision or time to make a diagnosis, the missing values are noted as "not provided" rather than estimated from the interval at which measurements have been

taken. Section 4 evaluates the limitations of comparing the results obtained in the different studies. The synthesis is qualitative; it has no intention of providing an overall evaluation of the performance of the methods considered nor of proposing an exhaustive overview of the scientific literature.

The primary contribution of this review study is a structured qualitative comparison of machine learning-based and traditional PV fault diagnostics with respect to fault category, required measurements, diagnostic function, and validation evidence. Instead of assuming that either one approach will be universally superior to all others, the comparative analysis provided an overview of the practical applications and limits of various fault diagnosis approaches.

The article uses a qualitative critical review of literature (and therefore does not use a systematic review/meta-analysis). Literature used for this review is grouped by category of faults with photovoltaics; and categories of diagnostic methods; and required sensing for diagnostics; fault detection capability/coverage; and supporting data/validation from the referenced sources. For conventional versus machine learning based diagnostic approaches, those two types of approaches are evaluated using the diagnostic capabilities/evaluation conditions listed in each source paper. If there were no available performance metrics/validations provided by the authors, then no values were estimated. It is also important to note that this review is not comprehensive; as well as there may be some limitations in terms of comparing directly between different studies due to variability in fault definition/datasets/systems being tested/experimental conditions.

1.3 Background

Faults are natural for any real time system operating in the outdoor environment. Same is the case for solar PV panels that may undergo faults of numerous natures. In solar PV systems, some faults are technical in nature like short-circuit or open-circuit and some are caused by environmental effects like shadowing or cloudy climate. Faults of heterogeneous nature and severity are discussed in articles [6–15, 20].

1.4 Significance of solar energy systems

Electrical power systems are the backbone of the industrial infrastructure of the country. Considering its significance, power generation always remains critical for the progress of the country. To generate power, usually power plants utilize traditional sources such as nuclear fuel and fossil fuels (coal, natural gas, and oil) for over the century. All these power plants use some energy conversion mechanism to produce electrical energy out of these fuels. Although power generation has its due benefits but one of the main concerns is environmental pollution. As the power generation capacity is increasing with time to fulfill demand, it also increases the emissions like CO2, NO2, coal ashes, and nuclear waste, produced because of these conversion mechanisms undergoing in the power plants. Such exponential increment of pollution is key remainder for environmental degradation.

1.5 Solar energy system

The heat energy from sun is because of fusion reactions in which hydrogen atoms combine to form helium nuclei with release of numerous energies (1).

$$4\left(1_1H\right) \rightarrow {}_2^4He + 26MeV \quad (1)$$

Only a tiny amount of this energy reaches the earth in the form of solar radiation. This minute of energy is still capable that even if we capture 30 minutes of this energy, it is enough to fulfill one year

demands of earth's population. But how can this energy be utilized? To extract solar energy from sunlight and transform it into a useful form, we have two mechanisms for it, referring to Figure 1.

- Solar Thermal Systems.
- Solar Photo-Voltaic (PV) Systems.

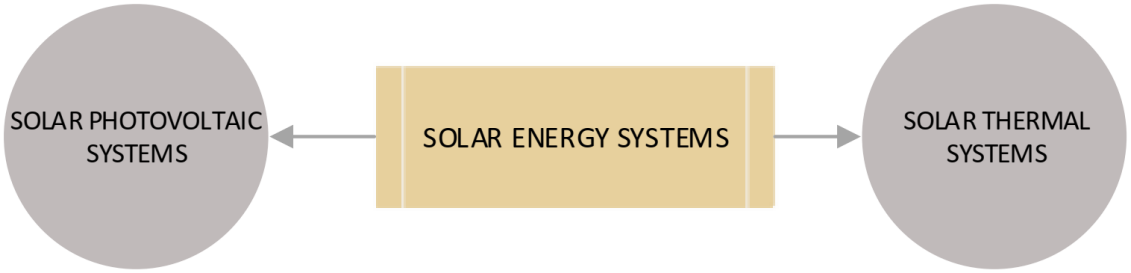


Figure 1. Solar energy systems.

1.5.1 Solar thermal systems

Such systems trap the heat energy from solar radiation and utilize it according to field of application. like flat plate and evacuated tube collectors use the heat energy of solar radiation to raise the temperature of any desired liquid material that is further treated following laws of convection. There are also other solar thermal collectors like that parabolic dish collector, parabolic trough collector, solar power tower, and linear Fresnel that concentrate the sunlight to a common point to heat up the fluid that is further treated accordingly. Like one of the applications is to heat up the water to produce steam that is further utilized to drive steam turbines for power generation.

1.5.2 Solar photo-voltaic (PV) systems

Photo-Voltaic can be described as any device or material that can transform the energy stored in the photons of sunlight to electrical energy. Usually, we employ PV cells and their combined geometry to extract energy from sunlight. A PV cell is a semiconductor that has chemical characteristics to directly transform the energy of solar radiation into electric energy. When sunlight falls upon the PV cell, it excites the electrons to jump across the junction between the different flavors of silicon.

Simulation based implementation is being widely popular in research, especially for large scale analysis [21]. PV module is the basic building block to construct the PV systems. The conventional technique to model the solar cell is to establish the mathematical expression based on the equivalent circuits of the cell. A solar cell consists of layers of semiconductor materials that exploit the photoelectric effect to convert the photon energy of the sun radiation into electricity. In terms of power electronics, solar cells can be considered as a current source that exhibits non-linear characteristics [22, 23].

This paper presents a mathematical model of solar PV cell based on an equivalent circuit [24]. It was applied to develop a 250W PV module to simulate its behavior. The results were compared to the original characteristics curves from the datasheet of the Soltech 1STH-215-P module. This model can generate the I-V and P-V characteristics of the PC cell and module. The model is designed to study different parameters variations effect on the output of PV module. MATLAB/Simulink software is used to develop this model, simulate and to obtain results.

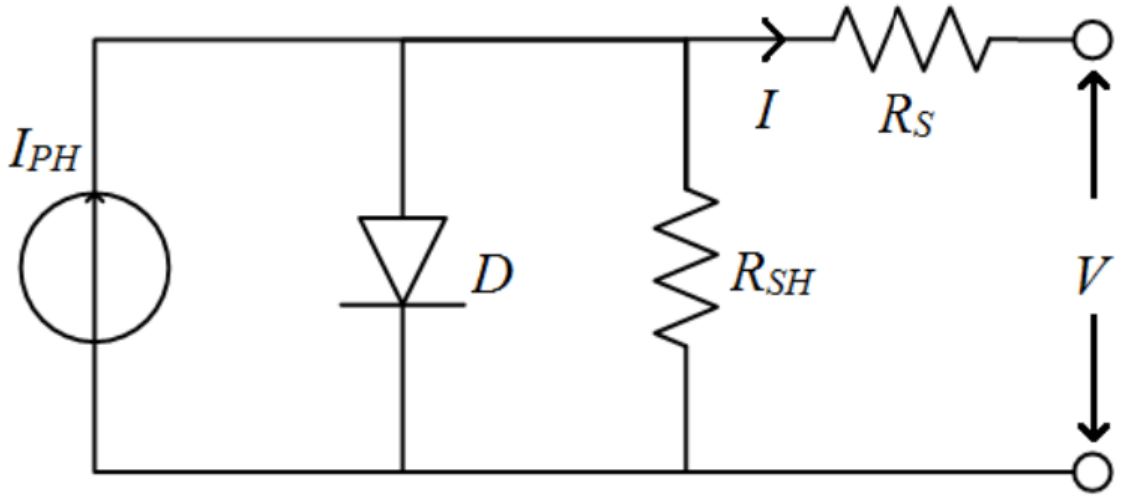


Figure 2. Equivalent model of PV cell.

1.5.3 Photovoltaic (PV) cell

In literature we can find various numbers of systematic models that are used to categorize the operations of solar PV module. The most used model is the one-diode model [23, 25]. This model is symbolized by a current source with parallel diode and series and shunt resistance to account for the losses as seen in Figure 2. PV module is the basic building block to construct the PV systems. The conventional technique to model the solar cell is to establish the mathematical expression based on the equivalent circuits of the cell. A solar cell consists of layers of semiconductor materials that exploit the photoelectric effect to convert the photon energy of the sun radiation into electricity. In terms of power electronics, the solar cell can be considered as a current source that exhibits non-linear characteristics [22].

The equivalent circuit of a solar photovoltaic (PV) cell is shown in Figure 2. It is categorized by a current course, diode, series, and shunt resistances [23, 26].

The I-V curve for a solar panel is non-linear. The maximum power point represents the best operating point to maximize the product of voltage (V) and current (I). Therefore, it should not be assumed to represent a point at which an increase in voltage will result in an increase in current and vice versa. Both irradiance and cell temperature can influence both the shape of the I-V curve and the relative positions of those points shown in figures 3-6.

Change in power from PV cells as change in irradiance can be observed in Figure 3 and Figure 4. Power generation also varies as the temperature varies. Power generation trends of PV cells with change in temperature can be observed in Figure 5 and Figure 6.

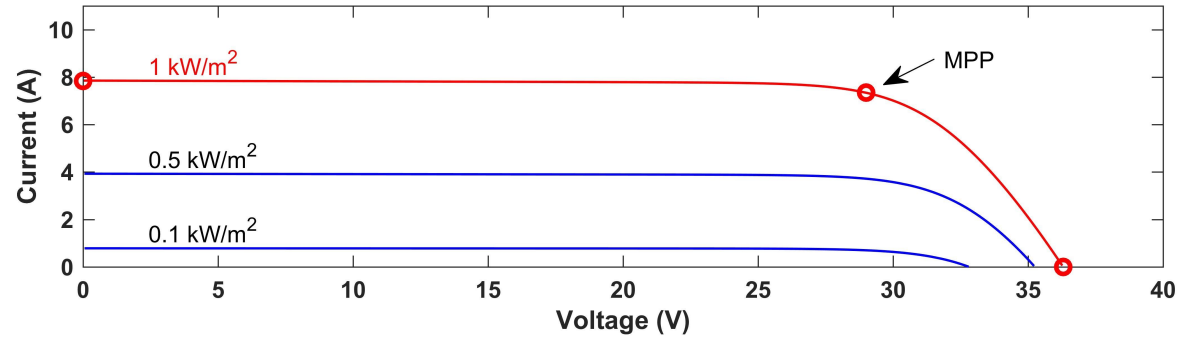


Figure 3. Current–voltage characteristics of a PV module at different irradiances.

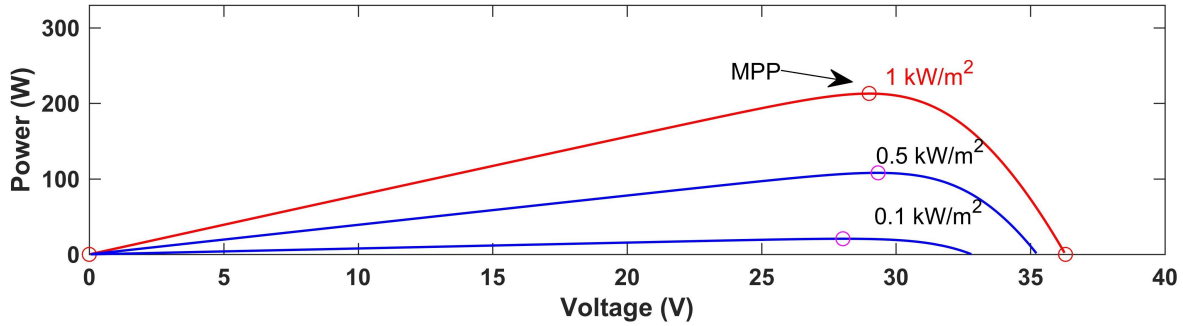


Figure 4. Power–voltage characteristics of a PV module at different irradiances.

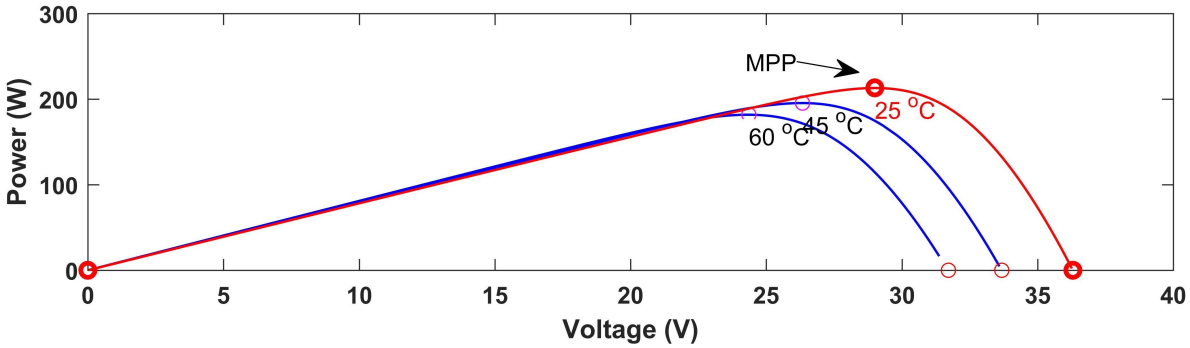


Figure 5. Power–voltage characteristics of a PV module at different temperatures.

