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A critical review of PV systems' faults with the relevant detection methods

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A R T I C L E I N F O

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A B S T R A C T

PhotoVoltaic (PV) systems are often subjected to operational faults which negatively affect their performance. Corresponding to different types and natures, such faults prevent the PV systems from achieving their nominal power output and attaining the required level of energy production. Regarding the operational optimization of PV systems, this paper aims primarily at surveying and categorizing different types of PV faults, classified as electrical, internal, and external, where each is thoroughly investigated: internal faults occur at the PV cellular level, and can either be short circuit, open circuit, bridging, or bypass diode faults. External faults on the other side are mainly classified as temporary (i.e., clouds shading, snowstorms, etc.) or permanent (e.g., glass breakage, frame defects, etc.) mismatch faults. Lastly, electrical faults involve common circuitry problems, such as short circuits (e.g., line to ground, line to line, etc.), power processing units' faults (e.g., inverter faults), and arc faults. As for the detection methods, six major fault detection methods are investigated for the AC side of the PV system with twenty-nine total AC based fault detection methods. On the other hand, eleven major fault detection methods are surveyed for the DC side of PV systems with seventy-three total DC based fault detection methods. The investigated methods are critically analyzed, and compared relevantly to each other, within the mutual sub-sets. The resulting tabulated comparative data assessments for PV faults (i.e., cause-effect relationships, impact on the PV system performance), as well as for faults detection methods (i.e., priority for application, etc.) compose a rich background for related PV systems' performance security fields, where a nexus future work is also suggested.

Introduction

Population growth and modern life commitments have led to an excessive consumption of fossil fuels. This in turn caused higher emissions of greenhouse gases, leaving future generations in danger [1]. The need for alternative power resources peaked as a result, due to the increase in electricity demand on one hand, and to the underproductive performances of existing generating units (diesel and gas-based engines) on the other hand [2]. Consequently, a worldwide increase in renewable energy studies, usages, and optimization has emerged [3].

Among different types of renewable energy supplies (wind, hydro, etc.) PhotoVoltaic (PV) systems are considered the cleanest and safest technology [4]. This is due to the fact that such systems do not involve any mechanically moving parts (i.e., actuators, shafts, etc.) and work silently. Thus, such systems in particular have achieved a global interest and a massive popularity as a promising solution for offsetting the underproductive problem of existing power resources and are considered to have a potential contribution to the future electricity mix [5].

Unfortunately, many obstacles exist and impede PV systems from functioning properly. Environmental factors, such as dust, temperature, snowfall, and humidity reduce the PV systems' capability in power production and cause various failure modes in the PV panels [6]. For instance, the dust accumulated over the PV modules' surfaces during the span of eight weeks under the desertic environment in Saharan environment, decreases the PV maximum power output by 8.41 % as compared to the same PV system without dust accumulation [7]. In other words, the stated environmental leftovers, aside than possibly damaging the PV panels, could create consequent problems for PV systems, preventing their power production sustainability: as another example, a power drop of 9.99 % and an average power reduction of 2.93 % is witnessed for an uncleaned PV system (from dust and dirt) in a

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Nomenclature

ABCO	Artificial bee colony optimization
AC	Alternating current
AFCI	Arc fault circuit interrupter
AITs	Artificial intelligence techniques
ANFIS	Adaptive neuro-fuzzy inference system
ANFIS-SM	Adaptive neuro-fuzzy inference system-sugeno model
ANN	Artificial neural network
ANOVA	ANalysis of variance
APRE	Absolute performance ratio error
AR	Auto regressive
BPNN	Back propagation neural network
CART	Classification and regression time
CBs	Circuit breakers
CCC	Current carrying conductor
CDIT	Climatic data independent technique
CM	Common mode
CMM	Comparison between measured and modeled
CR	Capacitive region
DC	Direct current
DC-DCFI	DC-DC converters fault identification
DE	Deviation error
DFI	Degradation fault identification
DLL	Dourly lower limit
D-S	Dampster-Shefer
DSP	Digital signal processor
DT	Decision tree
DUL	Dourly upper limit
ECM	Earth capacitance measurement
EGC	Earth ground conductors
EI	Electroluminescence imaging
ELM	Extreme learning machine
EM	Electrical measurement
EMI	Electro magnetic interference
EMR	Electro magnetic resonance
ERV	Estimating randomness in the voltage signal
EWMA	Experimentally weighted moving average
FBI/RBI	Forward bias imaging/reverse bias imaging
FDC	Fault detection and classification
FDD	Fault detection and diagnosis
FDTI	Fault detection techniques for three-phase inverters
FF	Fill factor
FFT	Fast Fourier transform
FIRBPS	Finite impulse response band pass filter
FPGA	Field programmable gate array
FRSA	FRequency spectrum analysis
FSA	Frequency spectrum analysis
FTD	Flash test driver
GCPVS	Grid connected photovoltaic system
GFDI	Ground fault detection and interruption fuse
GISTEL	GIsement solaire par teledetection
GUI	Graphical user interface
HET	Heat exchange and temperature
HF	High frequency
HIGF	High impedance ground fault
HMI	Human machine interface
HV/LV	High/low voltage
ICCD	Intensified charge coupled device
ICR	Inductance capacitance resistance
IDTs	Islanding detection techniques
IGBT	Insulated gate bipolar transistor
IMR	Insulation monitoring relay
In/ThI	Infrared/thermal imaging
IR	Infra-red
I-V	Current-voltage
KELM	Kernel extreme learning machine
kNN	k-nearest neighbors
LAPART-FD	Laterally primed adaptive resonance theory - fault detection
LCD	Liquid crystal display
LF	Low frequency
L-G	Line-to-ground
LIT	Lock in thermography
L-L	Line-to-line
LOF	Local outlier factor
MBDM	Model based difference measurement
MEWMA	Modified exponentially weighted moving average
ML	Machine learning
MPPT	Maximum power point tracker
MRAS	Model reference adaptive system
MSDP	Multistate data processing
MWPT	Modified wavelet packet transform
NDZ	Non detection zones
NOCT	Normal operating cell temperature
OC/SC	Open/short-circuited
OCPD	Over current protection device
Onm/offm	Online/offline model
OPC	Object linking and embedding for process control
PCC	Points of common coupling
PIC	Peripheral Interface controller
PLA	Power loss analysis
PNN	Probabilistic neural network
PPs	Peak points
PPU	Power processing unit
PS/CS	Partial/complete shading
PSMFD	Partially shaded modules fault detector
PV	Photovoltaic
P-V	Power-voltage
PVA	Photovoltaic array
PVLOF	LOF based on PV string current
Q-f	Reactive power-frequency
RCDs	Residual current devices
RCM	Reliability centered maintenance
RDM	Real-time difference measurement
RF	Random forest
RPS	Residential photovoltaic system
SCADA	Supervisory control and data acquisition
SFA	Subsection fluctuation analysis
SFS	Sandia frequency shift
SHLFNNs	Single hidden layer feedforward neural networks
SM	Sugeno model
SMS	Slip mode frequency shift
SPM	Signal processing methods
SR	Shunt resistance
SSTDR	Spread spectrum time domain reflectometry
STCs	Standard test conditions
STFT	Short time Fourier transform
TDR	Time domain reflectrometery
THD	Total harmonic distortion
TSKFR	Takagie-Sugeno Kahn fuzzy rule
TSKFRBS	Takagie-Sugeno kahn fuzzy rule based system
UIM	Ultrasonic inspection method
WOEWMA	Wavelet optimized exponentially weighted moving average
WPT	Wavelet packet transform
WT	Wavelet transforms

Mediterranean climate based region of installation, when compared to the same cleaned PV system [8].

Other than environmental implications, PV systems are seen to encounter inner faults for example, ranging from basic electrical faults (open-short/circuit) to Power Processing Units (PPU) faults such as Maximum Power Point Tracker (MPPT), and inverter malfunction [9, 10]. Consequently, such faults disturb the produced power waveforms and could eventually cause drastic interruptions on the users' end.

Regardless of the fault's types, their recurrence on PV systems, leaves bad impacts such as harmonics distortion, voltage unbalancing, current leakages, deviated waveforms, smaller consumable power quantities than expected and service interruption by partial/total blackouts. For a healthy state of PV systems, with an extended lifecycle and an acceptable performance, abundant research is taking place to mitigate fault residues on such systems: for example, in order to reduce the partial shading conditions consequences' (i.e., caused by the movements of clouds), which partially shade the sunrays for up to 75 % of the total PV array space, different PV array reconfiguration techniques can be adapted [11]. From a thermal optimization point of view, the decreased PV cell efficiency by 0.45 % for each temperature rise of 1 °C (due to high temperature environmental conditions) can be compensated by the application of phase change material, that are used to cool down the PV panels' operating temperature [12]. Adjusting the PV tilt angle from another side is recorded elevating the PV produced power by up to 50.36 % for different regions of PV systems installations, thus compensating the lost solar irradiance due to positioning and self-shading [13].

As intended to optimize the performance and extend the longevity of PV systems with minimum fault occurrences, it is imperative to know first the difference types of possible PV faults, then accordingly acknowledge the corresponding PV fault detection methods (that are to be applied in real PV applications). For this purpose, ample research took place in order to quantify different PV faults, with the relevant detection techniques: for instance, the work in the reference [290] has categorized all possible PV faults into five main categories, as mismatch, ground, line-to-line, arc, and other types of faults. As for the fault detection methods in the same study, the presented survey classified all fault detection techniques as either visual/thermal or electrical based methods, without considering the model-based measurements methods, for example. From another side, the similarly related work in [291], takes into consideration only the failure modes in the PV inverter's power modules. Moreover, the authors in [292] have only reviewed the PV fault detection methods through the application of artificial neural networks, such that the review in [293] has grouped the PV faults either as optical degradation, electrical mismatch, or other electrical and hardware faults, having only imaging technologies based resultant fault detection methods. From a different approach, the work in [294] focused mainly on the outer physical degradation of the PV encapsulant, while the most reviewed fault detection methods emphasized on the visual inspection. Accordingly, and for the purpose of a broader PV faults classification with better expanded faults detection methods, throughout this paper, different faults will be first categorized as either internal, external, or electrical. The consequences of each will be clearly presented in tabulated data, in order to record the affected parts of a PV system. Moreover, two major fault detection techniques classifications will take place, as either detection at the AC side of the PV system or at the DC side. For each part, there exist various sets of methods, and sometimes sub-methods. Each technique will be uniquely identified, investigated, and compared to others within the same set. A critical comparison between detection schemes and targeted faults will be presented. The rest of this paper consists as follows: Section 2 presents a general overview for a PV system with a fault detection scheme, Section 3 classifies and investigate all possible PV faults, where in Section 4 the fault detection methods are expanded and analyzed. Section 5 presents a discussion based on the results of the different reviewed faults and fault detection methods with a future work recommendation, where finally in Section 6 conclusions are derived.

Overview of a typical PV system with a fault detection structure

As an additive to a typical off/on-grid PV system, a fault detector is an extra equipment, with the ability to guide the PV system's operators about the existence of a fault, its type and location within the PV system. Consisting of different sensors, processing units, actuators, transducers, and different protective relays and circuit breakers, such a system can be installed at any node indicated by the dashed polylines in Fig. 1. On its output level, the fault detector contains a set of alarms, buzzers, and different forms of Graphical User Interface (GUI) to acknowledge the workers in the field about any fault incident. The full process of fault detection takes place within two distinct steps: monitoring and diagnosis.

Monitoring

To evaluate the PV system's performance, the monitoring system collects and analyzes a set of different parameters (voltage, current, power, etc.) [14]. This process is crucially important, as a prior step before detecting the fault, with a continuous tracking on the electrical power generation. For data acquisition of various attributes, sensors are the first input to the monitoring system. The data are then transferred through signal processing units, where at final stage, they would be stored for further investigations [14,15]. Fig. 2 reveals the cascaded monitoring process for a PV system, embedded within a fault detection scheme.

Diagnosis

The results of the monitoring system (in form of acquainted information) are injected to the fault diagnosis scheme as primal data. When compared with reference values, the inputted data can either declare a fault or not [16,17]. Its source of acquisition (whether from the DC or the AC side of the PV system) guides the fault detector about how to investigate upon it. Fig. 3 reveals the different steps of PV fault diagnosis in a cascaded form, beginning by information analysis to alarm launching.

Different PV system's faults

Due to their outdoor nature, PV systems encounter diverse faults, causing a massive decrease in the PV energy outcome, potential reduction, and most importantly the inability to satisfy various load demands. The fault classification can be mainly classified into three categories as follows:

- Internal
- External
- Electrical

The internal PV faults take place inside a PV module (underneath the protective glass), on the level of PV cells, and strings. External faults localize outside the PV module protective glass and are perceived as either temporary mismatch or permanent mismatch faults. Electrical faults on the other hand, refer to the perturbations of physical entities (i.e., voltage, current, power, etc.) in terms of quantities and waveforms. Fig. 4 entitles the triggers for each set of PV faults.