1.5.4 Working of PV cell

The conversion of sunlight into electrical energy by a solar cell is called the photo-voltaic effect, hence why we refer to solar cells as photo-voltaic as shown in Figure 7.

A solar photo-voltaic (PV) cell converts the sunlight into electricity in three steps:

Step 1: PV cells absorb light and use energy; it knocks out electrons: Sunlight strikes a photo-voltaic cell and is absorbed by the semi-conducting material it is made from. This incoming light energizes the electrons in silicon to be knocked loose, free electrons.

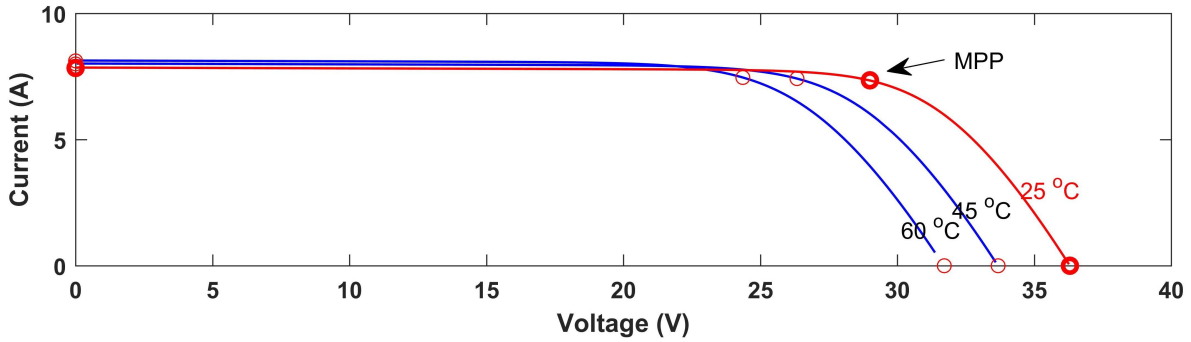


Figure 6. Current–voltage characteristics of a PV module at different temperatures.

Step 2: Flow of free electrons generates electric current: There are two layers of semiconductor material used in photo-voltaic cells; upper side is doped as N-type (electrons efficient) and P-type (electrons deficient). This will create an electric field in PV cells. This electric field causes loose electrons of flow in one direction through the solar cell, generating an electrical current.

Step 3: Flow of current is then feed to the load: Once an electrical current is generated by loose electrons, metal plates on the sides of each solar cell collect those electrons and transfer them to wires. At this point, electrons can flow as electricity through the wiring to a solar inverter and then throughout your home.

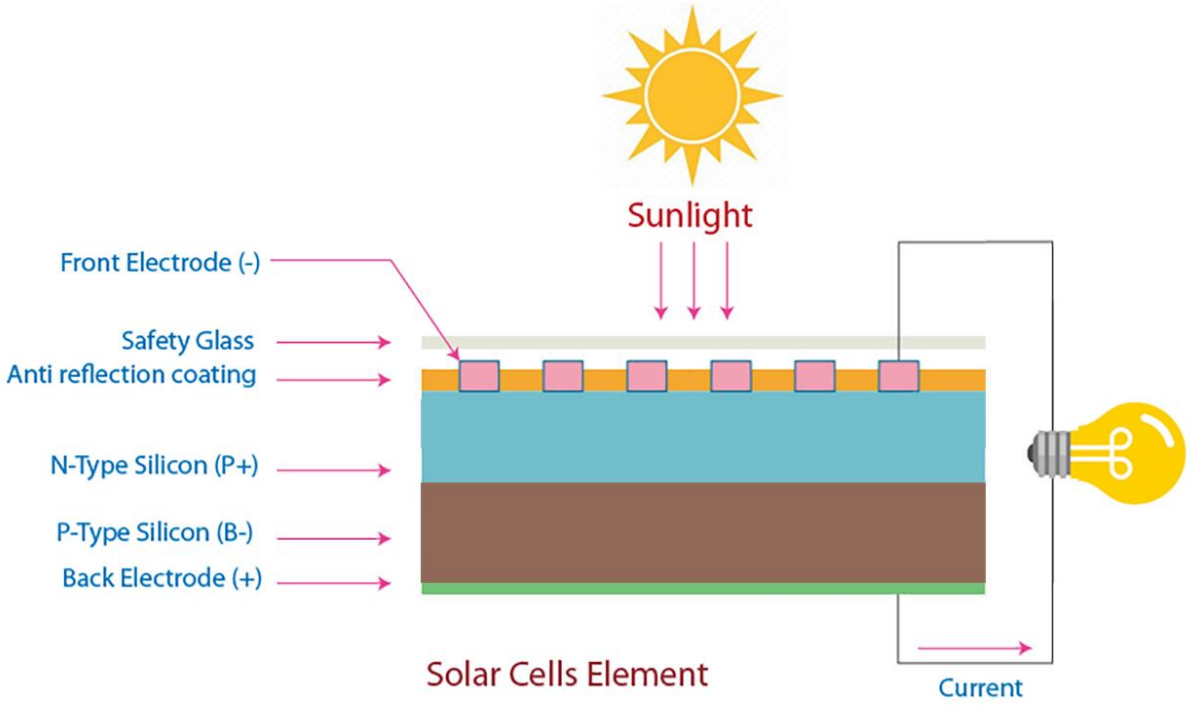


Figure 7. Working of a photovoltaic cell.

1.5.5 Diodes in PV panel

The PN-junction diode behaves as solid state one-way electrical valve allowing electrical current to flow in one direction only. These diodes are used to block the flow of electric current from one part to other parts of an electrical solar circuit.

- Bypass Diode: These are connected in parallel with a PV panel to shunt the current around it. The partially shaded cells or electrically weak or distorted PV panels behave as a load for healthy panels causing overheating and burning. Bypass diode bypasses the current(s) flowing from these unhealthy PV panels by providing a shunt path. Bypass diodes can be observed in green in Figure 8.
- Blocking Diode: These are connected in series with the PV panels to prevent current flowing back into them. Their purpose is to ensure that current (s) only flows in one direction OUT of the series array to the external load, controller, or batteries. Blocking diodes can be observed in red color in Figure 8.

The remainder of the paper is organised as follows. Section 2 discusses the classification of solar PV faults. Section 3 reviews solar PV fault diagnosis methods. Section 4 compares the diagnosis techniques. Section 5 provides conclusions and future research directions.

2 Classifications of PV faults

Any real time system operating in the outdoor environment is always prone to faults. Same is the case for solar PV panels that may undergo faults of numerous natures. Some faults are technical, some are environmental and some faults also occurred because of human error. Some are temporary that remains for some time and afterwards system restore its healthy condition like shadowing effect [13–15, 27] while some are permanent in nature like short-circuit fault, open circuit fault, module degradation [11 ,12, 28]. Faults of PV panels are shown in Figure 9. In later subsections, we will consider each type of fault specifically and then comprehensively formulate them in the form of Table 1.

2.1 Soiling

Solar panel generates energy from the incident sunlight. Maximum efficiency is achieved only when panels acquire sunlight without any obstacle. But as their application is outdoor so panels may subject to dust and particle accumulation over their surface. Now panels cannot catch the sunlight to their full potential which limits the energy generated [6, 29]. It is shown in Figure 10 by fault F0.

2.2 Hot spot

This is a condition in which solar panels rather than generation function as load for the system. This fault not only degrades solar panel physically but also reduces system performance [7, 30]. Hot spots may occur due to failure of bypass diode, partial or full shadowing or due to mismatch electrical characteristics between different panels. We can observe this fault in Figure 10 by fault F1.

2.3 Mal-orientation or inclination of panel

In case of fixed solar power plant without tracking mechanism, panel plates have fixed orientation and inclination calculated by the specified geographical site [8]. If the orientation and inclination is not in accordance with the maximum power point perimeters then system generates less power. Refer to Figure 10 by fault F2 are misaligned PV plates.

2.4 Aging and module degradation

Every panel has its life which degrades over time [9, 31]. With passage of time, panels degrade, thus limiting their generation efficiency. So, fault detecting mechanism may consider this shortage of generation capability as fault. This abnormal condition is dealt with here separately to distinguish it from other faults. It is depicted in Figure 10 by fault F3.

2.5 Lightning or storm

As solar panels are placed in the outer atmosphere there are highly environmental effects like lightning or storm may affect the solar infrastructure [10]. Lightning may damage plates and storms may displace them from their orientation thus hindering power generation. Effect of lightning can be rendered in Figure 10 by fault F4.

2.6 Short-circuit fault

This type of fault affects both the cell and the associated bypass diode. This fault bypasses the whole panel thus terminates its role in the generation also hinders the performance of other modules also. It may occur due to water deposition over module that may short circuit the opposite polarity terminals or may also occur due to aging of PV panels as shown in Figure 10 by fault F5. This fault cut short the power delivery equal to the product number of short-circuited modules and their associated capacity with addition of performance losses caused by the faulty module to other modules [11]. This fault is permanent in nature that can be rectified y by replacing the short-circuited modules.

2.7 Open circuit faults

This fault occurs when the current path of system may get opened as we can observe in Figure 10 by fault F6. This usually occurs due to fragile wiring that get broken by any reason [12, 32]. This fault affects the system depending upon the location of open circuit whether it is disconnecting only a series branch, bunch of series branches or the entire system. This fault is permanent in nature and can be rectified only by repairing the broken connections.

2.8 Shadowing

Solar panels generate energy by converting the sunlight into electrical energy. But if the panel cannot receive sunlight due to shadowing, then panel is not able to produce energy [13, 33]. That panel or series of panels subjected to shadowing, function as load for the remaining system. Shadowing may of two types:

- Partial Shadowing: When single module or minute portion is under shadow [14, 33]. It may affect the generation on limited range. Partial shadowing effecting PV plates can be analyzed in Figure 10 by fault F7.
- Full Shadowing: When major portion or entire system is under shadow [15, 28]. Under this fault, there is no generation or minimum generation. Influence of this fault is indicated in Figure 10 by fault F8.

These faults are temporary in nature and are rectified on its own as object casting shadow changes its location or someone displaces that object.

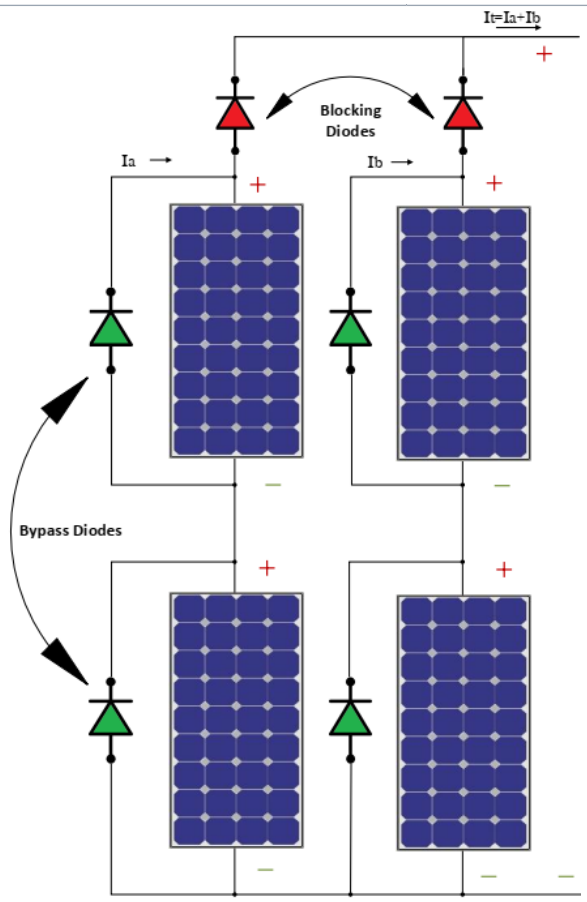


Figure 8. Solar PV panels with bypass and blocking diodes.

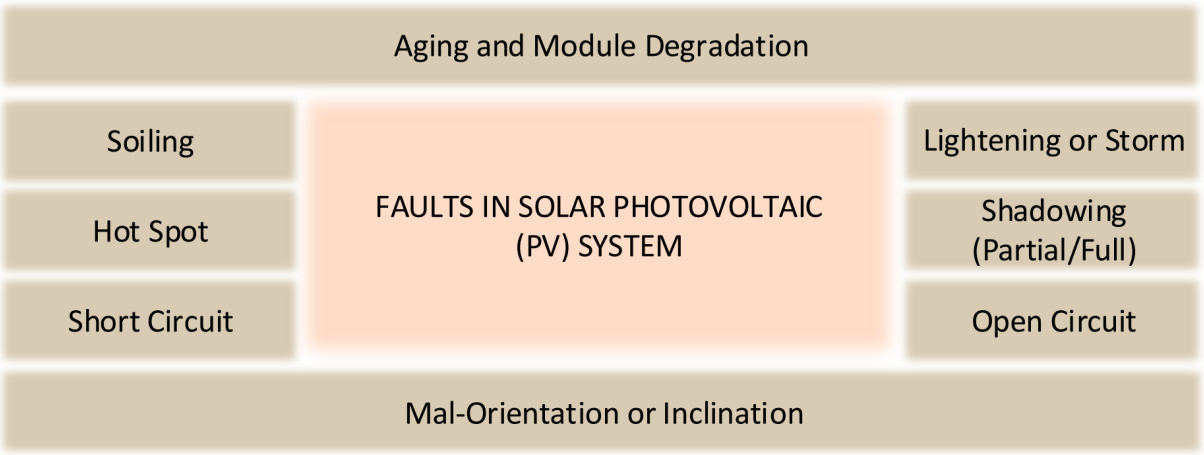


Figure 9. Faults in solar PV systems.

3 Solar PV fault diagnosis

Faults are natural for any real-time system, and they are diagnosed and rectified accordingly. Faults may occur for technical reasons, because of human or random errors, environmental effects or manufacturing defects [34, 35]. The most critical step in the fault mitigation process is fault diagnosis [35, 36]. The main faults are summarised in Table 1.

Table 1. Faults in solar PV systems.

Ref.	Fault Type	Description
[6]	Soiling	Accumulation of dust and other particles over PV panels.
[7]	Hot Spot	Solar PV panels rather than generation function as load for the system.
[8]	Mal-Orientation or inclination	Solar PV panels are not placed in the line of sight of sunlight for fixed orientation.
[9]	Module Degradation	Decrease in generation due to age of PV panels.
[10]	Lightning or Storm	Environmental effects like Lightning or storm on solar PV panels.
[11]	Short Circuit Fault	Any panel, or series of panel get short circuit and terminates its generation.
[12]	Open Circuit Fault	Panels get disconnected due to open wiring or connection breakup.
[14]	Partial Shadowing	When single module or minute portion is under shadowing
[15]	Full Shadowing	When major portion or entire system is under shadow

Fault rectification procedures can only be applied effectively when the nature and location of a fault are known. Since solar PV systems operate outdoors, atmospheric influences are present in addition to technical faults such as short circuits, open circuits or faults related to shadowing (Figure 10).

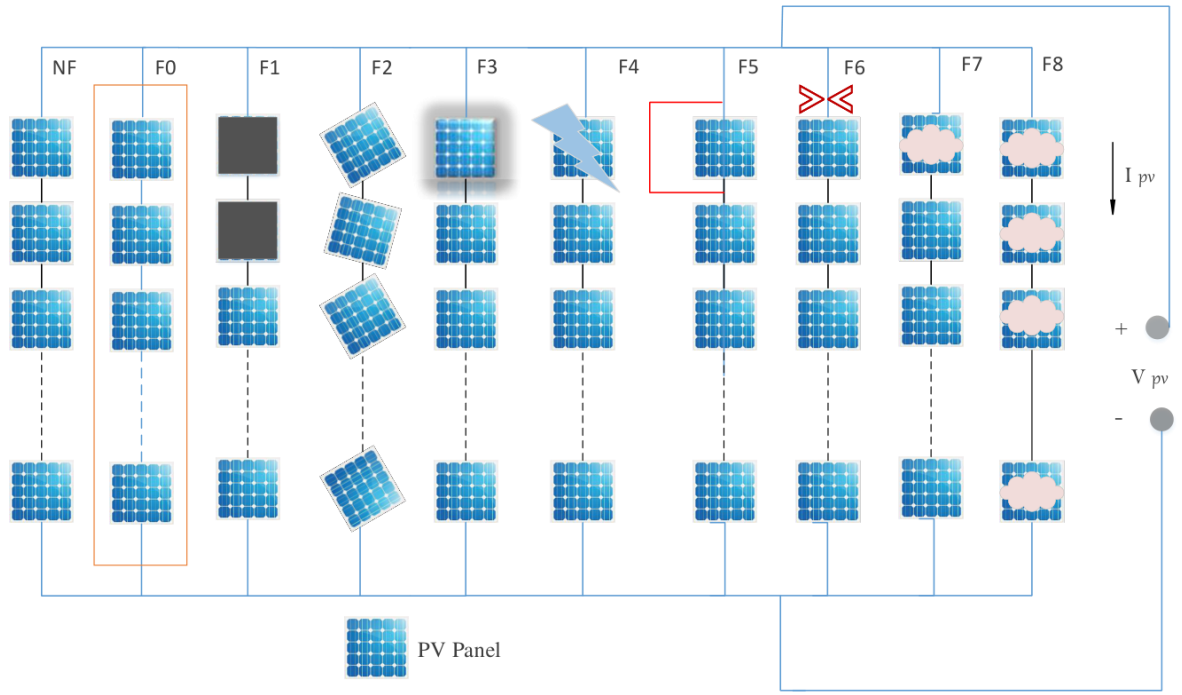


Figure 10. Faults of PV module.

3.1 Review of fault diagnosis methods

As the solar PV technology is in mature stages it has accommodated most of the fault and concerned diagnosis and mitigation methods. Some authors have used simulation-based models [15] and while some papers also suggest the application of experimental field data [22]. Studies also have incorporated statistical [37, 38] and optimization algorithms [39–42] for fault diagnosis like Meta-heuristic optimization, artificial neural networks, or inferential statistics. [38, 43] In this section we are study-

ing the efforts of various authors who have comprehensively considered such faults and provide fault diagnosis techniques as shown in Figure 11.

3.1.1 Optimization algorithm-based fault diagnosis

After the deployment of diagnosis algorithms, certain variation pertaining to cell condition and atmosphere conditions may occur offsetting the threshold parameters for faults. Application of optimization algorithm that inherent learning procedures to update the parameters upon variance in the outer conditions may serve the role to counter such above mentioned circumstances. Researchers have adopted such practices in the articles [44–47]. Article [44] compares the experimental and PSO based optimized simulation results to indicate fault in case of any mismatch while [46] focuses on the optimization using meta-heuristic optimization algorithm. In Table 2 we have discussed various authors who have performed such analysis and documented their findings in the form of research articles.

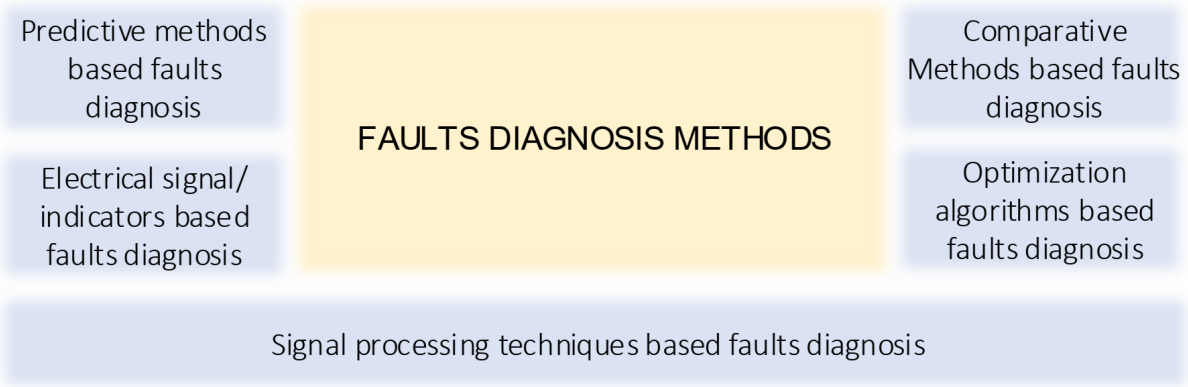


Figure 11. Fault diagnosis methods.

Table 2. Optimization algorithm-based fault diagnosis.

Ref.	Fault Type/ Method	Description
[44]	Particle Swarm Optimization (PSO)	Simulation results and experimental readings are compared to diagnose faults.
[45]	Voltage sensors optimization	Placement of voltage sensors is optimized for better fault diagnosis.
[46]	Meta-heuristic optimization	Diagnosis of short-circuit and open circuit faults.

3.1.2 Predictive methods-based faults diagnosis

Observing the real time response of the system under various conditions and analyzing the results using thermal imaging [48, 49] or by statistical approaches like minimum covariance determinant (MCD) [50], one can predict about the future faulty conditions. [39] is employing Inferential statistics while [40] applies Minimum Covariance Determinant (MCD) to check the performance on simulated instances of arc and ground faults is evaluated. Different authors have employed such approaches as referred to in Table 3.

Table 3. Predictive method-based fault diagnosis.

Ref.	Fault Type/ Method	Description
[48]	Thermal imaging	Application of thermal imaging to identify and predict faults.

Ref.	Fault Type/ Method	Description
[50]	Seven Indicators to predict faults	Preemptive fault indication for partial and full shadowing.
[39]	Inferential statistics	Analysis and prediction of faults using statistical methods.
[40]	Minimum Covariance Determinant (MCD)	Performance is evaluated on simulated instances of arc and ground faults.

3.1.3 Electrical signal/ indicator-based fault diagnosis

Solar PV system generates power in accordance with the health of the system and the atmospheric conditions. Authors suggested the use of statistics [41, 51] and optimization algorithm [52] to analyze these electrical parameters for fault diagnosis. In Table 4 findings are documented relating to the electrical characteristics [53, 54, 55] of the solar PV system with different faulty conditions, considering the irradiance and temperature, to diagnose the faulty condition.

Table 4. Electrical signal/indicator-based fault diagnosis.

Ref.	Fault Type/ Method	Description
[53]	Open circuit module, Internal short circuit, Faulty soldering, Shadowing, Degradation	Electrical and thermal properties of the solar module are considered for fault diagnosis.
[54]	Aging and grid faults	Monitoring of measured current and voltage of the system incorporated with temperature and irradiance sensors to diagnose faults. Experimentation readings are then verified by simulations.
[55]	Number of open and short circuit modules	Current and voltage measurement as product of number of panels can provide us with an estimation about short circuit and open circuit faults.
[41]	Statistical Approach	Utilization the direct current (DC) of the PV system, provided the given irradiance and temperature to diagnose faults.
[52]	Artificial Neural Networks (ANN)	Electrical parameters measured from field data are compared with simulated results and learning methods are deployed using Artificial Neural Network (ANN).

3.1.4 Comparative method-based fault diagnosis

In this technique, in addition to simulation results a small-scale test bench is also developed to counter verify the simulated results. For this purpose, relative comparison is performed using matter element model [56], observation method [57], or simple comparative method [46] in which each parameter is compared against its counterpart. Some articles observe the mismatch between healthy and faulty systems to diagnose shadowing effect [58, 59], cell degradation [60] and the effect of dust and other accumulations over PV cell [40, 57]. Relative comparison methods are mentioned in Table 5.

Table 5. Comparative method-based fault diagnosis.

Ref.	Fault Type/ Method	Description
[56]	Extension Theory (Matter Element Model)	Power profile of the system is collected for both the normal and mal-operational conditions to construct a matter-element model for PV generation systems. Like other optimization models, this model does not require any previous data.

Ref.	Fault Type/ Method	Description
[58]	Issues caused by shadowing Effect	When a panel is shadowing, it acts as load for remaining. This induces heating effects, thus increasing temperature and impedance. Comparison with the rated values indicate such faults.
[46]	Comparative Method	In this technique simulation results and experimental readings are compared to find any deviation from rated operation.
[59]	Partial shadowing, Overall shadowing, Open circuit	Relationship between healthy and faulty parameters is determined by establishing various hypothesis models. Then variance and meaning of these methods are found to have the most optimized model.
[60]	Position and value of degradation	Impedance mismatching between the reference points is observed. If impedance changes, series resistance also increases, thus indicating the fault.
[57]	Observation Method	Local and global parameters are continuously observed, compared and their control charts are then plotted. Observation of these control charts gives us information about the fault conditions.
[50]	Fault study under various configurations	Different configurations like series, parallel & series-parallel under faulty conditions are studies to find out their tolerance level for faults. System response is observed by subjecting different sections of the system under partial and full shadowing.
[61]	Effect of dust and other accumulations	Dust and other accumulations like water or moist sunlight to convert into energy. This study comprehensively analyzes the effects of these accumulations.

3.1.5 Signal processing techniques-based fault diagnosis

To analyze bulk sum of data and deduce the results to resolve the concerned issue, signal processing techniques [48, 62–67] find its application in vast field of technical areas. Researchers have deployed signal processing techniques like extreme learning machine (KELM) [62, 68] for shadowing faults, artificial neural network (ANN) [42, 52, 63, 64] for electrical abnormalities and least square method [66] for shadowing effect. In Table 6 and authors have established results using such optimization procedures. Table 7 summarizes the comparative studies of solar PV fault diagnosis techniques. Furthermore, Table 8 shows the comparison of signal processing and learning technique.

In order to select a diagnostic tool in a situation where some of the above diagnostic tools will be used in conjunction with one another (i.e., machine learning or pattern recognition, thermal imaging, etc.), you need to determine which measurement(s) is/are being measured and therefore, what type of diagnostic tool can be utilized. In other words, if it is possible to measure the output of the solar panel, then an electrical output based diagnostic method could be utilized.

Table 6. Signal processing technique-based fault diagnosis.

Ref.	Fault Type/ Method	Description
[63]	Short circuit faults / ANN	Diagnosis of short circuit, artificial neural network method is deployed.
[62]	Shadowing, Open circuit, short circuit, degradation / KELM	Kernel based extreme learning machine (KELM) for fault diagnosis using real time parameters of the solar plant and then applied to update diagnosis algorithm.
[41]	Statistical Approach	Utilized direct current (DC) of the PV system, provided the given irradiance and temperature. It diagnoses faults following the changing trends of DC.