Internal PV faults

Internal PV faults take place inside the PV module itself. Their initial cause is the manufacturer's defects, poor quality of fabrication, damages due to inconvenient packaging, and improper methods of wiring. Regardless of their root cause, internal faults are classified according to

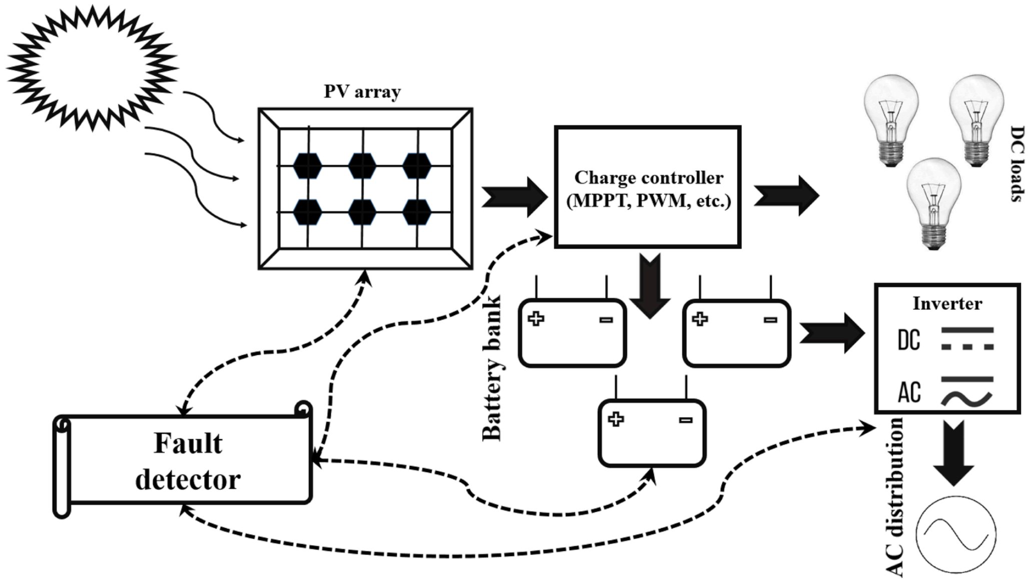

Fig. 1. Fault detector allocation in an off-grid PV system.

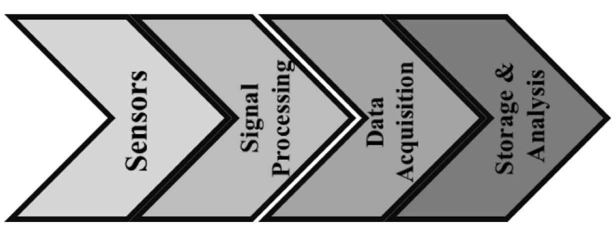

Fig. 2. Block diagram of PV monitoring system.

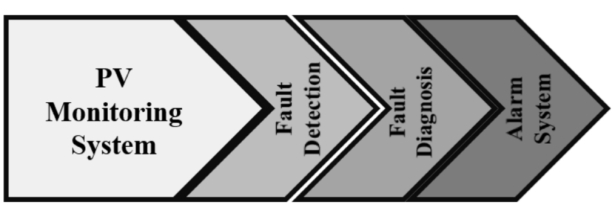

Fig. 3. Block diagram of PV fault diagnosis scheme.

the effects they impose on a PV system, as either open/short-circuit, bridging and bypass diode faults. Table 1 groups the causes to consequences of different internal faults.

Short circuit fault

Improper connections (low impedance and sometimes bolted pathways) between the solar cells, or defects from initial manufacturing circuitry [18,19], lead to a short circuit on the module or on the bypass diode [20].

Bridging fault

Improper connection (high impedance and sometimes complete open circuit) between PV modules [21], causes such types of faults where the output tends to become null.

Inverted bypass diode fault/bypass diode fault

Faulty wiring made by the operator [22,23], resulting in bypass diode fault, reflects as abnormal voltage conditions on the output level.

Open circuit with/without bypass diode fault

An open circuit fault, reflected as maximum cell's output voltage, with no ability of current to flow (hence no power output) is often caused by broken cells, damaged connections between them, loose connections, and defected power cables due to aging. The excessive plugging/unplugging routines, yield to faulty open-circuited terminals mainly at junction boxes [23].

External PV faults

Due to the fact that PV systems need to be installed outdoors to receive direct solar radiation, they often interact with undesired environmental conditions. The weather for instance can fluctuate, ranging from hot (elevated ambient temperature) to cold (rain/snow accumulation). Accordingly, PV modules would rarely operate under the Standard Test Conditions (STCs), thus their nameplate power is never attained.

Moreover, natural disasters like intense lightning can burn PV panels. On the other hand, dust/leave accumulation results in partial shading/impedance mismatch. From another part, PV panels fall from height as well as abuse by stones throwing inflects a permanent damage (glass/frames breakage). Table 2 encapsulates the causes-to-consequences relation for different external faults.

Temporary mismatch fault

When the irradiation varies, the PV system performance (i.e., in terms of power production) changes accordingly (e.g., low irradiation reflects lower power production, and vice-versa). Some regions of the PV system (i.e., zones of PV arrays) produce larger power quantities than others [24]. Even though, faulty PV regions due to temporary mismatch do not produce power as rated values or even close. This can be referred to a non-homogeneous PV output due to non-homogeneous shading [25–27].

This heterogeneity in power production which is caused by physical light barriers, such as trees, buildings, and overhead power lines, results in detrimental effects over the PV panels [28]. Depending on the climate conditions and geographical locations, snow can cover some panels of the PV system as well. From another part, biological conditions such as bird's droppings, and leaves accumulation on the surfaces of the PV modules can also lead to partial shading conditions [29,30]. Dust and dirt from another side, can cover the PV arrays' surfaces, and sometimes sudden natural disasters as lightning and storms can also leave a PV

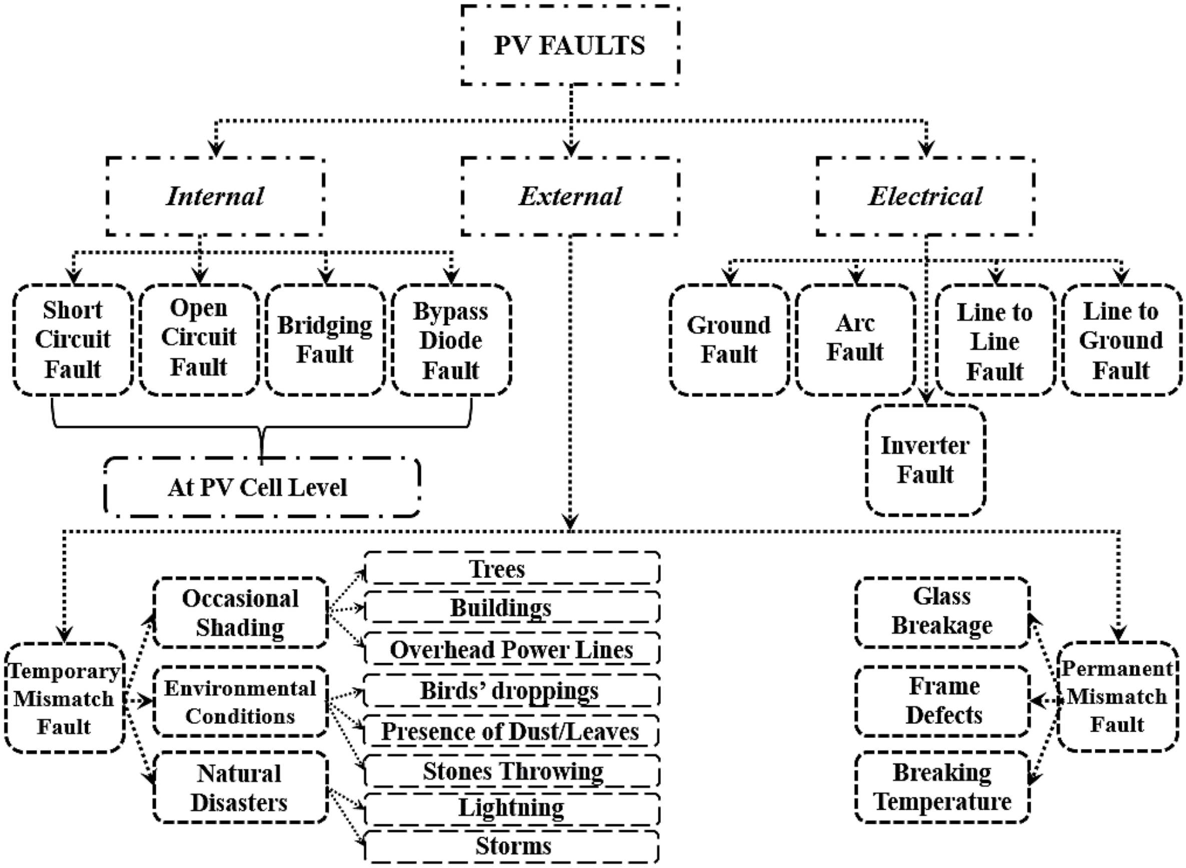

Fig. 4. Summarizing block diagram representation of PV fault types and characterization.

Table 1
Cause-effect relationship of different PV internal faults.

Internal faults			
Types	Causes	Results	Consequences
Short circuit	Manufacturer's defects	Low impedance/ bolted path between internal power rails	Inability to deliver power to DC load or to the power conditioning unit
Bridging	Manufacturer's defects/improper wiring	Creation of impedance faulted linking path	Null power output
Bypass diode	Manufacturer's defects/improper wiring	Bypass diode cannot be forward biased	Inability to mitigate hotspots events
Open circuit	Manufacturer's defects	Absence of link between power paths	Inability to deliver power to DC load or to the power conditioning unit

Table 2
Cause-effect relationship of different PV external faults.

External faults			
Types	Causes	Results	Consequences
Temporary mismatch fault	• Occasional shading • Environmental conditions • Natural disasters	Non homogeneous power production across PV surfaces and creation of hotspots	Low power production compared to standard values and risk of burning
Permanent mismatch fault	Equipment permanent damage	Null power production	Complete blackout

system with a non-uniform irradiance distribution [31,32].

Permanent mismatch fault

Unlike partial mismatch fault conditions, a permanent mismatch cannot be reversed. It can be a result of bad soldering, degradation of modules, glass breakage, delamination, discoloration, defects in frame, cell breakage and micro-cracks.

These triggers have a wide range of causes, of which some are manifested by bad operations such as manual soldering of the cell at a breaking temperature, or poor packaging during transportation. Permanent mismatch faults can also be triggered during manufacturing processes, like inconvenient wafer slicing, cell production stringing and other embedded operations that eventually lead to cell cracks.

Such causes are referred to manufacturing defects. Environmental conditions can lead also to permanent mismatch faults. For instance, heavy snow loads in cold regions can break PV modules. Also, frequent temperature changes can wear out the cell interconnections [33,34]. Fig. 5 reveals the physical delamination (indicated by red arrows) of the front encapsulation of a PV module, caused by external faults.

Electrical PV faults

Aside than the physical PV faults occurrence, driven by physical barriers (dust/snow/leaves accumulation) and internal manufacturing defects, PV systems also encounter intrinsic electrical faults. According to the PV system's electrical network distribution, electrical faults can occur as ground, line to line, line to ground, arc, and power conditioning units' faults. Table 3 summarizes the causes-to-consequences relation for different electrical faults.

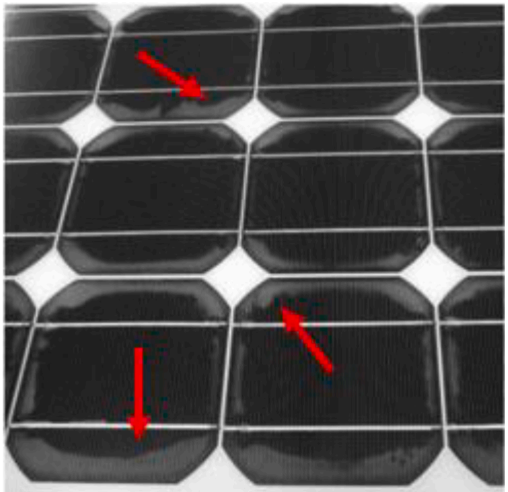

Fig. 5. Delamination of the PV module's front encapsulation [51].

Ground faults

The PV system includes parts that aren't designed nor supposed to be exposed to any current, like the metallic part of a PV array, the enclosures and other equipment [35,36]. These non-current carrying labels are protected using Earth Ground Conductors (EGC) in order to eliminate any possibility for an electric shock which the operators might examine when working in field, such that the sudden electric current find its way to the ground instead of being trapped inside the equipment [37,38]. When the ground contains active currents, the analysis turns to the case of a fault [39,40]. This type can be decomposed into two sub-parts:

- Upper ground fault: an unintentional low impedance or bolted path between the Current Carrying Conductors (CCC) of the last two modules in a PV string and the ground [41].
- Lower ground fault: an unintentional low impedance or bolted path between the CCC of the second and third modules in a PV string and the ground with large feedback current [41].

Line to line faults

The cascading of PV modules creates PV strings, which in turn are wired in parallel to create an array, in order to deliver higher power outputs. The Line to Line (L-L) faults denote erroneous connection between different strings/arrays potentials. By taking an example of a PV string, a L-L cross string fault exists between one string and another. Such faults are very hard to detect and cause severe losses in the overall output before being distinguished [42]. It can be summarized by unintentional connections between two or more nodes of the PV strings/arrays [43,44] and is considered as a top reason for inducing open-circuit faults (due to electrical switchgear tripping mechanisms).

Line to ground faults

When there is a physical connection between the current carrying conductor and the ground, whether directly or through a low impedance path, a Line to Ground (L-G) fault takes place [45]. A L-G fault is extremely hazardous, as it causes a massive electron flow, in a timely manner, across a faulty small path when compared to the total system's wiring, what would generally result in fire hazards.