Ref.	Fault Type/ Method	Description
[39]	Inferential statistics based on the ANOVA and Kruskal-Wallis tests	Application of statistical methods to identify and measure electrical parameters and predict faults using statistical methods.
[45]	Generic faults / Extended correlation model	Extended correlation function and the matter- element model were proposed to diagnose various faults of the solar PV system.
[64]	Partial Shadowing / ANN	Artificial neural network is deployed for ex-traction of measured quantities to diagnose partially shaded panels.
[65]	Short circuit, abnormal aging, and local shadow/ KELM	Improved radial basis function (RBF) and kernel extreme learning machine (KELM) are employed for fault diagnosis.
[48, 69]	Dusting, bird dropping and bypass diode failure/ fuzzy logic	This technique uses the heat radiation of the body, called thermo-graphy incorporated with optimization algorithm like fuzzy logic.
[52]	Artificial Neural Networks (ANN)	Electrical parameters measured from field data are compared with simulated results and learning methods are deployed using ANN.
[66]	Shaded cell condition/ least square	In this technique, all types of shadowing effects are considered using least square.

Table 7. Comparative synthesis of diagnosis method families.

Method type	Fault coverage described	Inputs or mechan-ism	Advantages in the descriptions	Limitations / evid-ence gaps	Accur-acy / speed
Optimization and model comparison [44, 45, 46]	Open- and short-circuit faults; general abnor-mal operation	Measured versus simulated re-sponse; optimized voltage-sensor placement	Combines model comparison with parameter or sensor optimization	Depends on the de-scribed model and sensor inputs; ro-bustness across sites is not quantified	NR / NR
Electrical indic-ators and stat-istics [41, 54, 55]	Open circuit, short circuit, aging, and grid faults	Current and voltage; irradiance and temperature com-pensation	Links measurable electrical deviations to fault identifica-tion or faulty-mod-ule count	Environmental meas-urements described; threshold transferab-ility is not reported	NR / NR
Thermal / fuzzy methods [48]	Dust, bird drop-pings, physical damage, and by-pass-diode fail-ure	Thermographic observations; op-tional fuzzy clas-sification	Non-destructive in-spection: thermal patterns support fault classification	Requires thermal ob-servations; compar-ative classification error and latency are not reported	NR / NR
ANN and KELM [52, 62, 63, 64, 65]	Short circuit, shading, open circuit, and de-gradation; cover-age varies by model	Measured electrical para-meters; learning-based or kernel-based diagnosis	Learns diagnostic relationships; KELM description includes environ-mental updating	Dataset size, train/ test split, and com-mon evaluation pro-tocol are not spe-cified	NR / NR
Reference and impedance comparison [57, 58, 60]	Shading, degrad-ation, and gener-al abnormal op-eration	Rated or refer-ence response; impedance changes; control charts	Deviations from healthy operation; impedance compar-ison supports de-gradation localiza-tion	Requires suitable ref-erence values; separ-ation of simultan-eous fault effects is not quantified	NR / NR

Method type	Fault coverage described	Inputs or mechanism	Advantages in the descriptions	Limitations / evidence gaps	Accuracy / speed
AC characterization / MPPT studies [70, 71, 72, 73]	Hot-spot-related behavior	AC parameters, thermal characteristics, electrical MPPT measurements	Connects hot-spot assessment with module behavior and mitigation studies	Detection and mitigation are different objectives; no common diagnostic benchmark is given	NR / NR

A revised compilation of the data from Tables 2–6 and 9–17. NR = information not available.

Table 8. Comparison of learning and signal-processing approaches.

Approach	Diagnostic role / faults	Data or processing described	Potential advantage	Limitation / missing evidence
ANN [52, 63, 64]	Short circuit and partial shading; electrical fault diagnosis	Field electrical measurements; comparison with simulation; feature extraction	learned relationships between electrical measurements & fault cond.	Accuracy, training-set size, test split, and inference time are not reported here
KELM [62]	Partial shading, open circuit, short circuit, and degradation	Real-time and simulated data; environmental parameters used to update diagnosis	Description explicitly addresses changing operating conditions	No quantified adaptation gain, accuracy or computational latency is supplied
RBF / KELM [65]	Short circuit, abnormal aging, and local shading	Improved radial-basis-function and kernel extreme-learning approach	Combines a stated kernel-learning approach with several fault categories	No shared dataset comparison against ANN or other KELM variants
Thermography with fuzzy logic [48]	Dust, bird droppings and bypass-diode failure	Thermal observations combined with fuzzy classification	Adds classification to non-destructive thermal inspection	Membership-rule design, accuracy, and processing time are not reported
Least-squares analysis [66]	Shaded-cell conditions	Least-squares processing across shadowing cases	Provides a stated analytical approach for evaluating shading conditions	Detection of non-shading faults and quantitative diagnostic are not mentioned
ICA [74, 75, 76, 77, 78, 79, 80, 81]	Signal recovery supporting downstream diagnosis	Blind separation of mixed sensor signals; statistical independence assumption	Does not require prior signal/channel information in the stated framework	Signal separation is not itself faulty; recovered signals still require diagnostic processing

A new comprehensive summary combining Table 6 and Section 3.3. The advantages of each method are a summary of the functions they have been shown to perform. Their limitations represent either missing information, or some dependency that has not been independently evaluated as a weakness.

3.2 Review of type of faults and associated techniques

Up till now we have considered diverse types of faults that may occur in solar PV systems and observe various generic techniques that we may use for fault diagnosis. Now we will analyze how these different researchers have utilized these techniques for solar PV fault diagnosis.

3.2.1 Soiling

Soiling is a run-time fault that can be diagnosed with sheer attention only as it compromises the performance of system on very minute level. Researchers have employed Infrared thermography [48, 82] for it and try to read it using changing current and voltage behaviors [54]. Moreover, any fault can be diagnosed only if analysis for its causes is performed keenly like the in the article [61]. All these techniques are summed in Table 9.

Recent assessment of infrared thermographic diagnosis extends comparison beyond accuracy to computational complexity, hardware requirements, affordability, deployment with attention to dataset preparation and real-time deep learning [83].

Table 9. Soiling.

Ref.	Fault Type/ Method	Description
[54]	Aging and grid faults	Diagnosis by using the measured current and voltage of the system incorporated with the temperature and irradiance sensors. Whenever any parameter exceeds its threshold value, diagnosis system initiate warnings accordingly. The experimentation readings are then verified by simulations.
[61]	Effect of dust and other accumulations	Dust and other accumulations like water or moist hinders the trap of sunlight to convert it into energy, also known as external resistance. This study comprehensively analyzes the effects of these accumulations.
[48]	Infrared thermo-graphy	Utilization of heat radiation of body, called as thermo-graphy to detect external faults such as accumulations like dusting or physical damage, bird dropping. This technique is highly efficient, dependable, and non-destructive technique. Optimization algorithms like fuzzy logic are also discussed.

3.2.2 Aging and module degradation

As the panels are put into service, they are subjected to outer atmosphere and undergo aging and degradation with time. [53, 54] discusses Aging and grid faults, Open circuit module, Internal short circuit, Faulty soldering, Shadowing, Degradation by considering both the electrical and thermal properties of the solar module and measured current and voltage of the system incorporated with the temperature and irradiance sensors. Abnormal aging is discussed in [65]. [60, 84] accounts for value of degradation. All these findings are presented in Table 10.

Table 10. Aging and module degradation.

Ref.	Fault Type/ Method	Description
[53]	Open circuit module, Internal short circuit, Faulty soldering, Shadowing, Degradation	In this technique both the electrical and thermal properties of the solar module are considered for fault diagnosis.
[65]	Short circuit, abnormal aging, and local shadow	State of art optimization techniques like improved radial basis function (RBF) and kernel extreme learning machine (ELM) are employed for fault diagnosis.
[54]	Aging and grid faults	Observation of measured current and voltage of the system incorporated with the temperature and irradiance sensors. Whenever any parameter exceeds its threshold value, diagnosis system initiates warnings accordingly. Experimental results are then verified by simulations.
[60]	Position and value of degradation	Impedance mismatching between the reference points is observed. If impedance changes, series resistance also increases, thus indicating the fault.

Ref.	Fault Type/ Method	Description
[84]	Potential-induced degradation (PID), Partial shadowing, Increased series resistance losses	Faults related to partial and full shadowing and its effects on panel performance.

3.2.3 Hot spot

The internal chemistry of the PV panels also affects power generation. Internal faults are considered under hot spots. [70] is dealing with degradation due to hot spot while [71] accounts for variations in thermal characteristic due to hot spot [72, 73] present analysis and novel algorithm based customized algorithm using the measured electrical parameters is deployed to efficiently detect hot spot. All these studies are mentioned in Table 11.

Table 11. Hot spot.

Ref.	Fault Type/ Method	Description
[70]	Degradation due to hot spot	Fault diagnosis of hot spot due to any reason is performed using AC Parameter Characterization.
[71]	Variations in thermal characteristics due to hot spot	Module integrity and performance degradation because of hot spot.
[72]	Maximum Power Point (MMPT)	Performed simulations and field tests of hot spots in PV systems with central and distributed MPPT. It has been shown that PV systems with DMPPT are less prone to hot spots than those with central MPPT.
[73]	Analysis and novel algorithm	A customized algorithm using the measured electrical parameters is deployed to efficiently detect hot spot.

3.2.4 Mal-orientation or inclination of panel

If any panel is not in the line of sunlight, then it is not able to fetch irradiance to full potential. The authors conducted a study on determining the best possible angle and orientation for Photovoltaic (PV) arrays to increase solar energy collection [85]. Instead of developing or testing an adaptive fault classification algorithm; this study provided both installation and performance optimization perspectives. Mal-orientation on power generation and its associated effects are discussed. Table 12 provides description of the mentioned studies.

Table 12. Mal-orientation or inclination of panel.

Ref.	Fault Type/ Method	Description
[85]	Learn and improve	Irradiance is observed and on upon any mal operation, system observe, learn, and act accordingly. Optimal tilt angle for orientation of solar photo-voltaic arrays is achieved to maximize power generation.
[86]	Effect of mal orientation	Optimal Orientation for maximizing solar irradiation for PV.

3.2.5 Lightning or storm

Environmental effects like Lightning or storm may lead to mal operation of PV grid like [87] is studying arc faults [88] is considering lightning faults as solar panels are deployed in the outer atmosphere so there are prone to lightning. In Table 13 thorough description of the faults is discussed.

Table 13. Lightning or storm.

Ref.	Fault Type/ Method	Description
[87]	Ground faults, Line-to-line faults, Arc faults	This technique considers the faults related to outer atmosphere of panels like panels operate in outer environment, so they are prone to lightning.
[88]	Lightning	As solar panels are deployed in the outer atmosphere so there are prone to lightning. Study the effects of external atmosphere.

3.2.6 Short circuit fault

In [62, 65], authors are utilizing kernel based extreme learning machines (KELM) to diagnosis faults while [53] consider both the electrical and thermal properties for fault diagnosis. Use of optimization algorithms like meta-heuristic optimization [44] and artificial neural network [63] method is also deployed. Article [55] is taking current and voltage measurement as product of number of panels installed can provide us with the estimation about short circuit and open circuit modules. Faults diagnosis techniques are summed in Table 14.

Table 14. Short-circuit fault.

Ref.	Fault Type/ Method	Description
[62]	Partial shadowing, Open circuit, short circuit, degradation	Data samples are gathered using both real time and simulated data which then processed via kernel based extreme learning machine (KELM) provides us with the requisite diagnosis system.
[53]	Open circuit module, Internal short circuit, Faulty soldering, Shadowing, Degradation	In this technique both the electrical and thermal properties of the solar module are considered for fault diagnosis.
[65]	Short circuit, abnormal aging, and local shadow	State of art optimization techniques like improved radial basis function (RBF) and kernel extreme learning machine (ELM) are employed for fault diagnosis.
[44]	Meta-heuristic optimization	To distinguish between short-circuit and open circuit, this technique is applied providing the irradiance and panel temperature.
[63]	Short circuit faults	To diagnose problems related to short-circuit, artificial neural network method is deployed.
[55]	Number of open and short circuit modules in system	Current and voltage measurement as product of number of panels installed can provide us with the estimation about short circuit and open circuit modules.

3.2.7 Open circuit fault

Article [62] is utilizing kernel based extreme learning machine (KELM) to diagnosis faults. while [53] consider both the electrical and thermal properties for fault diagnosis. Use of optimization algorithms like meta-heuristic optimization [44] method is also deployed. Study of relationship between healthy and faulty parameters considering electrical and thermal properties of the solar module are determined by establishing various hypothesis models to diagnose faults [53, 59]. Details of all faults diagnosis techniques are mentioned in Table 15.

Table 15. Open-circuit fault.

Ref.	Fault Type/ Method	Description
[55]	Number of open and short circuit modules in system	Current and voltage measurement as product of number of panels installed can provide us with the estimation about short circuit and open circuit modules.
[62]	Partial shadowing, Open circuit, short circuit, degradation	Data samples are gathered using kernel based extreme learning machine (KELM) which then processed to provide us with the requisite diagnosis system.
[59]	Partial shadowing, Overall shadowing, Open circuit faults	Relationship between healthy and faulty parameters is determined establishing various hypothesis models to diagnose faults
[53]	Open circuit module, Internal short circuit, Faulty soldering, Shadowing, Degradation	Electrical and thermal properties of the solar module are considered for fault diagnosis.
[44]	Meta-heuristic optimization	To distinguish between short-circuit and open circuit, this technique is applied providing the irradiance and panel temperature.

3.2.8 Partial shadowing

Partial shadowing is diagnosed in [62, 65], by utilizing kernel based extreme learning machine (KELM). Study of change in electrical properties of panels pertaining to shadowing is studied in [50, 58, 84]. Comparative analysis of different parameters considered is considered in [50, 59, 64]. All mentioned techniques are elaborated in detail in Table 16.

Table 16. Partial shadowing.

Ref.	Fault Type/ Method	Description
[84]	Potential-induced degradation (PID), Partial shadowing, Increased series resistance losses	This technique particularly focused on issues related to partial and full shadowing and its effects on panel performance.
[66]	Shaded cell condition	In this technique, all types of shadowing effects are considered using least square method.
[59]	Partial shadowing, Overall shadowing, Open circuit faults	Relationship between healthy and faulty parameters is determined by establishing various hypothesis models. Then variance and meaning of these methods are found to have the most optimized model.
[64]	Partial Shadowing	Here artificial neural network is deployed for extraction of measured quantities to diagnose partially shaded panels.
[53]	Open circuit module, Internal short circuit, Faulty soldering, Shadowing, Degradation	In this technique both the electrical and thermal properties of the solar module are considered for fault diagnosis.
[50]	Fault study under various configurations	In this technique different configurations like series, parallel & series parallel under faulty conditioned are studies to find out their tolerance level for faults. Afterwards, effect on behavior of system is observed by subjecting different sections of the system under partial and full shadowing.
[58]	Issues caused by shadowing Effect	When a panel is shadowing, it acts as a load for remaining strings. This induces heating effects on it. This increase of temperature also increases impedance. Comparison with the rated values indicates faults.

Ref.	Fault Type/ Method	Description
[65]	Short circuit, abnormal aging, and local shadow	State of art optimization techniques like improved radial basis function (RBF) and kernel extreme learning machine (ELM) are employed for fault diagnosis.
[62]	Partial shadowing, Open circuit, short circuit, degradation	Data samples are gathered using kernel based extreme learning machine (KELM)to provide us with the requisite diagnosis system.

3.2.9 *Full shadowing*

Comparative analysis of healthy and faulty panels is considered in [53, 59] to identify faulty conditions. Articles also suggest using techniques like KELM [65] and least square method [66], electrical properties of panel [50] and its thermal characteristics [58] to diagnose faults related to full shadowing. Description of all such techniques is mentioned in Table 17.

Table 17. Full shadowing.

Ref.	Fault Type/ Method	Description
[59]	Partial shadowing, Overall shadowing, Open circuit faults	Comparison of healthy and faulty parameters is considered to diagnose faults.
[53]	Open circuit module, Internal short circuit, Faulty soldering, Shadowing, Degradation	Comparative analysis of Electrical and thermal properties to diagnosis fault.
[66]	Shaded cell condition	Different cases of shadowing effects are considered using least square method.
[50]	Fault study under various config.	Different configurations like series, parallel and series-parallel under faulty conditioned are studies to find out their tolerance level for faults like partial and full shadowing.
[58]	Shadowing Effect	When a panel is shadowing, it acts as load for remaining string and induces heat in it. This increase of temperature also increases impedance. Comparison with the rated values indicates such faults.
[65]	Short circuit, abnormal aging, and local shadow	State of art optimization techniques like improved radial basis function (RBF) and kernel extreme learning machine (ELM) are employed for fault diagnosis.

Table 18 shows which fault categories have been explicitly mentioned in each method of diagnostics that was used as a reference for the study; it also states what type of evidence has been referred to by each row (the studies) but does NOT show how well an individual fault was detected.

Table 18. Fault coverage explicitly described for selected diagnosis approaches.

Approach / sources	Soiling	Hot spot	Degradation	Open circuit	Short circuit	Partial shading	Full shading
ANN / Elman descriptions [59, 63, 64]	NR	NR	NR	D	D	D	D
KELM / RBF-KELM [62, 65]	NR	NR	D	D	D	D	D
Electrical / thermal assessment [53]	NR	NR	D	D	D	D	D

Approach / sources	Soiling	Hot spot	Degradation	Open circuit	Short circuit	Partial shading	Full shading
Current / voltage indicators [54, 55]	NR	NR	D	D	D	NR	NR
Thermography / fuzzy logic [48]	D	NR	NR	NR	NR	NR	NR
Least-squares analysis [66]	NR	NR	NR	NR	NR	D	D
AC characterization / hot-spot studies [70, 71, 72, 73]	NR	D	NR	NR	NR	NR	NR
A consolidated analysis of Tables 4–6 and 9–17. D = discussed; NR = not explicitly addressed							

Note: D, described; NR, not reported.

3.3 Independent component analysis

Independent Component Analysis (ICA), which has applications to blind source separation [74, 75], analyzes data that are statistically independent of each other from their original mixture. ICA's utility for diagnostics relies heavily on its use as an application. Recovery of monitoring streams will not independently identify a specific PV Fault Class. Mixing model and source assumptions were made prior to determining if ICA should be applied. Measurements taken by the environment at the same facility may have correlations; therefore, it cannot be assumed that independence was achieved based solely on those measurements being produced by different sensor systems.

3.3.1 Applications

ICA finds its application in vast range of fields. It is used in the wireless transmission domain of the systems where mixed data is transmitted, unmixed, and recovered using this technique. We can find its applications in the fields of speech processing [75, 76], and signal processing [75, 77], wireless communication [37, 75], bio-medical signal processing [75, 78], vibration analysis [75, 79, 80] and for fault diagnosis [75, 81] as shown in Figure 12

3.3.2 Working of ICA

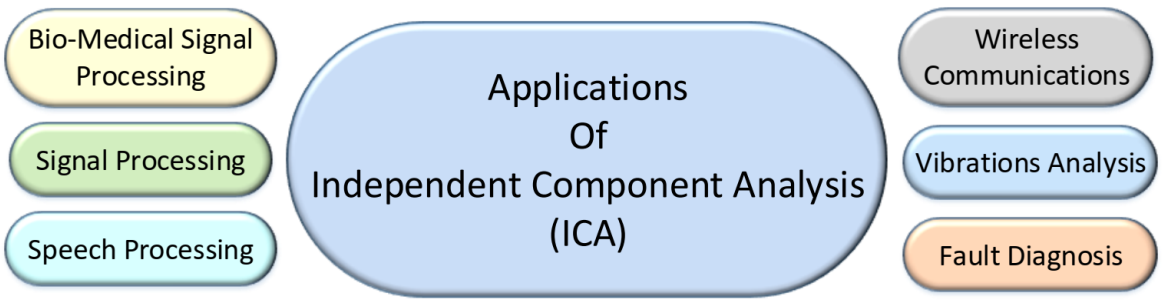


Figure 12. Applications for independent component analysis (ICA).

We have multi-user environment where we have multiple sending and receiving antennas, and the Multiple Input Multiple Output (MIMO) system as shown in Figure 13. We have n number of sending end and receiving end antennas considering both are equal for simplicity purposes. Here, transmitted signals vectors consisting of independent components are S = [s1, s2, s3, ..., sn]. At the receiving side, X = [x_1, x_2, x_3, ..., x_n] are received mixed signals under observation," A" is the mixing matrix and Y = [y_1,

y_2, y_3 ..., y_n] is the estimated original data reconstructed using ICA algorithm as to extract the original signals [74, 75].

Figure 14 depicts how PV monitoring measurements relate to signal recovery and subsequent diagnosis based on downstream diagnostics [74, 75]; ICA extracts source streams from the observed data; however, both the recovery of the source streams as well as whether a PV fault exists requires additional analysis.

3.4 Additional cross method comparisons

The comparisons below are used to distinguish fault observability, diagnostic function, and validation evidence. The purpose of these comparisons is to allow for an assessment of methodological appropriateness with the understanding that demonstrated capability will be separated from unreported capability.

Each fault category in Table 20 is related to available observation(s), diagnostic ambiguity(ies), and evidentiary need to distinguish fault signature overlap.

Table 19. Reported validation and acquisition intervals for selected surveyed studies.

Study / approach	PV system	Reported validation	Diagnosis scope	Sampling interval	Classification accuracy	Detection latency
KELM [62]	Stand-alone	Simulation and experiment	Array	10 min	NR	NR
PV-array diagnostic framework [89]	Stand-alone	Simulation	Array	30 s	NR	NR
Plant indices and monitoring models [90]	Grid-tied	Simulation and experiment	Array and module	5 min	NR	NR
Panel-level monitoring [91]	Stand-alone / grid-tied	Simulation and experiment	Module	10 min	NR	NR
Operating-voltage-window method [92]	Grid-tied	Simulation	Array	1 h	NR	NR
Modified neural networks [93]	Grid-tied	Simulation	Array	1 s	NR	NR
String-current diagnosis [44]	Stand-alone	Simulation and experiment	Array	1 min	NR	NR

Note: NR, not reported.

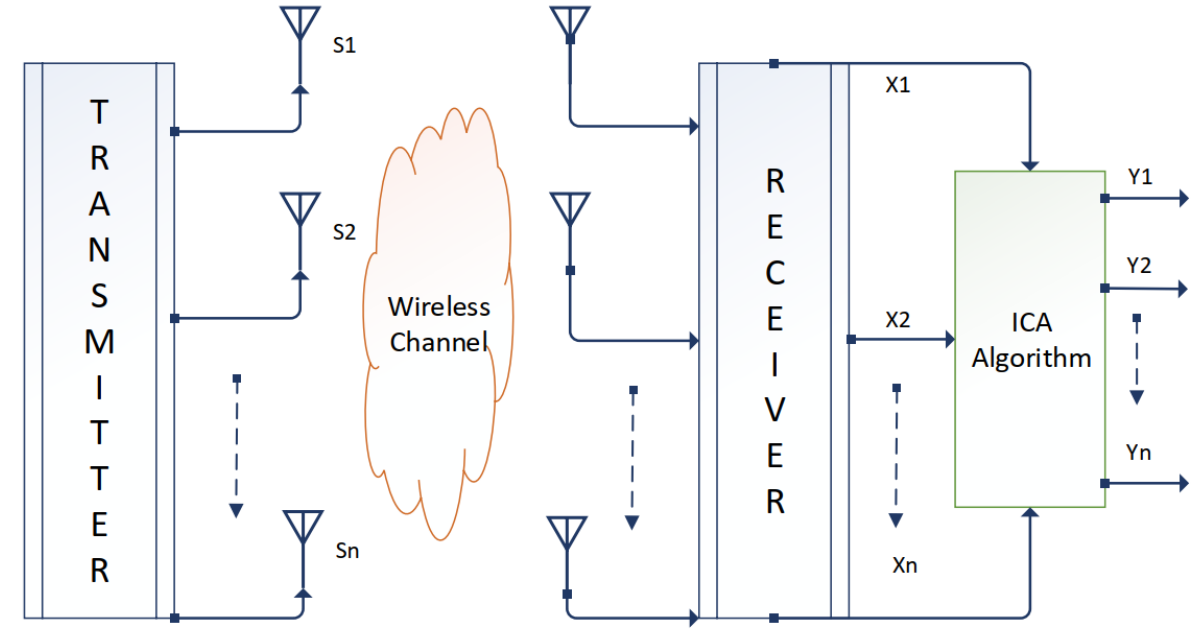


Figure 13. Working of independent component analysis (ICA).

Table 19 provides comparisons of selected study validation settings, diagnostic scope, and sampling intervals (and marks as NR the classification accuracy and detection latency that were not compared).

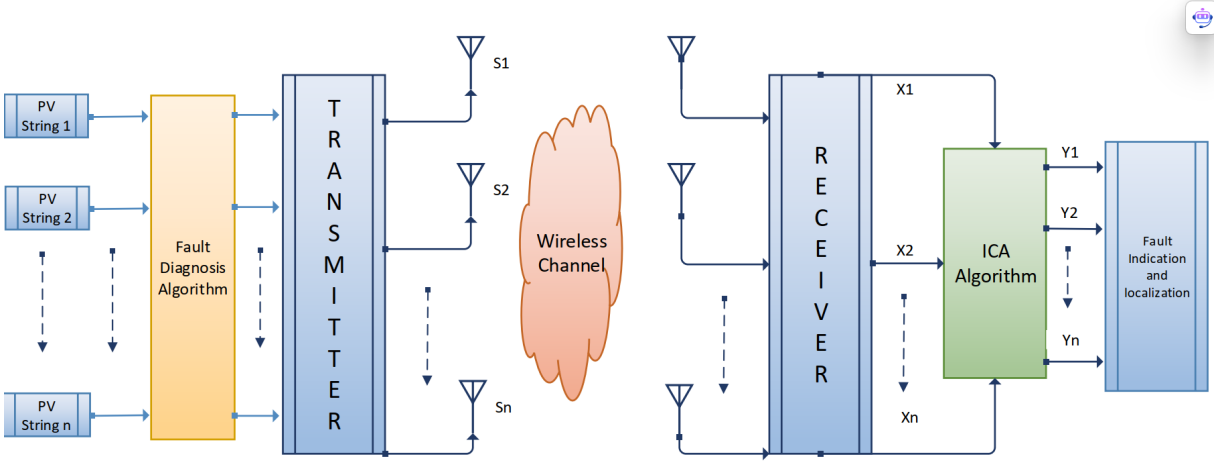


Figure 14. ICA-based solar PV fault diagnosis method.