Arc faults

The conductors used in electrical circuits, often confront corrosion and lack of conductivity due to their chemical reaction with the surrounding environments, and damages resulting of excessive usage. This phenomenon creates an arc current high enough to ignite the surrounding material [46,47]. Such faults are chaotic, random, and might be active for a dangerous amount of time before being detected or resolved. When there is an insulation breakdown, parallel arc faults are ignited. Series arc faults on the other hand, take place when the connections get loose, the connection cables are damaged, or in the event of hotspots [47]. The resultant spontaneous faulty current is often too small to be detected by safety equipment such as Residual Current Devices (RCDs) [48,49].

Power processing units' faults

The Power Processing Units (PPUs) are equipment that work on shaping the resultant signals waveforms or modifying their quantities. For PV systems, two main PPUs exist:

- Inverter: used to transform the original DC power to consumable AC power (since most industrial/residential loads operate on AC).
- Maximum Power Point Tracker (MPPT): included in charge controllers, to extract the maximum available power under partial shading conditions.

These elements in turn, can interact with faulty scenarios, prohibiting them from achieving their destined functions. The PPUs faults are

Table 4
Cause-effect relationship of different PPUs faults.

Power conditioning units faults			
Types	Causes	Results	Consequences
Inverter failure	• High temperature for prolonged amount of operating time • Excessive operations	Failure in switching mechanisms	• Disturbance in the resulting AC waveform • Load malfunctioning
MPPT failure	• Sensors malfunctioning • Algorithm bugs	• Delayed time for battery bank charging • Battery bank over-charging	• Shortening the life cycle of the batteries • Batteries permanent damage • Lowering the standby time under low irradiance conditions

Table 3
Cause-effect relationship of different electrical faults.

Electrical faults			
Types	Causes	Results	Consequences
Ground fault	Improper wiring of ground/earth connections	Existence of a large feedback current in the ground	Risk of operator electrocution and voltage instability
Line to line fault	Existence of a faulty connection link between different power rails	Power loss on the output level (three-phase system)	Risk of equipment burning and wire damage
Line to ground fault	Short circuit between current carrying conductor and the ground	Power loss on the output level (single-phase system)	Risk of equipment burning and wire damage
Arc fault	Loose connections/loss of conductivity	Creation of arc current/sparks	Risk of burning/fire
Power conditioning units fault	Malfunctioning of PPUs due to internal fault	Inability to efficiently charge the battery bank and existence of disturbances on the output AC waveform	Lowering the PV system efficiency and decreasing its standby time

summarized in Table 4.

Inverter failure. Inverters can have their efficiency reduced, with faulty operational behavior, when exposed for example to continuous high temperatures for a prolonged amount of time, and when experiencing an excessive mechanical stress on their power switches. For instance, when Insulated Gate Bipolar Transistor (IGBT) fails as a solid-state switch in conduction for example, the algorithm conducting other IGBTs resets and the entire power electronics switching circuit fails, hence the inverter fault [50].

MPPT fault. The MPPT works in collaboration with sensors and charge controllers, to be able to identify the Peak Points (PPs) in the characteristic Current–Voltage (I–V) curve of the PV module and calibrate the charging process of the batteries [52]. When sensors get disconnected/defected, and the MPPT's algorithm experiences an erroneous workflow, the MPPT zone within the PV system gets faulty [53].

When the MPPT fails, it often leads to a damage on the level of the battery bank: the charge controller abnormally selects reference voltage levels. This yields to over-charging where the bank is exposed to higher than standards voltage inputs, for prolonged amounts of time. Undercharging from another part also takes place when the MPPT fails: consequently, the electrodes are damaged inside the batteries due to low input voltage feeding [54]. Since each type of the faults affects the performance of the PV system in a specific severity, Table 5 in accordance provides a comparative assessment between the different reviewed PV faults.

Fault detection methods

The approaches to detect faults in PV systems are classified to work in either the DC or the AC regions of the PV system [246]. The entirety of techniques can be summed up as in Fig. 6, where six major techniques are listed on the AC side and eleven techniques on the DC side of the PV system.

Detection at AC side

This set of fault detection techniques covers up the zone in PV systems where all AC quantities exist. The red dashed area in Fig. 7 enfolds the referred region for detection. The output of the inverter is fed and distributed into the AC grid, by means of Main Distribution Boards (MDBs). Any power failure in the red dashed zone, needs AC relevant protective equipment, such as Circuit Breakers (CBs), Residual Current Devices (RCDs), and others protective switchgear. To be able to send tripping/switching commands to the AC safety switchgear, specific algorithms are required, which rely under Artificial Intelligence Techniques (AITs), Real-time Difference Measurement models (RDM), Fault Detection Techniques for three-phase Inverters (FDTI) and Islanding Detection Techniques (IDTs).

Artificial intelligence techniques (AIT)

Artificial intelligence used in PV systems' fault detection aims to transfer a certain knowledge into computers and make decisions accordingly. Based on computational algorithms, this set of techniques allows computers to learn using human-inspired reasoning. When applied, their implementation results in a faster and more accurate decision making [278]. The following methods represent some examples about AIT for PV fault detection:

a) PIC based extension matter.
b) SCADA for Ground Connected Photo Voltaic Systems GCPVS/NUI algorithm based on SCADA inputs.
c) Automated diagnostic signal software tool based on comparison of APRE.

Table 5
Comparison of different types of PV fault consequences.

Type	Reason									Reason						Possibility of occurrence	Fault severity			
	Environmental			Weather			Physical			Manufacturer defects		Circuitry					Complete blackout	Partial blackout	Non homogeneous power production	Impurities in output signals
	Leaves	Dust	Soil	Snow	Storms	Lightning	Stones	Bird dropping	Shading	Low quality	Bad design	L-L	L-G	Arc	MPPT					
Internal PV faults										✓	✓					Depending on the level of manufacturer fabrication and expertise in labor working		✓	✓	
External PV faults	✓	✓	✓	✓	✓	✓	✓	✓	✓							High	✓	✓	✓	
Electrical PV faults												✓	✓	✓	✓	Medium to high (depending on circuitry design and safety precautions)	✓	✓		✓

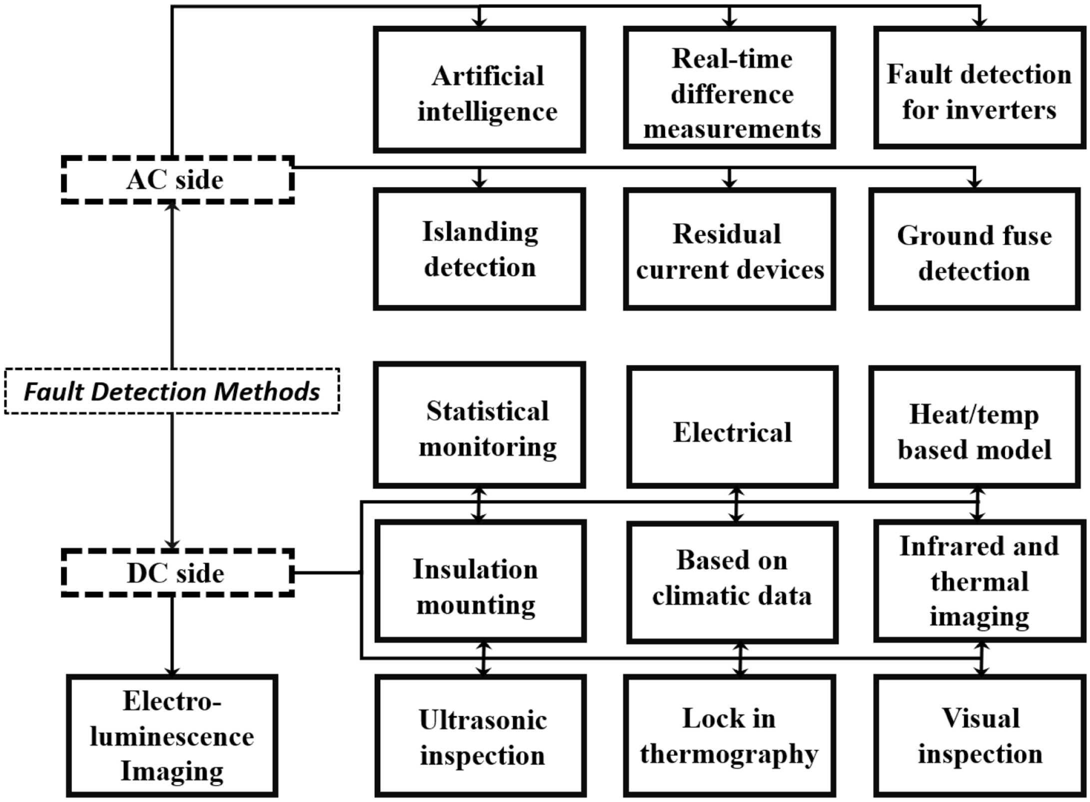

Fig. 6. Complete PV fault detection methods at AC/DC sides of the PV system.

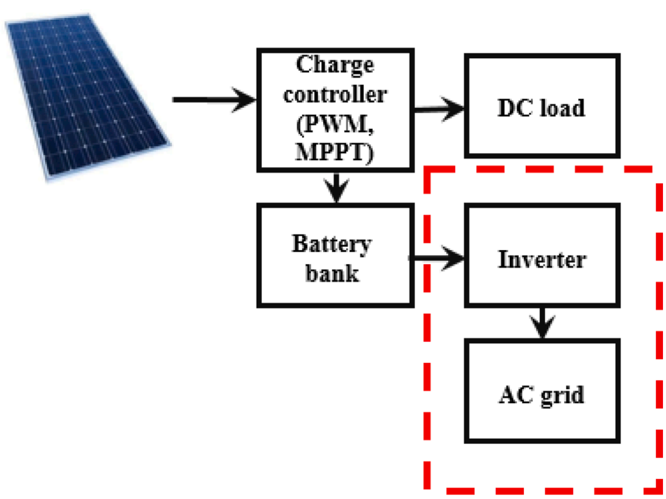

Fig. 7. AC detection zone.

d) SA-RBF Kernel Extreme Learning Machine KELM.
e) Predictive Maintenance and Anomaly detection.
f) ANN model detecting operational and environmental faults.

PIC based extension matter. A Peripheral Interface Controller (PIC) is implemented for fault diagnosis. By combination of PIC micro-controller, coded in assembly, with a ZigBee wireless sensor, a remote access is granted on monitoring the occurring faults in the AC parts of PV systems. The power generation of a PV system is firstly analyzed under normal/defected operations. Then by relying on extension theory, a matter-element model (problem solving tactic based on human thinking) is constructed from the initial data collections. This PV fault diagnosis only requires small amounts of data to construct the matter-element model, while providing a high fault detection accuracy [55]. Recent evolution in computerized and embedded systems has led to more powerful micro-controllers than the one used in [55], where in terms of computational speed, a programmable logic controller is better used to detect the PV faults.*SCADA for Ground Connected Photo Voltaic Systems GCPVS/NUI algorithm based on SCADA inputs*

This algorithm based model feeds input signals to a Supervisory Control And Data Acquisition (SCADA) system to categorize and identify different electrical faults such as string fault, short circuit fault and line to line fault for Grid Connected PhotoVoltaic System (GCPVS). The needed attributes are ambient temperature, irradiation (measured via a pyranometer), and power ratio [56]. The synoptic scheme for this model is shown in Fig. 8.

The fault detection model has achieved a high detection accuracy of 99.80 %, but this value may fluctuate due to the major system's dependability on meteorological/electrical sensors, which might give false readings due to false/inaccurate calibration [56]. Similarly, a fault detector for PV plants using a web server relying on Non-Uniformity Index (NUI) can also act as a remote server based on SCADA inputs. The NUI algorithm which allows remote supervision and fault detection has been examined and with such model, the faulty PV zones within a PV farm can be identified according to their produced energy levels either as acceptable or not. With the usage of special temperature/irradiance models, this system seems to have diminished the required number of sensors for PV fault identification [164].

Automated diagnostic signal software tool based on comparison of APRE. Using certain electrical quantities (i.e., voltage, current) as reference values, an automated diagnostic signal tool to detect non-recoverable faults at AC sides of a PV system can be established [57]. The failure identification process takes place with the two indicators R_C (DC current) and R_V (DC voltage) as shown in Eq. (1) and Eq. (2) respectively.