Table 20. Fault categories, observations and diagnostic ambiguities.

Fault or condition	Relevant evidence	Diagnostic ambiguity and comparison requirement	Sources
Open or short circuit	Current, voltage, I–V response; module or string observations	Separate the presence of faults from where they occurred and how severe they were, define what your topology is and the measurement that you're going to take.	[12, 32, 44, 54, 55, 62, 87]

Fault or condition	Relevant evidence	Diagnostic ambiguity and comparison requirement	Sources
Soiling and shading	Electrical response, irradiance, and inspection images	Distinguish persistent deposits from transient obstruction and environmental variability; verify the cause.	[6, 14, 29, 33, 48, 50, 58, 61, 64, 66, 84]
Hot spots and diode abnormalities	Thermal distribution with electrical inspection	A thermal anomaly does not establish a unique cause; separate detection from mitigation.	[7, 30, 48, 53, 69, 70, 71, 72, 73]
Aging and degradation	Longitudinal electrical response and reference measurements	Distinguish gradual change from soiling, environmental variation, and calibration drift.	[9, 11, 31, 60]
Orientation and weather-related damage	Geometry, site observations, and electrical consequences	Orientation optimization and lightning protection are contextual tasks, not equivalent to fault classification.	[8, 10, 85, 86, 87, 88]
Sensor or communication failure	Sensor consistency, missing records, and recovered signals	A monitoring failure can resemble a plant fault; assess the measurement chain separately.	[19, 37, 74, 75, 77, 94]

The primary role and trade-off characteristics of each family of methods are compared in Table 21 as an aid to determining which methods may be suitable for specific monitoring needs.

Table 21. Comparison of diagnostic roles and trade-offs among method families.

Family and sources	Inputs and role	Potential value	Evidence needed before selecting the method
Electrical indicators [44, 54, 55, 84, 92]	Electrical measurements; detect or localize deviations	Direct relation to monitored quantities	Environmental compensation, thresholds, topology, severity, and false alarms
Statistics and reference models [39, 40, 41, 51, 56, 57, 58, 60]	Reference distribution or expected response	Interpretable deviations from a baseline	Reference quality, adaptation rules, and separation of operating changes from faults
Thermal inspection [48, 49, 53]	Thermal images; optionally inverter measurements	Spatial thermal evidence complements electrical data	Acquisition conditions, verified causes and localization criteria
ANN and recurrent networks [52, 59, 63, 93]	Labeled measurements or features	Learned diagnostic boundaries	Class distribution, independent splits, baseline comparison, and per-class errors
Kernel and RBF learning [62, 65, 68]	Electrical characteristics; limited-sample adaptation in [68]	Alternative feature mappings and adaptation strategies	Matched label budgets, kernel tuning and independent target-site testing
Image-based ML and DL [33, 43, 67, 82]	Thermal, visual, or encoded I–V images	Learned representations for specified image tasks	Unit of prediction, acquisition protocol, module/site separation, and external tests
Hybrid optimization and neuro-fuzzy models [47, 69, 95]	Learning coupled with optimization, fuzzy inference, or a digital twin	Combines complementary processing roles	Ablations, calibration effort, computing cost, and physical-model uncertainty
ICA and signal recovery [37, 74, 75, 77, 80, 96]	Mixed sensor streams; preprocessing for diagnosis	Recovers signals for downstream analysis	Mixing assumptions, recovery errors, and effect on final diagnosis

Family and sources	Inputs and role	Potential value	Evidence needed before selecting the method
Embedded monitoring [19, 82, 94]	Sensors or images with local computing	Connects inference to operational monitoring	Measured end-to-end latency, power, memory, outages, and update behavior

Table 22 compares the study scope, validation setting and sampling cadence; these comparisons clarify the limits that can be placed on interpretations of the results reported by those studies.

The above comparative tables outline the methods that were employed to determine what data was required by each study. The tables do not provide an ordered list of accuracy for the studies. Sampling intervals define how frequently samples are collected (acquisition frequency) and are not indicative of the amount of time it takes to detect a fault after it has occurred (detection latency).

4 Comparative discussion and strength of evidence

4.1 Diagnostic evidence and timing measures

Comparative analysis is dependent upon distinguishing among sensor faults, communication failures and other anomalies present within the system being monitored. Localization of faults can only be determined from measurement based on the spatial resolution of those measurements. ICA will assist in recovering signals as well as classifying faults however there will need to be additional diagnostic logic applied to classify faults, and this will also need to have some form of evaluation.

The terms "sampling interval", "observation window" and "processing time" refer to three distinct phases of operation in a diagnostic system. Therefore, hourly/daily decisions made for degradations assessments and/or longer observation periods cannot be directly compared to the time needed for a classifier to make an inference. Both table 19 and table 22 maintain this distinction when considering how the study descriptions provided are interpreted.

Table 22. Comparison of study scope, validation settings and interpretation limits among selected monitoring studies.

Study	System and diagnosis scope	Reported validation	Sampling cadence	Interpretive boundary
[44] String-current method	Stand-alone; array	Simulation + experiment	1 min	No common accuracy or alarm-delay metric supplied
[62] KELM	Stand-alone; array	Simulation + experiment	10 min	Sampling is not inferencing time
[89] BIPV diagnosis	Stand-alone; array	Simulation	30 s	Transfer to field conditions is not established by this entry
[97] Intelligent detection	Stand-alone; array	Simulation + experiment	1 h	Experimental duration and independence not specified here
[90] Plant indices	Grid-tied; array and module	Simulation + experiment	5 min	Localization targets differ from array-only studies
[91] Panel monitoring	Stand-alone / grid-tied; module	Simulation + experiment	10 min	Sensor coverage and localization differ from array methods
[98] Online detection	Grid-tied; array	Simulation + experiment	1 h	Real-time label does not quantify alarm delay

Study	System and diagnosis scope	Reported validation	Sampling cadence	Interpretive boundary
[92] Voltage-window method	Grid-tied; array	Simulation	1 h	Threshold transferability not quantified here
[93] Modified neural networks	Grid-tied; array	Simulation	1 s	Faster sampling does not prove faster diagnosis

4.2 Comparison of published monitoring studies

Table 23 is a comparison of the configuration used in the monitoring described in several studies [44, 62, 89–93, 97–99]. A variety of aspects of the studies' configurations are summarized including sensing, acquisition, validation, and localization. Due to their heterogeneity, they should not be considered as a controlled test bench for classifiers. Additionally, reference [99] deals with STATCOM converter faults which is a topic separate from PV-array fault classification.

Table 23 makes a distinction on the configuration and reporting scope, as opposed to diagnostic excellence. Qualitative cost designations are made without a common currency and therefore do not allow for an economical ordering. A separate report [99] was conducted regarding a different type of equipment, and there were two citations [16, 100] that refer to a single publication rather than two independent publications. Better comparisons can be made by having faults defined consistently with explicit descriptions of datasets, training/testing splits, false positives, location errors, and time stamping for hardware. Comparisons using numerical ratings over multiple studies must have identical testing/evaluation requirements or provide a valid means of evaluating how to account for differences.

The environmental data resources utilized in the monitoring research include NREL [101]; meteoblue [102]; and NASA [103]. References to providers require identification of which product is being referenced and when it was acquired so that the same assessment can be replicated.

PV Modeling [21, 104] and FastICA source separation [80, 96] both deal with completely various aspects of interpreting measurements, each requiring distinct sets of criteria for validating.

Table 23. Comparative solar PV configurations.

Ref.	Type of PV System	Parameters	Sensors / Array	Sample Time	Type Faults Considered		Simulation Tool	Validation		Transmission of Data	Scope of Diagnosis	Cost
					DC Side	AC Side		Simulated	Experimented			
[90]	Grid-tied	Gg, Gd, Varr, Vsc, Iarr, Iac, Tm, Ta, Sw	7, 2 for each	5 mints	✓	✓	PVSyst	✓	✓	✗	Both array and module level	High

Ref.	Type of PV System	Parameters	Sensors / Array	Sample Time	Type Faults Considered		Simulation Tool	Validation		Transmission of Data	Scope of Diagnosis	Cost
					DC Side	AC Side		Simulated	Experimented			
[62]	Stand-alone	Gg, Varr, Voc, Iarr, Isc, Tm	5, 2 for each	10 mints	✓	✗	MAT-LAB	✓	✓	✗	Array level	Low
[89]	Stand-alone	Gg, Varr, Iarr, Tm	4, 2 for each	30 secs	✓	✗	LAB-VIEW	✓	✗	✗	Array level	Low
[91]	Stand-alone Grid-tied	Gg, Vmod, Imod, Tm	4, 2 for each module	10 mints	✓	✗	LAB-VIEW	✓	✓	✗	Module level	High
[98]	Grid-tied	Gg, Varr, Iarr, Tm	4, 2 for each	1 hour	✓	✓	SunInspector	✓	✓	✗	Array level	Low
[92]	Grid-tied	Gg, Parr, Tm	4, 2 for each	1 hour	✓	✗	PSIM	✓	✗	✗	Array level	Low
[99]	Grid-tied	Vdclink	1	2 msec	✗	✓	PSCAD / EMDTC	✓	✓	✗	Grid level	Very low
[97]	Stand-alone	Gg, Varr, Iarr, Parr, Tm	4, 2 for each	1 hour	✓	✗	MAT-LAB	✓	✓	✗	Array level	Low
[93]	Grid-tied	Gg, Varr, Iarr, Tm	4, 2 for each	1 sec	✓	✗	MAT-LAB	✓	✗	✗	Array level	Low
[44]	stand-alone	Gg, Tm, Iarr, Varr,	4, 2 for each	1 mint	✓	✗	MAT-LAB	✓	✓	✗	Array level	Medium

Note: Gd, diffuse solar radiation; Gg, global solar radiation; Garr, array irradiance; Varr, array voltage; Vsc, short-circuit voltage; Voc, open-circuit voltage; Vmod, module voltage; Iarr, array current; Isc, short-circuit current; Imod, module current; Parr, array power; Tarr, array temperature; Tm, module temperature; Ta, ambient temperature; Sw, wind speed; Vdclink, DC-link voltage; CTp, current transformer.

5 Conclusion and future research directions

5.1 Conclusion

Traditional solar photovoltaic (PV) fault diagnosis has been based on several methods of monitoring PV systems including threshold-based monitoring, electrical parameter measurement, and thermal inspections. As we transition to utilizing machine learning and deep learning methods for PV system monitoring and fault detection, traditional fault diagnosis methods continue to provide value due to their ability to link observed anomalies in electrical and/or thermal measurements to specific operating conditions. In contrast, the use of learning-based methods extends the fault diagnosis capabilities of traditional methods by providing insight into previously unidentified interdependencies within measured operational parameters and inspection images. Therefore, it can be concluded that recent developments are a combination of both physically based diagnostics along with data driven interpretations as opposed to completely replacing traditional methods. The fact that the most recent surveys have demonstrated the continued relevance of dataset characteristics and performance metrics, demonstrates the diversity of methodologies used today [100].

A major finding of this review was that fault diagnosis suitability cannot be determined solely by the accuracy of classifications. Other factors include fault coverage, required data, sensitivity to environment, computational resource requirements, spatial localization abilities, and testing/evaluation procedures. For example, high performance in simulation studies or with single test datasets does not imply similar performance when applied to a wide variety of installed systems. Sampling frequencies, time intervals associated with diagnostic observations, and computational processing times all measure different quantities and should each be provided separately.

5.2 Future research directions

5.2.1 Hybrid AI and physics-informed diagnostic models

A potentially fruitful area of study is to develop a single diagnostic architecture that incorporates both physical photovoltaic (PV) models, signal processing, and machine learning into a unified diagnostic system. The hybrid architecture should integrate these complementary components in such a way that each provides a unique function, e.g., physical models provide the expected operation of the PV system; signal processing identifies relevant features in the data; and machine learning identifies when there are significant variations from the expected operation. An example of how this broader approach has been implemented includes the development of a digital twin combined with a shifted-window transformer, which is based on optimizing the PV system performance, but it was limited to the conditions examined by the authors [95]. Future studies should determine if including electrical operating constraints would enhance the robustness of the overall diagnostic system as conditions change regarding irradiance, temperature, shading, and degradation. Three candidate approaches to achieving enhanced robustness are:

1. physics informed loss functions;
2. residuals used to detect anomalies;
3. temporal networks paired with image classification systems.

5.2.2 Integration of IoT and digital twins

The smart sensor technology used in both Digital Twin and IoT monitoring methods are complimentary ways that can be used as an association between measurement data and interpretive diagnostics.