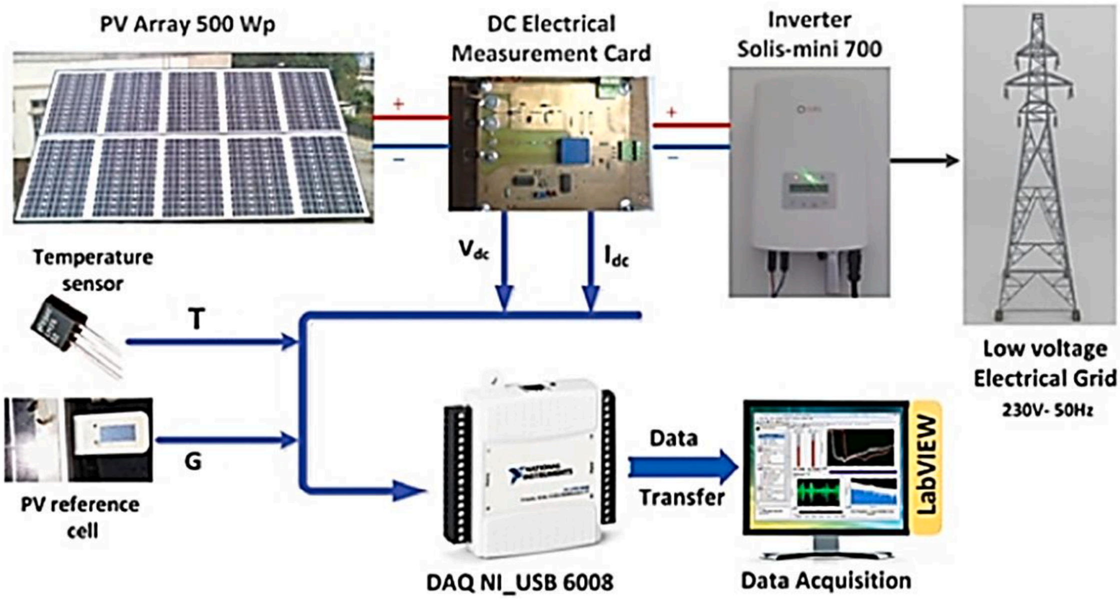

Fig. 8. Synoptic scheme for GCPVS [56].

$$R_C = \frac{I_{pv\_sim}}{I_{pv\_meas}} \tag{1}$$

$$R_V = \frac{V_{pv\_sim}}{V_{pv\_meas}} \tag{2}$$

with I_{pv_sim}, I_{pv_meas} denoting the simulated and measured array's DC current respectively and V_{pv_sim}, V_{pv_meas} the simulated and measured array's DC voltage respectively. A set of comparison takes place for the two equations where each translates into a specific fault situation. The entire procedure is based on Absolute Performance Ratio Error ((APRE) which represents a performance metric for machine learning), where the fault is located inside a GCPV plant by monitoring the DC and AC power ratio. The model has resulted in a good detection accuracy with a great potential for future adaptation as a widespread tool for GCPV [57].

SA-RBF kernel extreme learning machine (KELM). This intelligent fault diagnostic tool uses simulated annealing algorithm based on radial function Kernel Extreme Learning Machine (KELM). The method begins by establishing the fault model and optimizes it using the Simulated Annealing (SA) algorithm [62]. The adopted KELM function Ω_{ELM} is shown in the following equation.

$$\Omega_{ELM} = \exp\left(-\frac{|x - x_i|^2}{2\sigma^2}\right) \tag{3}$$

where σ is the radial width parameter and x, x_i composers of target value vector. The SA algorithm optimizes the parameters for radial basis function KELM, where the resultant algorithm can quickly and effectively identify short circuit, aging and PV faults related to partial shading [62].

Predictive maintenance and anomaly detection. Working upon historical data, specifically using the actual two-year measurements of irradiance, temperature, and other climatic conditions as historical data to be fed into a predictive algorithm database, a learning-approach-based model can detect any reduced output fault by comparing both measured and predicted values of AC power [63]. Two normal operation limits were classified as Dourly Lower Limit (DLL) and Dourly Upper Limit (DUL), are expressed in Eq. (4) and Eq. (5) respectively.

$$DLL = 3\sigma_d \tag{4}$$

$$DUL = 5\sigma_d \tag{5}$$

where σ_d denotes a daily-equivalent standard deviation index. Samples which are numerically compared to the thresholds *DLL* and *DUL* represent normal/faulty operations of the PV system [63].

ANN model detecting operational and environmental faults. A two-layer Artificial Neural Network (ANN) based model that works as a Supervisory Control and Data Acquisition (SCADA) system, operates as a monitoring tool on PV assets as well as on their environmental conditions. This methodology can perform also economic evaluations about the current PV system's states, also on upgrading the previously designed PV systems to supply larger loads. It consists of a two-layer ANN model that states any lack of insulation, or solar tracker blockage using a private logic decision making [66]. Fig. 9 reveals the connections between the input/output layers of the algorithm, where b represents the bias, n the neuron, $W_{j,i}$ the weight of the input (j, i), and $W_{\hat{y}\,d,j}$ the output weight of the ANN.

Different attributes, such as internal and ambient temperatures, radiation and time of performance are mutually linked to different nodes within the hidden layer. The probabilities of occurrence of an attribute within a specific node, are all taken into consideration. This would finally result in an estimated accumulated active energy level, to deduce the fault impact on the overall power production.

Real-time difference measurement (RDM)

Real-time difference measurement systems acquire instantaneous physical samples (voltage, current, etc.), resulting from experimental/analytical measurements to dynamically provide data concerning the process of PV functioning (fault detection). This set of methods contains the following sub-methods:

a) Using AC output data
b) Using capacitance change criteria

Using AC output data. Using AC output data in PV system, a preliminary method consisting of three sub-methods used entirely to detect faults. The first sub-method relies on comparing both measured output values

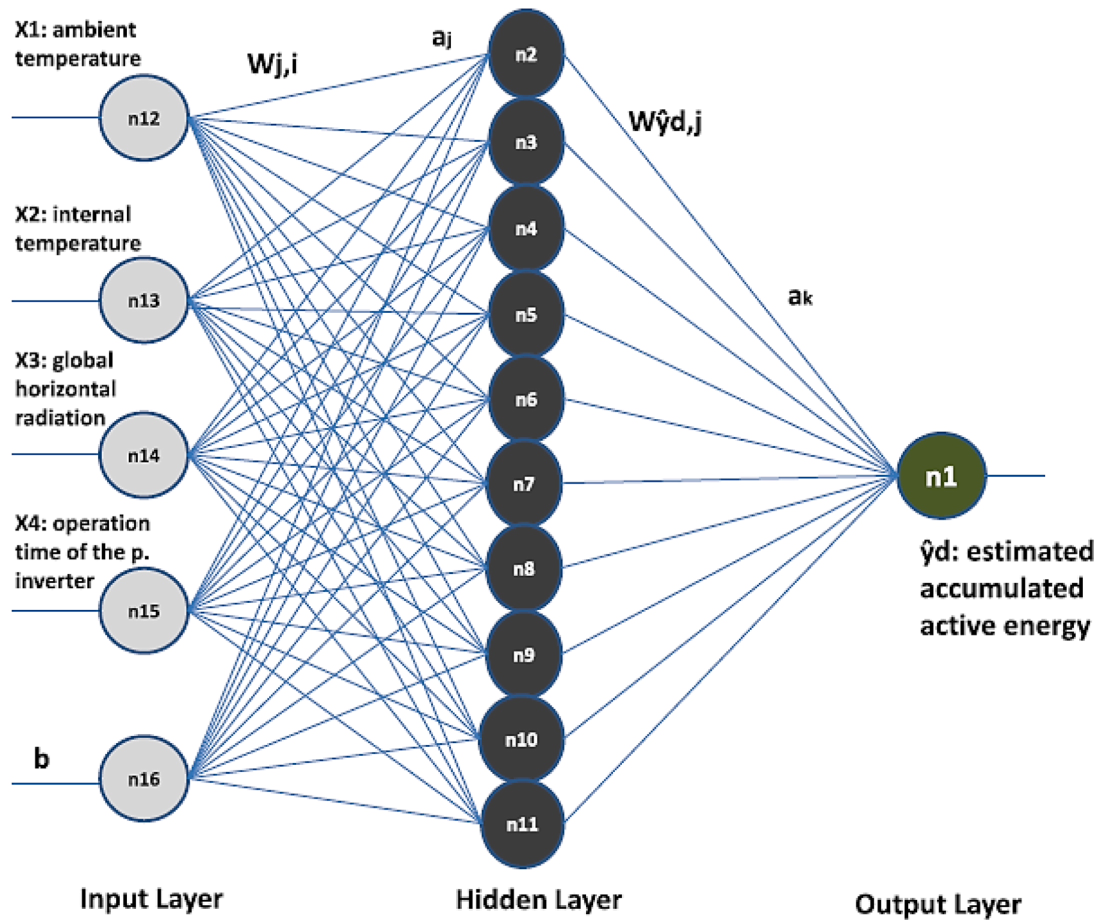

Fig. 9. Multi-layer ANN back propagation [66].

and estimated values. The second deals with present and past performance ratios and finally the last relies on comparing present and past output differences. By combining these three sub-methods, the resultant model overcomes the erroneous fault identification of other AC based PV fault methods for specific PV circuitry [68].

Using capacitance change criteria. Using AC parameter characterization, hot spots in PV systems can be detected by noticing the capacitance change within a single cell (that is comprised of series/parallel resistances and parallel capacitance). The measuring the AC impedance value in the range of 10–70 kHz the capacitance change is detected by monitoring first a High Frequency (HF) in the Capacitive Region (CR) and Low Frequency (LF) in DC impedance region. Such a fault detection system does not only help in identifying the formation of hotspots but can also help in the optimization of MPPT algorithms [155].

Fault detection techniques for three-phase inverters (FDTI)

Embodying the raw source of AC power in a PV system, good monitoring and control techniques are required for inverters for a safe switch off, and an optimum overall performance of the system. Locating the fault of the inverter enables the usage of standby equipment (to get rid of blackouts) and modifications in the functional strategy [80–88]. There are two general ways to detect faults in inverters:

- I Signal-based methods
  - 1 By measurements of inverter’s output voltages
  - 2 By measurements of load currents
- II Models-based methods

Signal-based methods

These methods require the measurements of inverter output voltages [110–116], or load currents [117–120,173–181].

Measurements of inverter’s output voltages

Mass center of the voltage pattern. To identify an open switch fault inside the inverter, an analysis of the pattern mass center derives an algorithm for that aim. First the algorithm starts by acquiring the AC voltages of the inverter and results of histograms created according to Eq. (6) [89].

$$\begin{cases} PR\ oj_{V_a(V_a)} = n_k \\ PR\ oj_{V_b(V_b)} = n_k \\ PR\ oj_{V_c(V_c)} = n_k \end{cases} \tag{6}$$

where PR represents the reference for the inverter’s histogram voltage representations, V_a, V_b and V_c are the voltage magnitudes for each phase and n_k is the sample’s number during one period of the signal. Successively, the left and right mass centers are calculated. From the mass center of each zone, the normalized diagnostic variables are calculated where any transistor open fault is identified by means of a Schmitt-trigger circuit. This method is characterized by its low computational requirements [89].

Open circuit fault identification rule for the inverter. Depending on the voltage variation of PV arrays, residual voltage errors are calculated. Basing on the amount of such errors, an open circuit fault identification rule is identified for the inverter as shown in the following equation.

$$R_i = \ [sign\ (r_i) + 1] \cdot \ (p_{min} - p_{pOi}) \tag{7}$$

where R_i represents the improved judgment criterion, *sign* refers to the signum function, r_i is the voltage residual error, p_{min} the minimum output power of PV and p_{pOi} the ith PV panel power. Designed for grid-connected PV systems, this method has shown reliability and flexibility, with a robustness in detecting PV faults under maximum power points variations [94].

Measurements of load currents

Current comparator method. By comparing the current between any two identical branches inside the AC distribution network, the inverter fault can be detected based on the fact that these two currents must be equal [90]. By setting a small constraint ε which corresponds to a maximum tolerance level, the difference between two nodes' currents ΔI_{Nm} must obey the inequality of the following equation.

$$\Delta I_{Nm} < \varepsilon \tag{8}$$

with N, m representing the currents' nodes. Therefore, when the difference between the two nodes' currents ΔI_{Nm} equals or surpasses ε an inverter fault is detected [90,99].

State observer method. To detect an open-circuit fault for an inverter in a grid-tied PV, a mathematical model is first built for the converter. Then, a state observer is constructed with the aim to generate any occurring current residuals. The fault is detected by means of a comparison between the residual error with the setting threshold. For PV inverters open-circuit faults, this method is validated with a good feasibility [92].

Knowledge-based models. Based on a knowledge-model, an inverter's fault detection technique is established by using two approaches, the current vector trajectory, and the instantaneous frequency. Hence, an open transistor fault in the inverter is detected [96]. For three phase inverters, fault diagnosis is based on the most probable defect, as a way to overcome the lack of Fourier analysis in proceeding explicit determination of the fault [97].

Similarity measurements based methods. When inverters interfere with failures, the semiconductor devices' based topologies become non symmetrical. Therefore, the resultant three phase current become nonsymmetrical in turn. Based on the residuals of current ordered-sequence Mannharden distance, the measuring algorithm can detect and locate the open-circuit faults [98].

Based on information fusion. For inverters' open-circuit fault detection, an improvement of Dempster–Shafer (D–S) evidence theory is achieved by the mixture of Back-Propagation Neural Network (BPNN) with Classification And Regression Tree (CART) algorithms. The load current signals are processed using Wavelet Transforms (WT). In other words, WT is used to extract fault characteristics (such as transistor faults in inverters). At a second order, BPNN and CART are used to diagnose the open-circuit faults. The improvement to the decision level concerning fault detection is held by means of the improved D–S [100–103].

Park's vector method. The open-circuit fault as well as other defects in the power switches (IGBT, MOSFET, etc.) are detected by calculating the position of the current trajectory's midpoint. The Park's vector transformation allows the obtainment of both magnitude and phase angle of the pre-calculated three-phase average currents. An open fault exists if the magnitude of the space vector is nonzero and greater than a threshold [104–107].

Model-based methods. These methods require the accurate system model's design to achieve an optimum algorithm and consist of four distinct sub-methods.

Observer-based diagnosis scheme. As a way for detecting faults related to power switches inside an inverter, a directional residual evaluation in the frame is employed [108]. The fault detection process is held by residual vector evaluation shown in windowed norm as in the following equation.

$$||r_{dq}||_{2,t,T} = \sqrt{\int_{t-T}^{t} ||r_{dq}||^2 dt} \tag{9}$$

where r_{dq} is the current residual vector and t, T are time constants. The algorithm for the inverter's fault detection used in this model is independent of the load torque, where simultaneous faults can be isolated, in a quantitative way with no need of extra measurements for voltage/current required for implementation [108,91].

MRAS-based diagnosis. The open-switch inverter faults are detected by the employment of a permanent magnet synchronous motor. The model relies on reference adaptive system techniques, corresponding to normal voltage balancing/sequencing in each phase. In other words, in order to detect open circuit faults, this method takes into account the input voltages to the inverter and observes any voltage distortion at the output level. This proposed method can be well combined with the corrective maintenance schemes, such as the reconfiguration of inverter, while demanding less extra circuitry (e.g., voltage/current sensors), and low computing facility [109].

Multistate data processing and subsection fluctuation analysis for photovoltaic inverter. Composed of three distinct blocks: Multistate Data Processing (MSDP), Subsection Fluctuation Analysis (SFA) and Artificial Neural Network (ANN), the MSDP retains the main fault features and abducts the influence of load's change (to distinguish between this scenario and a fault). Secondly, the SFA classifies the different states of the inverter's switches. Finally, ANN combines MSDP and SFA to adapt an intelligent classification of faults [93].

Combination of a model-based and data processing perspective. Different fault scenarios (under model-based topology) are estimated by means of an additive model, which employs in turn sliding-mode proportional-integral observers. Then by performing a directional residual evaluation within a fixed reference frame, through data processor, faults can be detected in the inverter [95].

Islanding detection technique (IDT)

An over-current fault is noticed inside the AC region of the PV system, by means of Circuit Breakers (CBs). The CBs tripping, provided by an internal electro-mechanical mechanism, is executed to reduce any wires/equipment damaging. Islanding consists of switching off a faulty zone in the AC distribution panel, similarly to the operation of CBs. To detect islanding means to figure out where the fault has taken place, hence allowing its quick removal, therefore restoring power back to the faulty zone. The islanding detection technique possesses two different sub-techniques:

a) Central remote techniques
   1 System state monitoring
   2 Switch rate monitoring
   3 Inter-tripping
b) Local islanding techniques
   1 Passive techniques
   2 Active techniques
   3 Hybrid techniques

Central remote techniques

System state monitoring. Unintentional islanding here can be detected using parameter distribution quantity measurements such as voltage, frequency and transients in these two labels [185]. This method plays a complementary role to the SCADA and needs fewer number of state measurements [121–123]. Machine language can be as well added to the monitoring process of the system's state by means of Decision Tree (DT) algorithms [182–184].

Switch rate monitoring. A tripped CB is a clear indicator about an over-current fault, yielding in islanding some zones of the PV system.

Hence, a transfer trip detection technique scheme can be used to monitor all CBs that might cause the islanding of the PV inverter. The integration of a SCADA with the trip detection technique would help in the monitoring process [124–126].

Inter-tripping. Figured on a special communication between sensors and generating units, this method detects any open-circuits at the points of disconnection and generates a feedback signal to the sites' data monitors [127,128].

Local islanding techniques

Passive techniques. This area of research has four main categories of measurements that help revealing a local islanding fault. The first method takes into consideration the voltage and frequency fluctuations, above and under optimum values. It is considered as a primitive method in detecting unbalances, using protective relays that indicate a fault based on the power flow at Points of Common Coupling (PCC) between the utility and the inverter [129].

The second detects any voltage phase jump, where it monitors the difference between the current and the terminal voltage of the inverter to identify any surge occurrence [130].

The third category in this part is about harmonics measurements. It measures any change in the Total Harmonic Distortion (THD) at PCC, where the careful selection of the basis threshold reduces any false tripping [131]. Extra monitoring parameters can be added as THD of the current and unbalanced voltage to detect any islanding fault [132] that in turns present a harmonic impedance measuring [133] of the electric system, what results in islanding fault detection.

The last sub-part of this set of techniques operates by detecting the voltage unbalance, due to changes in the network topology and load [134,135] that could result in islanding sub-parts of the PV systems. Such operation is achieved by continuously analyzing the output three-phase voltage at low time cycles [136].

Active techniques. Beginning with the impedance measurement technique, where source impedance is calculated using short circuit current and reduced supply voltage (due to islanding) [137], islanding detection zones can be identified, but not all of them, as this method have Non Detection Zones (NDZ) [138]. On the other hand, the Slip Mode frequency Shift (SMS) is considered as an active technique used to detect islanding, by taking advantage of a positive feedback carrying info about frequency, amplitude, and phase detection.

An improvement to this method (since it presents phase shift perturbation leading to measurement inaccuracy) is called improved SMS [139] where an additional phase shift is maintained that results in lower NDZ.

Hybrid techniques. Presenting a total of four different hybrid techniques, the first hybrid IDT bases on the voltage unbalance and THD, to identify an islanded AC zone due to CBs tripping. It can be added to a positive feedback based technique [140]. The limitation of each technique (hybrid-positive feedback) is overcome when both of the methods operate simultaneously.

A second hybrid technique is based on voltage and real power shifting where it is considered as a solution to overcome the limitations of other IDT techniques and takes advantages of individual passive and active techniques. This method uses an average rate of the real power shift in active technique and voltage change in passive one [141]. Such working methodology can lead to islanding detection even for multiple generating units.

The third method states that after the injection of an intentional voltage fluctuation by means of a high impedance load [142], a rate of change is afterwards calculated for voltage and a correlation factor, using digital signal processing, yielding eventually to islanding detection.

The last one represents a curve modeling for islanding detection, based on Sandia Frequency Shift (SFS) and reactive power versus frequency (Q-f) proposal [143]: this method reduces the NDZ by calculating the optimum SFS where the bacterial foraging algorithm is used to derive the optimal SFS gain.

Residual current monitoring devices (RCD)

Any residual between entering and leaving currents from a node inside the AC network, indicates a leakage, where the RCD's coil is sufficiently energized and tripped to stop that phenomenon. For a PV system, an RCD protects against L-L and L-G faults where it can be installed either for the entire string or one complete array [213]. The RCD sensitivity must be carefully chosen to avoid any false tripping [214].

Ground fault detection and interruption fuse (GFDI)

In a complete circuit, the current created from the supply feeds the load and returns in the ground conductor. When there is any abnormality in this return current, the GFDI operates to immediately switch off the inverter [215,216]. Sometimes leakage currents exist, inducting a false GFDI tripping. There are also certain environmental conditions such as relative humidity, ambient temperature, and salt mist, which negatively affect a proper operation of a GFDI fuse, causing a false tripping. Therefore, the sensitivity of the GFDI must also be properly selected [217,218].

The classification of AITs (Artificial Intelligence Techniques) submethods rely on the algorithm of implementation. Whether ANN, DT, KELM or others, the back-propagation, data-mining, and decision making with the corresponding degrees of accuracy and data acquisition time is what characterize each. They all share a complex programming process in common. Different RDM based techniques aim to detect various electrical faults. Beginning with open-circuit/short-current faults, arriving at detecting failures in power conditioning units, they differentiate in their accuracy and data acquisition time.

Regardless that FTDI attributed methods might contain implemented artificial intelligence algorithms, they differentiate from AIT with their case-specified algorithms. The learning/decision algorithms are driven according to each converter datasheet. On the AC side of a PV system, the CBs are a must to neglect any form of overloading. This in turn reduces the potential of equipment damaging and cable burning. The islanding detection techniques give the possibility to figure out the faulty zone, hence restoring normal functioning at the load side (e.g., reduce any form of partial/complete blackout). The application of IDT gives the system a more reliable and consistent performance.

The RCDs and GFDI based techniques refer to fault detection methods by means of safety switchgear. From one side, RCDs reduce any possibility of current leakages, hence avoiding any risk of personnel electrocution. On the other hand, GFDI ensures that no current is present in the ground. This avoids in turn any voltage unbalancing. The safety switchgear (CBs, RCDs, GFDI) cannot be avoided in the AC side of the PV system. No fault detection at the AC side of the PV system can be set for execution without such devices (whether actively or remotely via SCADA). The electro-mechanical tripping phenomenon of these devices is the clear indicator for a fault detection.

The islanding detection technique can be mixed with RCDs and GFDI by means of Residual Current Breaker with Over-current devices (RCBOs). When RCBOs are used, any trip can be detected using islanding detection, at the same time while avoiding any personnel electrocution, voltage unbalancing and equipment (wires, loads) damaging. This would reduce the need of extra components, causing a more financially affordable PV protective system. Table 6 reveals the potential need for applying different fault detection methods and the consequences when not being applied.

Detection at DC side

With DC detection techniques, the entire DC zone within a PV system is monitored. The blue dashed area in Fig. 10 entitles the corresponding region for fault detection. The received DC power from the solar module

Table 6
Consequences of not applying different AC fault detection techniques.

Detection technique	Necessity for application	Consequences when *not* applied	Effects
AIT	Optional	Errors between measured and predicted electrical quantities	Reduction in system's financial competencies
RDM	Optional	Errors between measured and calculated electrical quantities	Reduction of system overall efficiency
FDTI	Medium to high	Converters internal failure	Distorted AC waveforms
IDT	Must	CBs excessive false tripping	Partial/complete blackout
RCD	Must	Presence of current leakages	Personnel electrocution
GFDI	Must	Abnormal quantities of return current	Voltage unbalancing

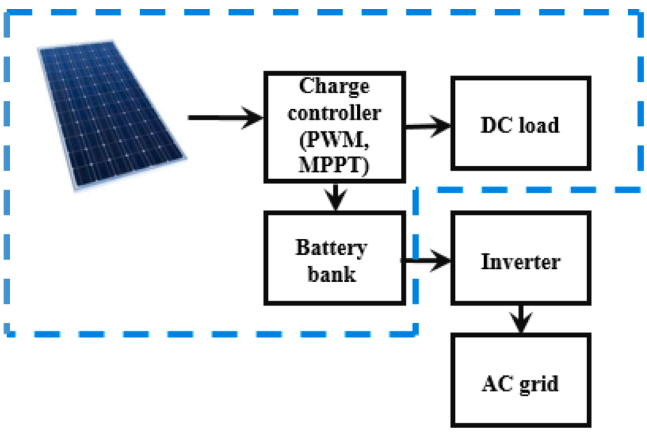

Fig. 10. DC detection zone.

in Fig. 10 is fed into the charge controller. DC loads are supplied from the charge controller, at the same time while the battery bank gets charged and monitored.

Statistical monitoring method

Statistical monitoring based fault detection methods for PV systems rely on collecting PV performance data, calculate a statistic test to define the acceptance/rejection regions of the data set, then draw a final conclusion accordingly. A statistical monitoring method relying on Modified Exponentially Weighted Moving Average (MEWMA) algorithm can detect non-recoverable faults at the DC side of a PV system. The tactic starts with the one-diode model identification, to simulation of PV system, and end up with applying the algorithm [169]. Fig. 11 exposes the fault detection/identification phases of MEWMA algorithm.

The procedure shown in Fig. 11, indicates that the PV system is running optimally if no residuals from the compared outputs exist between the simulated version of the prototype and the real hardware itself. In case of any differences in the outputs, the MEWMA algorithm can classify the existence of a fault, as either faulty module, faulty string, or partial shading due to ageing. This strategy was tested experimentally on a GCPV showing a good capacity in PV fault detection [169].

Electrical methods

This set of methods rely on Current–Voltage (I–V) characteristics analysis, to detect a fault in the DC detection zone. It covers up the following sub-methods:

a) Model Based Difference Measurement (MBDM)
   1 DC to AC power ratio monitoring
   2 Comparison between DC voltage/current deviated error with respect to reference values
   3 Base fault diagnosis combined with Wald-test technique
   4 Comparison of simulated I–V characteristic curve with experimental data
   5 Comparison of measured values with model prediction results
   6 MPPT fault locator
   7 Shading fault detector based on Deviation Error (DE)
   8 Short circuit current detector
   9 Dynamic I–V characteristics based fault diagnosis
   10 Shading and electrical faults detector based on Bishop model
   11 Experimentally Weighted Moving Average (EWMA) control for shading effect on PV modules detection
   12 T-test statistical method for physical fault detection/algorithm for fault detection
   13 Electrical and environmental fault detection based on WOEWMA
   14 OPC monitoring
   15 Comparison between Measured and Modeled (CMM) PV system outputs
   16 Analysis of solar photovoltaic power generation
b) Spread Spectrum Time Domain Reflectometry (SSTDR)
c) Estimating Randomness in the Voltage signal (ERV)
d) Power Loss Analysis technique (PLA)
e) Electrical current-voltage I–V Measurement (EM)
f) Open/Short-Circuited modules in PV string (OC/SC)
g) High/Low Voltage fault diagnosis sections (HV/LV)
h) Partial/Complete Shading fault detector (PS/CS)
i) Online/offline model (Onm/offm)
j) Degradation Fault Identification (DFI) based on string current
k) DC–DC converters Fault Identification (DC-DCFI)

Model based difference measurement (MBDM). Model based difference measurement methods consist of modeling the optimum cases (theoretical) for current/voltage values (reference values). The second modeling includes the actual experimental values for the quantities being studied. The difference between these two models yields to a clear representation of the deviation error. The value of the deviated error represents in turn a clear sign of the fault's type.

DC to AC power ratio monitoring. By monitoring the DC to AC power ratio, the location of a fault in a Grid Connected PhotoVoltaic (GCPV) system is located. Accompanied with a developed software tool the identification of different sub-faults in the different regions of the PV system (on the level of PV string, module, MPPT, etc.) is enabled. The failures taking place at the DC side of the system are indicated by means of capture losses L_c given in the following equation.

$$L_c = Y_r - Y_a \tag{10}$$

where Y_r and Y_a denote the reference yield and energy produced by PV array over a specific time period respectively. Accordingly, the calculated values of losses yield in a clear representation of the fault's type and its causals (e.g., soil, electrical interconnections, etc.) [187].