A digital twin is developed in [95], which has combined a Photovoltaic (PV) model with a PSO optimized shifted-window transformer for PV Fault Diagnosis. SmartPV-AIoT uses electrical sensors; environmental sensors; provides embedded diagnosis; remote monitoring capabilities. These examples create the need for assessing how models synchronize communication; assess reliability and the impact of missing or incomplete measurements when making diagnostic assessments...

Research should investigate how often a digital twin needs to be synchronized when changes occur in the module characteristics, sensor calibrations, or operating conditions. Additionally, researchers should differentiate between normal degradation and faults during parameter updates; and ensure that the system does not allow adaptations that mask degrading conditions. Researchers will need to examine various issues such as, what are acceptable synchronization interval values? How do you handle missing measurements? What happens if there is loss of communication? What level of uncertainty can exist within model parameters?

Synthetic fault scenarios generated via a twin can serve as a means of developing/training algorithms, however the diagnostic capability of these synthetic fault scenarios needs to be verified using independent physical measurements. Additionally, comparative studies should be conducted regarding the increased maintenance/calibration requirements for the use of a digital twin versus the benefits realized through the utilization of a less complex monitoring model.

5.2.3 Edge computing for on-site diagnosis

Deployment of inference-based diagnostics in the vicinity of the PV system is another critical path to viable implementation. Edge enabled PV monitoring has been shown as possible with embedded computing platforms such as a framework based on a residual bidirectional long-short term memory network implemented on a Raspberry Pi. These examples demonstrate the feasibility of specific configurations but do not prove that all forms of deep learning models can meet both the processing speed and resource constraints required for operation [94].

In future research, it will be necessary to study model pruning, model quantization, knowledge distillation, and other lightweight architectures and measure how each impact's fault sensitivity and false alarms. Each report of results should include end-to-end alarm latency, pre-processing time, memory usage, CPU load, and power usage for the deployed hardware. As edge-cloud systems provide real-time inference at the edge of the network and allow for distributed training and large-scale analysis via cloud resources, testing should also consider the implications of intermittent connectivity (e.g., packet loss), frequent device restarts, delayed communication due to buffering of measurement data, and failure to update models when needed. It is not sufficient for a given model to produce fast inference if there are significant delays in collecting or communicating data, resulting in a delay in making a diagnosis.

5.2.4 Dataset standardization and reproducible benchmarking

The need for high-quality dataset comparison remains a top priority for researchers. One study recently surveyed available "open" datasets regarding PV system reliability and found that data fragmentation (i.e., lack of consistent format), limited availability/accessibility, and inconsistent quality were major issues with respect to all three types of data (environmental data, operational data and inspection data) [105].

Collecting massive quantities of data is insufficient for resolving the issues presented above. The process of collecting and publishing benchmark datasets will require development of uniform data collection practices among those involved in this activity. Future benchmark datasets should provide

documentation on the type of modules installed within each test array, the type of sensors used to collect data and their specifications, the sampling frequency used during data collection, environmental conditions under which data was collected, the degree to which each fault observed impacts the operation of the PV module, and procedures followed to determine if an actual failure occurred. It is also recommended that labels be assigned to indicate whether the faults were confirmed to have occurred if they were identified as possibly having occurred, but no evidence of the occurrence could be confirmed or if it remained unknown. Researchers should report the proportion of examples in each class and describe how simultaneous failures, missing data points, maintenance activities, and sensor failures are handled. Test/train partitioning of datasets should occur using one of the following criteria: a) location of installations b) unique identifiers for specific equipment c) specific time periods. Related images or overlapping time segments cannot exist in both train and test sets. Evaluation reports should include metrics such as class-specific precision/recall, macro-average F1 score, number of false alarms generated, accuracy of localizing faults, and the range of uncertainty associated with repeated runs. Providing shared preprocessing techniques and access to evaluation code will improve the reproducibility of comparisons made to assess improvement in models and/or variations in preparatory methods for experimentation.

PVF-10 is an extensive UAV thermal infrared imagery collection which has been used to assess five deep learning model performance metrics in fine grained PV fault detection [106].

5.2.5 *Learning with limited labels and generalization across installations*

Another key goal is to reduce reliance on an abundance of fault identification. As a result of recent developments in methodology there is now emphasis on developing diagnostics based upon various levels of available data and the need for enormous amounts of comprehensive publicly available data sets [107]. Therefore, future studies assessing learning methods using vast amounts of healthy operational data and fewer examples of confirmed faults will help to evaluate self-supervised learning, semi-supervised learning, transfer learning, and domain adaptation.

The effectiveness of each of these learning methods can be demonstrated by their ability to transfer between two or more installations with differing environmental conditions, equipment configurations, and operating histories. Each comparison must include a description of the pre-adaptation performance, post-adaptation performance, the number of labels needed from the target site and if there was degradation to previously learned fault classes. Additionally unknown-fault detection needs to be assessed in such a manner that new anomalies do not have to fit within previous categories. Synthetic representations may be used as supplemental examples when representative faults occur rarely; however, all evaluations must use independently measured values from real events.

5.2.6 *Long-term field validation and predictive maintenance*

The predictive maintenance problem extends the basic diagnostic question of when a failure will occur, to what type of failure it is (development), how severe it is (severity) and its effects on operation (operational consequences). The cost-effective diagnosis via data-driven methods presents an alternative methodological approach to this problem [107], but longitudinal analysis is necessary to find out if such approaches can be shown to provide better maintenance decision making in the face of changing operating conditions.

The next step in validating diagnostic systems for PV systems needs to include the following factors: seasonal variations, increasing age of the system as well as the effects of maintenance performed, and

any changes made to the structure of the PV system. The outcome measure of diagnostics should compare previously alerted issues with subsequent verification of conditions of equipment. It also needs to differentiate predictive fault diagnosis from detecting faults once they have already developed. The outcome measures need to include failed diagnostics, unnecessary maintenance, the delay before a fault is detected, avoided lost power generation, and associated costs of performing maintenance. Any comparison needs to have matched operational conditions and a clearly defined baseline. These requirements will allow for clearer determination of if advanced diagnostic systems produce sustained benefits to the operation of PV systems greater than those determined through tests conducted on individual data sets.

6 Statements and declarations

Funding: Both authors confirm that no funding was received for this research.

Competing interests: Both authors declare no competing interests.

Ethics approval and consent: Not applicable.

Data availability: Both authors confirm that all sources used in this review are cited in the reference list.

Author contributions: F.A.Q. conceived the study, conducted the literature review, collected and analyzed the relevant literature, developed the manuscript structure, and prepared the original manuscript. Z.U.D. supervised the original research work, provided academic guidance, reviewed the manuscript, and contributed to proofreading and critical revision. Both authors reviewed and approved the final manuscript.

Declaration of generative AI use: ChatGPT (OpenAI) assisted with literature discovery, organization, and formatting. The authors are responsible for verifying the sources, interpretations, and final manuscript.

Previous publication and related work: This review builds on the first author's previously published ICA-based solar PV fault diagnosis study [109]. While the earlier work focused on a specific fault diagnosis approach, the present review provides a broader critical synthesis of conventional and machine learning techniques, their advantages, limitations, and research gaps. Previously published findings were acknowledged and are not claimed as new contributions.

References

[1] Panwar N, et al. Role of renewable energy sources in environmental protection: A review. *Renewable and Sustainable Energy Reviews*. 2011;15(3):1513–1524.

[2] Tolón-Becerra A, et al. Proposal for territorial distribution of the EU 2020 political renewable energy goal. *Renewable Energy*. 2011;36(8):2067–2077.

[3] Daly PA, Morrison J. Understanding the potential benefits of distributed generation on power delivery systems. In: 2001 Rural Electric Power Conference. Papers Presented at the 45th Annual Conference (Cat. No.01CH37214); 2001.

[4] Liu G, et al. General indicator for techno-economic assessment of renewable energy resources. *Energy Conversion and Management*. 2018;156:416–426.

[5] Lam AYS, et al. Electric vehicle charging station placement: Formulation, complexity, and solutions. *IEEE Transactions on Smart Grid*. 2014;5:2846–2856.

[6] Olivares D, et al. Characterization of soiling on PV modules in the Atacama desert. *Energy Procedia*. 2017;124:547–553.

[7] Dhimish M, et al. Novel hot spot mitigation technique to enhance photovoltaic solar panels output power performance. *Solar Energy Materials and Solar Cells*. 2018;179:72–79.

[8] Babatunde A, et al. Analysis of the impact of dust, tilt angle and orientation on performance of PV plants. *Renewable and Sustainable Energy Reviews*. 2018;90:1017–1026.

[9] Soon JJ, et al. *A photovoltaic model-based method to monitor solar array degradation on-board a micro-satellite*. IEEE Transactions on Aerospace and Electronic Systems. 2018:1–1.

[10] Tóth Z, et al. Some significant problems of lightning protection in flexible energy systems. In: Camarinha-Matos LM, Adu-Kankam KO, Julashokri M, editors. *Technological innovation for resilient systems*. Cham: Springer International Publishing; 2018. p. 293–299.

[11] Sharma V, Chandel S. Performance and degradation analysis for long term reliability of solar photovoltaic systems: A review. *Renewable and Sustainable Energy Reviews*. 2013;27:753–767.

[12] Tevi GJ, et al. Solar photovoltaic panels failures causing power losses: A review. In: *2018 7th International Energy and Sustainability Conference (IESC)*; 2018. p. 1–9.

[13] Manokar AM, et al. Comparative study of an inclined solar panel basin solar still in passive and active mode. *Solar Energy*. 2018;169:206–216.

[14] Babu TS, et al. Particle swarm optimization based solar PV array reconfiguration of the maximum power extraction under partial shading conditions. *IEEE Transactions on Sustainable Energy*. 2018;9:74–85.

[15] Popa LG, Brumaru M. Optimizing buildings' energy performance through photovoltaic panel integration within a mobile shading system. *Procedia Manufacturing*. 2018;22:765–772.

[16] Liu Y, Wu Y. Fault diagnosis of photovoltaic modules: A review. *Solar Energy*. 2025;293:113489.

[17] Zhao Y, et al. Graph-based semi-supervised learning for fault detection and classification in solar photovoltaic arrays. *IEEE Transactions on Power Electronics*. 2015;30:2848–2858.

[18] Hijjawi U, et al. A review of automated solar photovoltaic defect detection systems: Approaches, challenges, and future orientations. *Solar Energy*. 2023;266:112186.

[19] Mellit A, et al. An embedded system for remote monitoring and fault diagnosis of photovoltaic arrays using machine learning and the internet of things. *Renewable Energy*. 2023;208:399–408.

[20] Tang W, et al. Module defect detection and diagnosis for intelligent maintenance of solar photovoltaic plants: Techniques, systems and perspectives. *Energy*. 2024;297:131222.

[21] Shen W, et al. Mathematical model of a solar module for energy yield simulation in photovoltaic systems. In: *2009 International Conference on Power Electronics and Drive Systems (PEDS)*; 2009. p. 336–341.

[22] Islam MA, et al. Modeling solar photovoltaic cell and simulated performance analysis of a 250 W PV module. In: *2013 IEEE Electrical Power & Energy Conference*; 2013. p. 1–6.

[23] Deotti LMP, da Silva Junior IC. A survey on the parameter extraction problem of the photovoltaic single diode model from a current–voltage curve. *Solar Energy*. 2023;263:111930.

[24] Ünlü M, Çamur S. A simple photovoltaic simulator based on a one-diode equivalent circuit model. In: *2017 4th International Conference on Electrical and Electronic Engineering (ICEEE)*; 2017. p. 33–36.

[25] Jiang Y, et al. MATLAB/PSpice hybrid simulation modeling of solar PV cell/module. In: *2011 Twenty-Sixth Annual IEEE Applied Power Electronics Conference and Exposition (APEC)*; 2011. p. 1244–1250.

[26] Chen W, et al. Evaluation of performance of MPPT devices in PV systems with storage batteries. *Renewable Energy*. 2007;32(9):1611–1622.

[27] Osmani K, et al. A critical review of PV systems' faults with the relevant detection methods. *Energy Nexus*. 2023;12:100257.

[28] Thakfan A, Salamah YB. Artificial-intelligence-based detection of defects and faults in photovoltaic systems: A survey. *Energies*. 2024;17(19):4807.

[29] Parsay A, et al. Enhancing photovoltaic efficiency: An in-depth systematic review and critical analysis of dust monitoring, mitigation, and cleaning techniques. *Applied Energy*. 2025;388:125668.

[30] Ghosh S, et al. Experimental investigation of hotspot phenomenon in PV arrays under mismatch conditions. *Solar Energy*. 2023;253:219–230.

[31] Chang Z, Han T. Prognostics and health management of photovoltaic systems based on deep learning: A state-of-the-art review and future perspectives. *Renewable and Sustainable Energy Reviews*. 2024;205:114861.

[32] Lavador-Osorio M, et al. An enhanced frequency analysis and machine learning based approach for open circuit failures in PV systems. *IEEE Access*. 2024;12:96342–96357.

[33] He Z, et al. Shading type and severity diagnosis in photovoltaic systems via I-V curve imaging and two-stream deep neural network. *Energy Conversion and Management*. 2025;324:119311.