Comparison between DC voltage/current deviated error with respect to reference values. Relying on the comparison between the simulated and measured data of the PV system's performance a fault is detected then identified by analyzing and comparing the number of errors deviated between the DC voltage and current with respect to the evaluated thresholds of a reference fault-free system. For capture losses monitoring, the error parameter EL_c is established as shown in the following equation.

$$EL_c = |L_{c_{meas}} - L_{c_{sim}}| \tag{11}$$

with $L_{c_{meas}}$ and $L_{c_{sim}}$ correspond to measured and simulated power losses respectively. The different established thresholds for fault detection and diagnosis procedures the most likely occurring fault can be determined

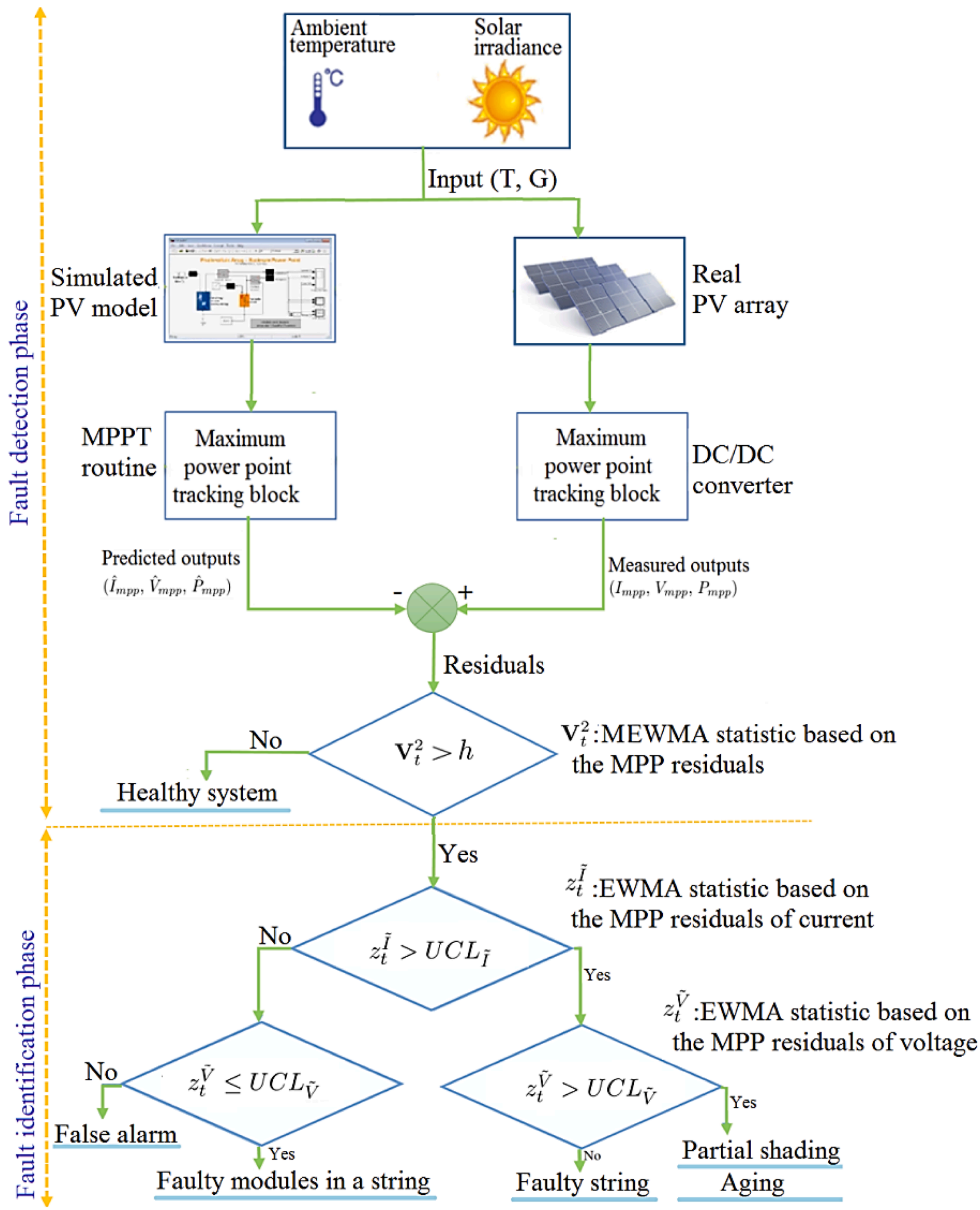

Fig. 11. MEWMA flowchart [169].

[188].

Base fault diagnosis combined with Wald-test technique. Targeting for Residential Photovoltaic System (RPS) fault detection, an algorithm emphasizing on active and passive parts of the PV system, is used to first diagnose the problem using a base fault diagnosis to check for any fault's alarm signal using an arbitrary data. After so, in the passive part, and in order to investigate the temporary mismatch resulting fault, Wald-test technique is statistically used. Then a proposed Flash Test Driver (FTD) device is used on the power conditioning units to increase the efficiency as well as the reliability of the RPS. The suggested flash test method can be integrated with artificial intelligence-based techniques, thus expanding its PV fault detection types, cost-effectively [189].

Comparison of simulated I–V characteristic curve with experimental data. Targeting the faults that might occur on the level of a PV array such as temporary mismatch and electrical faults, different intended fault scenarios were exerted on the system. The comparison between the Matlab simulated I–V characteristic curve and the generated experimental data of the same PV system, helps in identifying the nature of the fault. The categorization of different faults is generated from normal operation to bypass diode fault. Such PV fault detection technique can lead designers to an accurate prediction of possible faults [191]. From another part, the single diode model (projected to regional environmental inputs, such as temperature and irradiance) can be first estimated. Then, the type of the fault to be identified will be based on a threshold approach: a 10 % deviation of the PV cell's measured power do not indicate any presence of a fault. Contrarily, any significant decrease/increase (by more than 90 %) in the measured voltage and/or current, indicates the presence of a fault. Similarly, a difference of more than 10 % between the measured/estimated fill factors leads also to a fault declaration by the algorithm [296].

Online comparison of measured values with model prediction results. On the level of PV panels, a fault detector is established by comparing the measured values with model prediction results. The prediction relies on the theoretically calculated PV power production resulting from solar irradiance and PV panel temperature measurements. With a low complexity and high fault detection rate, this method results in a fault detection rate greater than 90 % for different irradiance intervals models [192].

MPPT fault locator. For shading and converter faults in PV arrays, when comparing the Maximum Power Point Tracker (MPPT) output under shading conditions with respect to the same output under normal irradiance, faults are detected (e.g., the PV power output is smaller compared to standard conditions). If the PV load is too small, the fault cannot be accurately identified, hence, a defined voltage ratio technique takes place over the normal difference method [193].

From another point of view, the modification of the MPPT algorithm is another way to detect the PV faults in the DC region. Basing the algorithm on the variation of the aspect ratio of the rectangle parametrized by the origin $(0;0)$ and the Maximum Power Point (MPP) $(V_{MPP};I_{MPP})$ within the Power–Voltage (P–V) characteristic curve, the non-recoverable faults as faulty interconnections, bridge earth, and shunt path development can be detected [262]. The MPPT algorithm can be adjusted as well to detect different physical faults on the level of PV cell, such as shading, aging, degradation, and possible hotspots, due to environmental triggers [263]. On the other hand, a faulty MPPT can negatively affect the PV system's efficiency and reliability (i.e., false decision making, inaccurate duty ratios signaling, etc.). Accordingly, in order to restore a proper MPPT operation, the standard activation must be allowed [70].

Shading fault detector based on deviation error (DE). When partial shading occurs on the level of PV cells, the PV modules in turn overheat and bypass diodes get activated. Accordingly, the mathematical equation corresponding to the normalized error DE resulting from comparing the actual I–V curve data with reference ones can lead to error identification. By means of this method, shading faults can be online dissociated between homogeneous and non-homogeneous. In addition, the bypass diodes activation is detected with a derivative calculation between the standard error and the PV module voltage [194].

Short circuit current detector. The output current of a PV system is highly dependable on external climatic conditions, therefore faulty currents can be misinterpreted by PV current fluctuation (high values under high irradiance profiles, low values under cloudy days). In order to eliminate such confusion, a dynamic state estimation-based algorithm can be a solution to identify the short circuit currents especially when the series fuse is not operating due to the reduced value of the short circuit current which is limited by the blocking diode. The proposed algorithm is effective for a PV fault on the cellular level [195].

Dynamic current–voltage characteristics based fault diagnosis. A simultaneous way of investigation between sampled data of voltage–current characteristics of a PV panel and the determination of its intrinsic parameters can lead to a dynamic fault diagnosis. With a fast parameter estimation, this technique allows a deep knowledge upon the state of the PV panel, what reflects as identifying the different sorts of external faults [196].

Shading and electrical faults detector based on bishop model. By relying on the least squares method, the diagnosis of Solar Energy Production Source System (SEPSS), based on Bishop model is exposed where shading faults, as well as different electrical faults are taken into consideration. When the direct signal analysis (i.e., by temporal power/voltage variations) does not contribute well in the PV fault detection, the proposed least square based fault detection overcomes such obstacles. In the process of fault detecting decision, a fuzzy logic approach is employed, with less needed time for calculation and ease of implementation [197].

Experimentally weighted moving average (EWMA) control for shading effect on PV modules detection. For an early detection of shading effects on PV modules, as well as other faults on the DC side of the system, the usage of a mixed combination of the simple one-diode model in collaboration with the extended capacity of the EWMA control scheme, can detect the mentioned faults [199]. First, the one-diode model is used to make a reference of a healthy PV array maximum power coordinates. Then, all residuals (resulting from the difference of measurements between predicted and actually measured data) serve as fault indicators. When uncorrelated residuals exist, EWMA executes to identify the fault's type.

T-test statistical method for physical fault detection/algorithm for fault detection. To detect faults on the DC sides of a Grid Connected PhotoVoltaic (GCPV) system, a fault detection algorithm based on T-test statistical method is used to detect different types of physical faults [201] where for a given solar irradiance and temperature inputs, attributes such as voltage and power ratio of the PV strings, are measured. The needed inputs of the algorithm are solar irradiance, modules temperatures, voltage, and power ratios [166].

Electrical and environmental fault detection based on WOEWMA. Using the upgraded Wavelet Optimized Exponentially Weighted Moving Average (WOEWMA) algorithm, electrical as well as environmental faults of PV grid connected systems can be detected [163]. The overall system can classify false alarms and missed detection rates. Fig. 12 presents the two online/offline monitoring phases for the WOEWMA algorithm. Control limits are calculated from the off-line modeling phase and compared with the detection chart obtained during the on-line monitoring phase. The fault is declared after violating the permissible threshold between the detection chart and its control limits.

OPC monitoring. In an Object linking and embedding for Process Control (OPC) environment for PV simulation, a remote supervision and fault detection technique based on voltage/current comparison tactic is proposed [165]. The system itself is a decision maker where it analyses the monitored data and evaluates the expected behavior of PV arrays in terms of output voltage, current and produced power. The current and voltage indicators that were used for fault detection are shown in Eq. (12) and Eq. (13) respectively.

$$NR_c = \frac{I_m}{I_{scg}} \tag{12}$$

$$NR_v = \frac{V_m}{V_{ocg}} \tag{13}$$

with I_m and V_m representing the current and voltage quantities at the maximum power point respectively while I_{scg} and V_{ocg} representing the real-time measured current and voltage quantities. This method was experimentally tested on a real PV system, where the root mean square errors between real/simulated data were below 3.6 % [165].

Comparison between measured and modeled PV system outputs (CMM). The analysis of the difference between actual PV measured values (i.e., DC current and voltage) and modeled ones, could predict the electrical fault within a PV system. Predictive models get simulated with aid of computers, to fabricate a theoretical threshold. In other words, a reference value for which all non-equal values, represents a specific fault type. Based on the reference thresholds for fault detection as well as diagnosis procedures, the most likely PV fault to occur can be identified [251]. Under the same perspective, based on an extended correlation function and on the matter model [253] predictive PV faults detection are improved.

Analysis of solar photovoltaic power generation. Under dynamic PV systems operations, sometimes exists an inability to distinguish between the effects of undesirable environmental conditions (i.e., clouds, snow

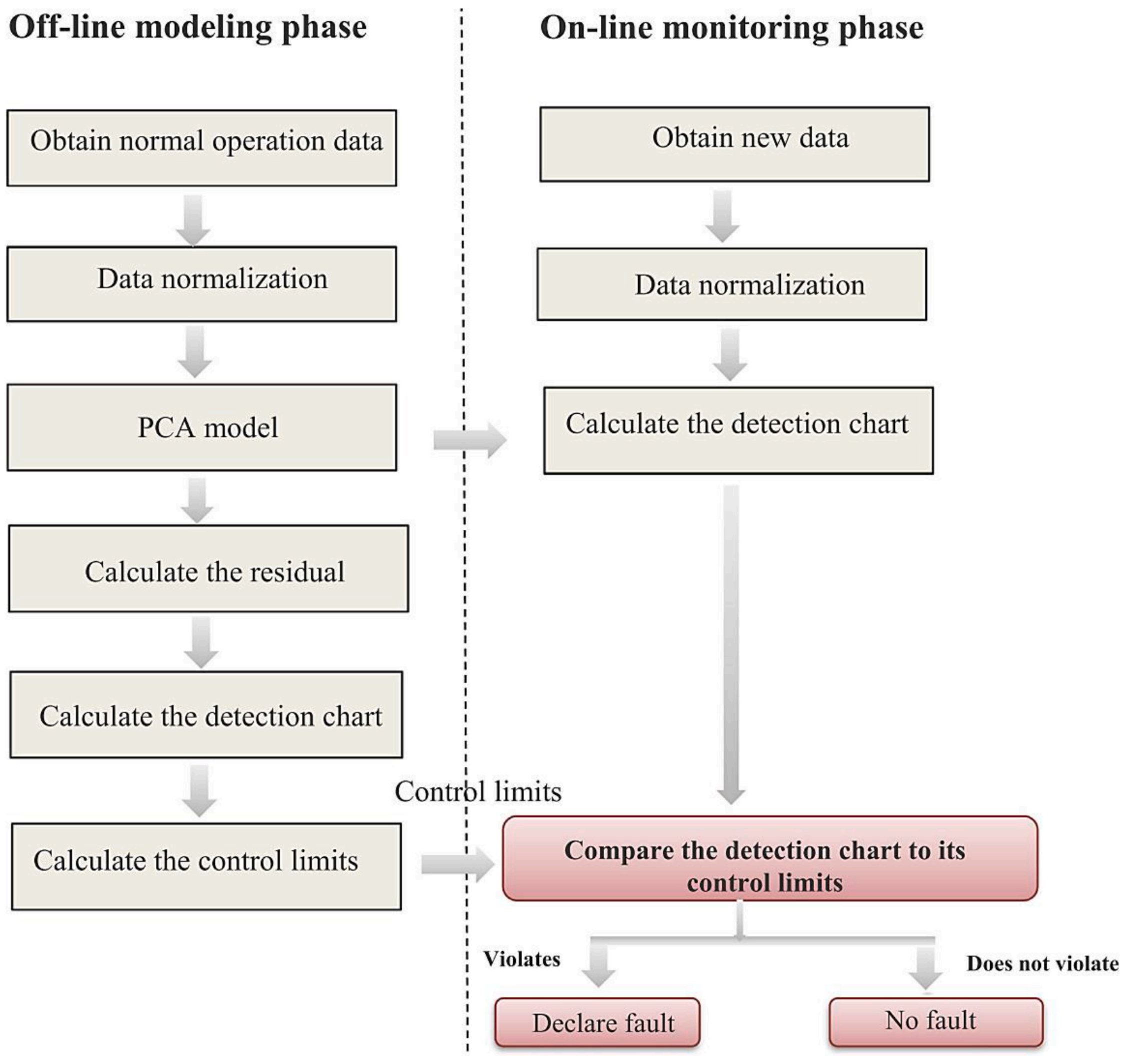

Fig. 12. General diagram of detector scheme [163].

accumulation, etc.), which lead to the same results of fault conditions (i.e., decrease in power generation capacity). Accordingly, for a proper operation description the test method based on the analysis of solar photovoltaic power generation performance reveals a voltage and current based fault detection method. Unlike conventional voltage/current based PV fault detection methods, this scheme is able to distinguish between environmental factors and concrete PV cell faults [69].

Spread spectrum time domain reflectometry (SSTDR). The fault is detected using a plot, which in turns is created using the incident and reflected signals. Referred to as "auto-correction plot", it can be used to identify different faults without the need to disconnect the inverter, as it checks the losses/disturbances between the two signals. The fault is hence identified after the analysis of the plot's changes [204].

From the same perspective, the incorporation of a fault detection algorithm with SSTDR results in a tool to detect wiring faults even with the existence of impedance varieties throughout the PV system. Such combined system can detect PV ground faults for different PV systems' architectures and distinguish ground faults that GFDI cannot detect [205].

Similarly, mixing the Time Domain Reflectometery (TDR) principle with Earth Capacitance Measurement (ECM) a fault detector for disconnection and degradation problem is achieved [247]. The model investigated can be implemented in a PV system in two ways, the first as a fault inspector, the second as a temporary detector to find the degradations in the PV system.

Estimating randomness in the voltage signal (ERV). A Finite Impulse Response Band Pass Filter (FIRBPS) can detect an arc fault in the DC wiring, by estimating the corruption between the output signal with reference to the input signal. If the difference is low/high in comparison with a threshold, arc faults' existence can be investigated [206].

The randomness in the voltage signal can be estimated as well by means of a modified one-diode model. The one-diode model can be completed by combining the Artificial Bee Colony Optimization (ABCO) and Differential Evolution (DE) algorithms to digitally model a PV array and extract the ABCO-DE parameter [207]. Hence, an I–V curve based PV module fault detector can be launched as a fault detector using ABCO-DE parameter extraction technique.

Power loss analysis technique (PLA). PV Faults can be detected based on power losses. This can be done by comparing the monitored data (e.g., DC output power) with the simulation outcomes [242]. Basing on PLA, the faults occurring between the PV array and the converter can be detected [250,243]. Current and voltage ratios can also be used as a skeleton for PLA based fault detection algorithm [244].

Electrical current–voltage I–V measurement (EM). PV faults can be detected by depending only on I–V measurements on the output level

[255]. The EM based methods can be as well ameliorated using a micro-controller [256] as a central decision making unit [257]. Such methods are also applicable for GCPV [258], where the derivatives of I–V indicators signal the detection partial shading phenomenon [259]. The addition of other performance indicators (e.g., Fill Factor (FF)), and electrical characteristics (e.g., Shunt Resistance (SR)) to the crude I–V measurements, yields in a wider overview of the PV system's performance [260].

Following the same perspective, by comparing the actual electrical parameters (e.g., voltage, current) from the I–V characteristic curve and theoretical ones, faulty connections can be investigated. The technique relies on analyzing the shape of the I–V characteristic of a PhotoVoltaic Array (PVA) [254].

Open/short-circuited modules in PV string (OC/SC). By emphasizing only on the quantity of transducers, such as the number of sensors and power meters, a simple diagnostic technique is achieved [71] to detect the number of open/short circuited modules in a PV string.

Also based on current and voltage indicators, a procedure to calculate the thresholds needed to identify the fault is presented [72] where the PV array that is formed from series and parallel interconnection of PV modules, forms a reference for the thresholds' calculation. For an automatic process to identify OC/SC modules, without any manual interventions, the design's principles and runtime control algorithm are presented [73] to detect the bypass PV cell faults.

High/low voltage fault diagnosis sections (HV/LV). The localization of the defected PV modules is done by analyzing the terminal I–V curve, which is divided into high and low voltage fault diagnosis sections. In each section, the healthy and defected working points of string modules are analyzed for both of I–V sides [74] where at the end, any faulty PV module is located by probing into different working points.

Therefore, faulty conditions are regionally characterized inside the detection zones within the I–V characteristic curves [75]. Such zones are defined after subtracting the measured from the maximum set point values of I–V signals.

Partial/complete shading fault detector (PS/CS). Using three input variables, such as measured values of array voltage, current and irradiance, a method to detect faults and partial shading under every irradiance situation is established [76]. Such method is able to classify the status of PV arrays into three states as normal, partially shaded, or faulty mode. From another side, and based on DC power measurements, shading faults are detected by focusing on real-time fault diagnosis (i.e., instantaneous power measurement under real PV working conditions). Accordingly, the detection, location, and identification of different types of PV shadows patterns are injected to the output DC power analysis, hence yielding in timely PV fault detections [77].

Online/offline model (Onm/offm). After evaluating three PV coefficients (current, voltage, and power coefficients), a two-step model relies first on an offline step that uses a PV simulated model. From the other side, the online step compares real measured PV coefficients with respect to those obtained in offline step. The combination of both online and offline steps results in a differential PV fault detector [78].

Degradation fault identification based on string current (DFI). Based on the degradation faults, a fault diagnostic method that takes into account the relationship between the level of degradation and PV plant faults (including current faults), identifies the process between PV degradation and the decrease in a PV string current. In other words, the relationship between the level of PV modules' degradation and the PV plant's faults is investigated. After intentional short circuit scenarios, this method succeeds in identifying different PV faults, that were undetectable when using conventional protection settings [79].

DC-DC converters fault identification (DC-DCFI). Apart from MPPTs, old techniques for battery charging control relies on Pulse Width Modulation (PWM). The purpose of PWM is to efficiently extract power from PV arrays while safely charging the battery bank [203], providing various ranges of output stages [248]. Labeled as DC-DC converters, such devices can encounter faults, preventing them from functioning or implying an erroneous behavior [249]. To detect the fault within such devices, the diagnosis can rely on:

- Magnetic component voltages equation [170]
- Short-circuit fault diagnosis [171]
- DC-link current pulse shapes [172]

To conclude on this section, Table 7 encapsulates a comparative assessment of different electrical sub-methods.

Signal processing methods (SPM)

PV faults can be detected by the analysis of the output signals, such as current and voltage waveforms, by means of mathematical interpretation and the recordings of measured quantities. The synthesis of the recorded signals gives a clear representation on its status (whether normal or corrupted), what results in various faults detection. This set of methods contains the following sub-methods:

a) Wavelet transform/Wavelet transform with multi-level decomposition/GCPV fault detector
b) S-transform
c) Local Outlier Factor LOF/PVLOF
d) High Impedance Ground Fault detection HIGF
e) Generalized local likelihood ratio test algorithm
f) Differential current based fault detection

Wavelet transform with multi-level decomposition. The wavelet transform represents a mathematical modeling for dynamic signals using small waves [144]. It comprehends both frequency and time information simultaneously, which accordingly, it can detect discontinuities in the varying signals that are results to islanding. By correlating discontinuities with respect to time, the localization of islanding is performed for PV systems [145], using five decomposition levels [146].

When the raw wavelet transform is decomposed to a multi-level decomposition wavelet transformation, different faults can be detected using a diagnostic function based on the normalized standard deviation of the wavelet coefficients [153]. Since wavelet-based transforms are accurate at detecting discontinuities in signal waveforms, the random, dynamic, and non-periodic arc faults are efficiently discovered. In a particular case, the wavelet decomposition and arc discrimination are presented as algorithms for an arc detector platform using Digital Signal Processor (DSP) [159]. The fault identification accuracy of a wavelet based PV fault detector can be as well improved by means of wavelet packets using the available data of the PV array's I–V curve [162]. Accordingly, the fault detector becomes then able to distinguish between undesired environmental conditions and PV faults.

When creating a modification on the Wavelet Packet Transform (WPT), the resultant tool becomes able to detect the disturbances resulting from faults in Grid Connected PhotoVoltaic System (GCPVS) [167], as shown in Fig. 13. Such scheme compares the results between WPT and Modified Wavelet Packet Transform (MWPT), yielding in fault identification by means of indices' calculation, such as energy and standard deviation.

S-transform. The S-transform is simply an improved version of the previous WT transform, which eliminates the inability of islanding detection under noisy conditions [147,148]. It produces dual axis representation of time: the real and the frequency dependent resolution

Table 7
Comparative assessment of different electrical based fault detection methods.

Detection manner		Targeted faults	Scalability of PV system	Detection level	Algorithm-based	Simulation	Model-type
MBDM	1. [187]		GCPV	PV string/ module/MPPT	●		
	2. [188]						Deviated error Comparative
	3. [189]		RPS		●		Statistical
	4. [191]	Bypass Diode		PV array		●	
	[296]	Open-circuit, short-circuit, mismatch		PV string/module/ MPPT	●		Deviated error
	5. [192]			PV panel			Experimental Predictive
	6. [193,262,263,70]	External, PPUs		DC/DC DC/AC	●		
	7. [194]			PV cells			Deviated error, Mathematical
	8. [195]	Short-Circuit			●		
	9. [196]	External		PV Panel			Experimental Tabulated data
	10. [197]	Shading electrical		PV module	●		
	11. [199]			PV module	●		Deviated error
	12. [166,201]	External	GCPV		●		Statistical Experimental
	13. [163]	Electrical External	Grid-tied		●		
	14. [165]	Electrical		PV array	●		
	15. [251,253]						Deviated error, Experimental
	16. [69]	External		PV array			Experimental
SSTDR	[204,205,247]	Electrical External			●	●	Hardware
ERV	[206,207]	Arc			●		Deviated error
PLA	[242,244,250]			PV array converter	●		
EM	[254–260]	Partial shading	GCPV				Mathematical, software
OC/SC	[71,73]	Electrical		PV string			Hardware
HV/LV	[74,75]	Electrical		PV string PV array			Experimental Comparative
PS/CS	[76,77]			PV array			Comparative Real-time
Onm/ offm	[78]					●	Comparative
DFI	[79]	External		PV string			Mathematical
DC-DCFI	[170–172,248,249, 203]	Electrical		DC/DC	●	●	Real-time Hardware Comparative

which constitutes the imaginary spectra. During an islanding, the voltage sequence becomes negative (backward on the x-y plane). In order to calculate both voltage and current sequences, they are both processed through the S-transform and the spectral energy content is used within the calculation [149].

Local outlier factor (LOF/PVLOF). By relying on the instantaneous PV string current, without the need for weather measurement inputs, outlier detection rules are proposed as fault diagnostic methods. Specifically, the 'Hampel' identifier and Boxplot rule are the most recommended among other outlier detection based methods to detect faults in PV systems [150].