[34] Gao Z, et al. A survey of fault diagnosis and fault-tolerant techniques—Part II: Fault diagnosis with knowledge-based and hybrid/active approaches. *IEEE Transactions on Industrial Electronics*. 2015;62:3768–3774.

[35] El-Banby GM, et al. Photovoltaic system fault detection techniques: a review. *Neural Computing and Applications*. 2023;35(35):24829–24842.

[36] Abdulla H, et al. Photovoltaic systems operation and maintenance: A review and future directions. *Renewable and Sustainable Energy Reviews*. 2024;195:114342.

[37] Obradovic D, et al. Independent component analysis for semi-blind signal separation in MIMO mobile frequency selective communication channels. In: 2004 IEEE International Joint Conference on Neural Networks (IEEE Cat. No.04CH37541); 2004. Vol. 1. p. 53–58.

[38] Islam M, et al. Artificial intelligence in photovoltaic fault identification and diagnosis: A systematic review. *Energies*. 2023;16(21):7417.

[39] Vergura S, et al. Inferential statistics for monitoring and fault forecasting of PV plants. In: *2008 IEEE International Symposium on Industrial Electronics*; 2008. p. 2414–2419.

[40] Braun H, et al. Signal processing for fault detection in photovoltaic arrays. In: *2012 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*; 2012. p. 1681–1684.

[41] Harrou F, et al. Reliable fault detection and diagnosis of photovoltaic systems based on statistical monitoring approaches. *Renewable Energy*. 2018;116:22–37.

[42] Toche Tchio GM, et al. A comprehensive review of supervised learning algorithms for the diagnosis of photovoltaic systems, proposing a new approach using an ensemble learning algorithm. *Applied Sciences*. 2024;14(5):2072.

[43] Boubaker S, et al. Assessment of machine and deep learning approaches for fault diagnosis in photovoltaic systems using infrared thermography. *Remote Sensing*. 2023;15(6):1686.

[44] Hazra A, et al. An efficient fault diagnosis method for PV systems following string current. *Journal of Cleaner Production*. 2017;154:220–232.

[45] Hu Y, et al. Online two-section PV array fault diagnosis with optimized voltage sensor locations. *IEEE Transactions on Industrial Electronics*. 2015;62:7237–7246.

[46] Ali MH, et al. Real time fault detection in photovoltaic systems. *Energy Procedia*. 2017;111:914–923.

[47] Eldeghady GS, et al. Fault diagnosis for PV system using a deep learning optimized via PSO heuristic combination technique. *Electrical Engineering*. 2023;105(4):2287–2301.

[48] Jaffery ZA, et al. Scheme for predictive fault diagnosis in photo-voltaic modules using thermal imaging. *Infrared Physics & Technology*. 2017;83:182–187.

[49] Baltacı Ö, et al. Thermal image and inverter data analysis for fault detection and diagnosis of PV systems. Applied Sciences. 2024;14(9):3671.

[50] Dhimish M, et al. Seven indicators' variations for multiple PV array configurations under partial shading and faulty PV conditions. *Renewable Energy*. 2017;113:438–460.

[51] Hajji M, et al. Fault detection and diagnosis in grid-connected PV systems under irradiance variations. *Energy Reports*. 2023;9:4005–4017.

[52] Chine W, et al. A novel fault diagnosis technique for photovoltaic systems based on artificial neural networks. *Renewable Energy*. 2016;90:501–512.

[53] Tsanakas JA, et al. Faults and infrared thermographic diagnosis in operating c-Si photovoltaic modules: A review of research and future challenges. *Renewable and Sustainable Energy Reviews*. 2016;62:695–709.

[54] Silvestre S, et al. New procedure for fault detection in grid connected PV systems based on the evaluation of current and voltage indicators. *Energy Conversion and Management*. 2014;86:241–249.

[55] Gokmen N, et al. Simple diagnostic approach for determining faulted PV modules in string based PV arrays. *Solar Energy*. 2012;86(11):3364–3377.

[56] Chao KH, Chen CT. A remote supervision fault diagnosis meter for photovoltaic power generation systems. *Measurement*. 2017;104:93–104.

[57] Mallor F, et al. A method for detecting malfunctions in PV solar panels based on electricity production monitoring. *Solar Energy*. 2017;153:51–63.

[58] Bressan M, et al. A shadow fault detection method based on the standard error analysis of I-V curves. *Renewable Energy*. 2016;99:1181–1190.

[59] Liu G, Yu W. A fault detection and diagnosis technique for solar system based on Elman neural network. In: *2017 IEEE 2nd Information Technology, Networking, Electronic and Automation Control Conference (ITNEC)*; 2017. p. 473–480.

[60] Takashima T, et al. Experimental studies of fault location in PV module strings. *Solar Energy Materials and Solar Cells*. 2009;93(6):1079–1082.

[61] Sulaiman SA, et al. Influence of dirt accumulation on performance of PV panels. *Energy Procedia*. 2014;50:50–56.

[62] Chen Z, et al. Intelligent fault diagnosis of photovoltaic arrays based on optimized kernel extreme learning machine and I-V characteristics. *Applied Energy*. 2017;204:912–931.

[63] Syafaruddin, et al. Controlling of artificial neural network for fault diagnosis of photovoltaic array. In: *2011 16th International Conference on Intelligent System Applications to Power Systems*; 2011. p. 1–6.

[64] Karatepe E, et al. Development of a suitable model for characterizing photovoltaic arrays with shaded solar cells. *Solar Energy*. 2007;81(8):977–992.

[65] Wu Y, et al. An intelligent fault diagnosis approach for PV array based on SA-RBF kernel extreme learning machine. *Energy Procedia*. 2017;105:1070–1076.

[66] Andrianajaina T, et al. PV fault detection using the least squares method. In: *2016 International Conference and Exposition on Electrical and Power Engineering (EPE)*; 2016. p. 846–851.

[67] Sridharan NV, et al. *Weightless neural network-based detection and diagnosis of visual faults in photovoltaic modules*. Energies. 2023;16(15).

[68] Yang J, et al. A novel hybrid approach combining kernel extreme learning machine and model-agnostic meta-learning for photovoltaic fault diagnosis with limited samples. *Energy*. 2025;334:137549.

[69] Eltuhamy RA, et al. Fault detection and classification of CIGS thin-film PV modules using an adaptive neuro-fuzzy inference scheme. *Sensors*. 2023;23(3):1280.

[70] Kim KA, et al. Photovoltaic hot spot detection for solar panel substrings using AC parameter characterization. *IEEE Transactions on Power Electronics*. 2016;31(2):1121–1130.

[71] Danner M, Bucher K. Reverse characteristics of commercial silicon solar cells-impact on hot spot temperatures and module integrity. In: *Conference Record of the Twenty Sixth IEEE Photovoltaic Specialists Conference - 1997*; 1997.

[72] Solórzano J, Egido M. Hot-spot mitigation in PV arrays with distributed MPPT (DMPPT). *Solar Energy*. 2014;101:131–137.

[73] Itako K, et al. Proposition of novel real time hot-spot detection method for PV generation system. In: *2017 IEEE International Conference on Smart Grid and Smart Cities (ICSGSC)*; 2017. p. 99–102.

[74] Uddin Z, et al. *Applications of independent component analysis in wireless communication systems*. Wireless Personal Communications. 2015;83.

[75] Ansari S, et al. A survey of artificial intelligence approaches blind source separation. *Neurocomputing*. 2023;561:126895.

[76] Mehrabian H, et al. *Calculation of intravascular signal in dynamic contrast enhanced-MRI using adaptive complex independent component analysis*. IEEE Transactions on Medical Imaging. 2013;32.

[77] Yu M. The blind separation of wireless communication signals utilizing USRP. In: 2016 5th International Conference on Computer Science and Network Technology (ICCSNT); 2016. p. 677–680.

[78] Martis RJ, et al. ECG beat classification using PCA, LDA, ICA and discrete wavelet transform. *Biomedical Signal Processing and Control*. 2013;8(5):437–448.

[79] Gelle G, et al. *Blind source separation: A tool for rotating machine monitoring by vibrations analysis?* Journal of Sound and Vibration. 2001;248(5).

[80] Yue X, Liu S. The improved fast ICA algorithm in the application of vibration signal analysis research. In: 2015 7th International Conference on Intelligent Human-Machine Systems and Cybernetics; 2015. Vol. 1. p. 173–176.

[81] Lou W, et al. Research and application of ICA technique in fault diagnosis for equipments. In: 2009 IEEE International Conference on Intelligent Computing and Intelligent Systems; 2009. Vol. 4.

[82] Benghanem M, et al. Embedded hybrid model (CNN–ML) for fault diagnosis of photovoltaic modules using thermographic images. *Sustainability*. 2023;15(10):7811.

[83] Mellit A, Kalogirou S. Recent advances in the application of infrared thermographic imaging and embedded artificial intelligence for fault diagnosis and predictive maintenance of photovoltaic plants: Challenges and future directions. *Renewable and Sustainable Energy Reviews*. 2025;223:116057.

[84] Spataru S, et al. Diagnostic method for photovoltaic systems based on light I–V measurements. *Solar Energy*. 2015;119:29–44.

[85] Mehleri E, et al. Determination of the optimal tilt angle and orientation for solar photovoltaic arrays. *Renewable Energy*. 2010;35(11):2468–2475.

[86] Khoo YS, et al. Optimal orientation and tilt angle for maximizing in-plane solar irradiation for PV applications in Singapore. *IEEE Journal of Photovoltaics*. 2014;4:647–653.

[87] Alam MK, et al. A comprehensive review of catastrophic faults in PV arrays: Types, detection, and mitigation techniques. *IEEE Journal of Photovoltaics*. 2015;5:982–997.

[88] Ahmad N, et al. Lightning protection on photovoltaic systems: A review on current and recommended practices. *Renewable and Sustainable Energy Reviews*. 2018;82:1611–1619.

[89] Hachana O, et al. *PV array fault diagnostic technique for BIPV systems*. Energy and Buildings. 2016;126.

[90] Ventura C, Tina GM. Utility scale photovoltaic plant indices and models for online monitoring and fault detection purposes. *Electric Power Systems Research*. 2016;136:43–56.

[91] Andò B, et al. Sentinella: Smart monitoring of photovoltaic systems at panel level. *IEEE Transactions on Instrumentation and Measurement*. 2015;64:2188–2199.

[92] Gokmen N, et al. *An efficient fault diagnosis method for PV systems based on operating voltage-window*. Energy Conversion and Management. 2013;73.

[93] Chao KH, et al. A novel fault diagnosis method based-on modified neural networks for photovoltaic systems. In: Tan Y, Shi Y, Tan KC, editors. *Advances in swarm intelligence*. Berlin, Heidelberg: Springer; 2010. p. 531–539.

[94] Lodhi E, et al. SmartPV-AIoT: An AIoT-integrated framework for fault diagnosis and remote monitoring in photovoltaic systems. *Energy Conversion and Management: X*. 2025;27:101117.

[95] Hong YY, Pula R. Diagnosis of photovoltaic faults using digital twin and PSO-optimized shifted window transformer. *Applied Soft Computing*. 2024;150:111092.

[96] Yang L, et al. Blind source separation based on FastICA. In: 2009 Ninth International Conference on Hybrid Intelligent Systems; 2009. Vol. 2.

[97] Ducange P, et al. An intelligent system for detecting faults in photovoltaic fields. In: *2011 11th International Conference on Intelligent Systems Design and Applications*; 2011. p. 1341–1346.

[98] Ciampi A, et al. An intelligent system for real time fault detection in PV plants. In: M'Sirdi N, Namaane A, Howlett RJ, Jain LC, editors. *Sustainability in energy and buildings*. Berlin, Heidelberg: Springer; 2012. p. 235–244.

[99] Yazdani A, et al. Fault detection and mitigation in multilevel converter STATCOMs. *IEEE Transactions on Industrial Electronics*. 2011;58:1307–1315.

[100] Liu Y, Wu Y. *Fault diagnosis of photovoltaic modules: A review*. Solar Energy. 2025;293.

[101] National Renewable Energy Laboratory (NREL). *NREL maps*. Available from: https://maps.nrel.gov

[102] meteoblue. *Local weather*. Available from: https://www.meteoblue.com

[103] NASA Center for Climate Simulation. *Data sets*. Available from: https://www.nccs.nasa.gov

[104] Durgadevi A, et al. Photovoltaic modeling and its characteristics. In: *2011 International Conference on Emerging Trends in Electrical and Computer Technology*; 2011. p. 469–475.

[105] Chen X, et al. Open data sets for assessing photovoltaic system reliability. *Applied Energy*. 2025;395:126132.

[106] Wang B, et al. PVF-10: A high-resolution unmanned aerial vehicle thermal infrared image dataset for fine-grained photovoltaic fault classification. *Applied Energy*. 2024;376:124187.

[107] Liu Y, et al. A methodological review of cost-effective data-driven fault detection and diagnosis in distributed photovoltaic systems. *Applied Energy*. 2025;401:126636.

[108] Hamza A, et al. A multi-stage review framework for AI-driven predictive maintenance and fault diagnosis in photovoltaic systems. *Applied Energy*. 2025;393:126108.

[109] Qureshi FA, et al. ICA-based solar photovoltaic fault diagnosis. *International Transactions on Electrical Energy Systems*. 2020;30(8):e12456.