When discussing the transient state and post-fault behavior in the DC side of the PV system, it can be noticed that some of the hotspots becomes undiscoverable (i.e., the occurring fault is not detectable by an Over Current Protection Device (OCPD)). When outlier statistic rules are applied, false alarms may be caused. Accordingly, the Local Outlier Factor (LOF) is developed inside a PV installation [151]. The addition of a specific algorithm to the LOF based on PV string current (PVLOF) to determine the electrical and shading faults on smaller scaled PV plants, the fault detection rate is better enhanced where the fault range is identified through seven steps [168].

High impedance ground fault detection (HIGF). With cost efficiency improvement, apart from the GFDI and SSTDR based PV fault detection methods, while implying on the Common Mode (CM) model of the full-wave inverter, the High Impedance Ground Fault (HIGF) detection scheme is accomplished. The CM model includes a simplified model for the transformer-less circuitry employed in a PV system architecture. This model includes the CM voltage source, ground capacitors and a capacitive path for an Electro Magnetic Interference (EMI) filter. This model detects the ground faults in PV systems [152].

Generalized local likelihood ratio test algorithm. By imposing a change detection algorithm (based on the generalized local likelihood ratio test) on the vector Auto Regressive (AR) model, the time correlation of the faulty signal and signal correlation among different meters (that are employed to measure different output signals of the system) are exploited. Hence this framework detects any sequential change and provide a PV fault detection algorithm [156].

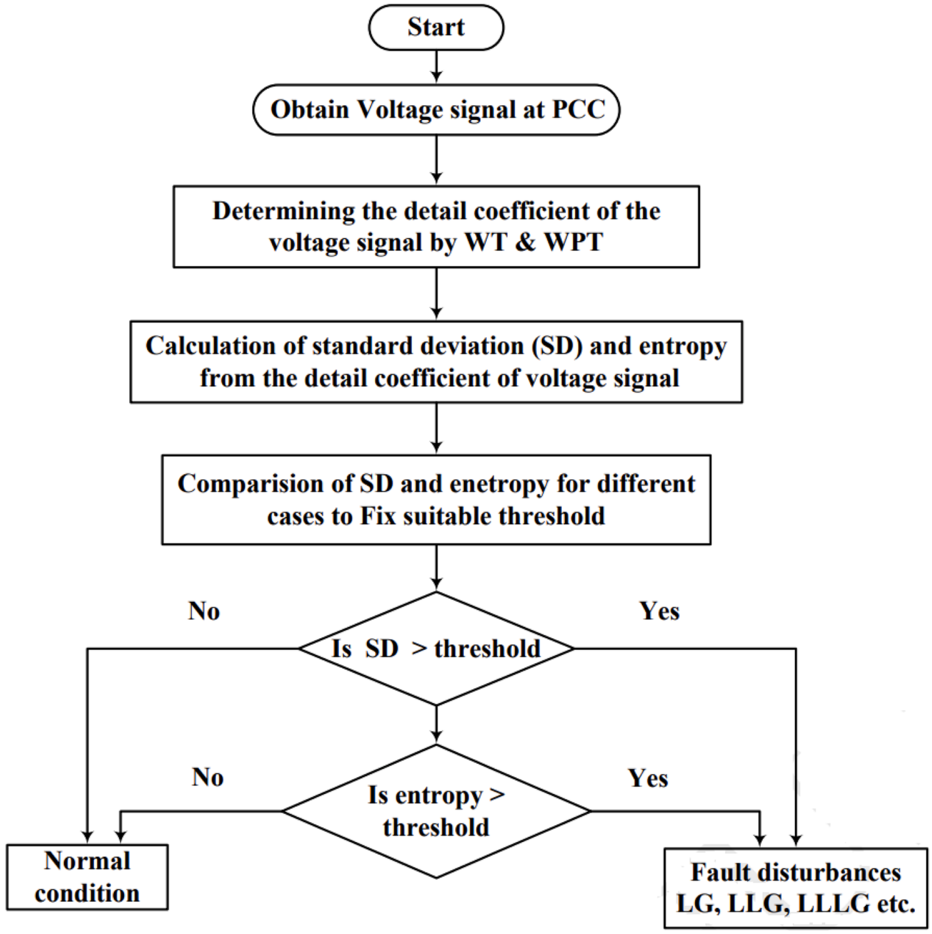

Fig. 13. MWPT flowchart [167].

Differential current based fault detection. A differential current-based fault detection, with a fast acting DC switch as an actuator can calculate the distance to fault by calculating the unknown cable resistance, relying on non-iterative Moore-Penrose pseudo inverse technique. In addition, with the special DC cable connected to the PV system, the DC arc faults could also be identified [160].

Machine learning (ML) techniques

Enabling PV systems to learn from past experiences of faults existence, Machine Learning (ML) techniques allow such systems to learn new knowledge which is not already pre-programmed. This happens by means of large observations, learning algorithms and data mining [279]. Through this survey, twenty different ML techniques were found as follows:

a) Takagie-Sugeno Kahn Fuzzy Rule (TSKFR)
b) Decision Tree algorithm (DT)
c) Probabilistic Neural Network (PNN)
d) Multiple-layer ANN
e) LAterally Primed Adaptive Resonance Theory based Fault Detection (LAPART-FD)
f) Nelder-Mead optimization technique
g) Adaptive Neuro-Fuzzy Inference System-Sugeno Model (ANFIS-SM)
h) Fuzzy logic
i) Random Forest algorithm (RF)
j) DC arc faults
   1 Based on Tsallis entropy factor
   2 Based on electromagnetic radiation
   3 Based on a joint detection method
   4 Based on Frequency Spectrum Analysis (FSA) of V/I waveforms
k) Partially Shaded Modules Fault Detector (PSMFD)
l) GISTEL combined with fuzzy logic
m) ANN based fault locator using electrical attributes
n) String Current Algorithm for OC/SC fault detection
o) Mamdani-Sugeno fuzzy Logic
p) Electrical and Partial Shading faults based on kNN rule
q) Neuro-fuzzy bypass/blocking diodes faults classifier
r) Third-order polynomial function samples with fuzzy logic classification
s) Multiresolution signal decomposition
t) Multiresolution signal decomposition with two-stage support vector machine
u) Logistic regression

Takagie-Sugeno kahn fuzzy rule (TSKFR). This ML based technique inspire learning by training, then occupying the acquainted information into the central processor unit (e.g., microprocessor, microcontroller, etc.). Each new faulty scenario (e.g., decreased power generation) can be referred to an old existing one [221]. This is done using a recursive algorithm that could train a model for several power input/output patterns, to eliminate the difficulty of detecting a fault in changing climatic conditions [222]. To classify the obtained fault within a PV array, Artificial Neural Network (ANN) is used [223].

Decision tree algorithm (DT). In the Decision Tree (DT) algorithm, the PV array voltage, current, operating temperature, and irradiance (referred as attributes) are used in the training and test sets where DT accurately detect and classify PV faults during the test set. This particular process of model training is easy to implement, where the resultant trained model detects PV faults by an accuracy up to 99.98 %, and a classification accuracy of 99.8 % [232].

Probabilistic neural network (PNN). To detect and classify PV faults as short/open-circuit in real time, the Probabilistic Neural Network (PNN) is used, which requires specific information from the PV manufacturers' datasheet under Normal Operating Cell Temperature (NOCT) conditions and STCs [233]. Such model is able to represent the characteristics of PV systems under different environmental as well as electrical conditions.

Multi-layer (ANN). To overcome the low PV fault detection efficiency of manual checking, and to ensure that the PV system is functioning at its best, a three-layered ANN is injected into a fault diagnostic algorithm [234]. The performance of this three-layered ANN model surpasses the single ANN model which does not provide accurate precision for PV fault detection.

Similarly, and using only a two-layered ANN model, an automatic fault detector can provide detailed fault information with high accuracy about PV fault's types and locations. The multi-layered ANN plays the role of a comparator between both predicted power and the measured one. Based on this diagnosis, tasks are achieved in a way that the open circuit voltage and short circuit current of each PV string are to be determined using analytical equations. The resultant current/voltage data end up categorizing six different fault types [235]. In recent research, the multi-output ANN based technique, has shown the ability to be flexibly incorporated with other PV faults detection method, such as the exploration of the characteristic I–V curve [297]. Other algorithms such as Takagie–Sugeno Kahn Fuzzy Rule Based System (TSKFRBS), three-layered ANN can be found in [224–231].

Laterally primed adaptive resonance theory based fault detection (LAPART-FD). To increase the reliability of PV systems an important factor is to design the PV fault detection system with the minimum number of sensors and data acquisition for Reliability Centered Maintenance (RCM) [237]. Accordingly, a Fault Detection and Diagnosis (FDD) tool based on Laterally Primed Adaptive Resonance Theory based Fault Detection (LAPART-FD) can be used. This tool automatically discovers different PV faults, such as temporary mismatch faults on the module level, and it relies on the algorithm which in turns is based on actual and synthetic data tests. The LAPART-FD PV fault detection probability recorded at highest an efficiency value of 86% [236].

Nelder–Mead optimization technique. The physical faults (i.e., degradation, partial shading, and short/open-circuit faults) in a PV system can be detected using the I–V characteristics' curves. Such a process requires the implementation of these characteristics on a Kernel extreme learning machine with the addition of Nelder–Mead simplex optimization technique [238]. The resultant fault detections can be simulated on a Single Hidden Layer Feedforward Neural Networks (SHLFNNs) based fault diagnosis model. The algorithm begins with the fundamentals of Extreme Learning Machine (ELM), returns to parameter optimization of the Kernel Extreme Learning Machine (KELM), heads toward data pre-processing and feature selection, and finally, establishes the fault diagnosis model.

Adaptive neuro-fuzzy inference system-sugeno model (ANFIS-SM). Combining the Adaptive Neuro-Fuzzy Inference System (ANFIS) with its common architecture, the Sugeno model, a faulty curve can be drawn inside the MPPT rectangle to identify shading faults, such as the reduction in the power extractability area. For this purpose, the model has to have six attributes to work accordingly, such as maximum power point current (I_{Mpp}), maximum power point voltage (V_{Mpp}), short circuit current (I_{SC}), open circuit voltage (V_{OC}), I–V step curve, S1 and S2 [239]. The sets of inputs/outputs are firstly classified, then the ANFIS is generated, to later on trains and tests itself.

Fuzzy logic. A fuzzy logic algorithm based model detects PV short circuits faults by taking voltage and power ratios as inputs. The correspondent fuzzy logic consists of voltage/power ratio inputs, where the membership for each input is decomposed into five fuzzy sets. Including machine learning and targeting for Grid Connected PhotoVoltaic System (GCPVS), the proposed system can detect Short Circuit Faults (SCF) by means of theoretical curves of voltage and power ratios. Additionally, the suggested algorithm is capable of detecting hotspots formation in PV system, where its minimum detection accuracy is of 98.8 % [240].

Random forest algorithm (RF). A Random Forest (RF) algorithm detects PV array faults using array voltage and string currents. Implemented in Matlab, the system can detect electrical faults as well as temporary mismatch faults, as presented in its flowchart in Fig. 14. The RF combines multiple learning algorithms and takes only real-time values of voltage and current. The results of such algorithm indicate its superiority over the DT algorithm in detecting and classifying a PV array's faults [241].

DC arc faults. The detection of DC arc faults can be achieved with a method that uses Fast Fourier Transform (FFT), Short Time Fourier Transform (STFT) and wavelet transforms to create a statistic model under Artificial Neural Network (ANN) routine [59]. The decision making takes its final step after sensing elements and acquaint different PV physical data, while the model simulation is injected for signal processing purposes. Under the same point of view, and by using the time and frequency characteristics of a parallel capacitor current, DC arc faults are detected and classified as series and switch arc faults, where this entire system is upgradable to easily investigate harmonics [264]. Generally, DC arc faults in PV systems are detected according to the four following major schemes:

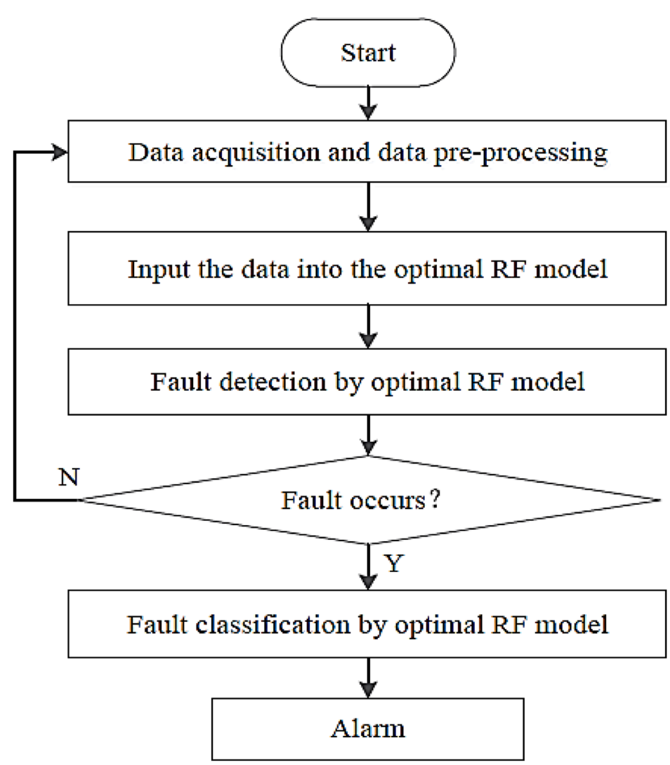

Fig. 14. The RF flowchart [241].

Based on Tsallis entropy factor. The presence of an arc fault is identified by calculating the modified Tsallis entropy factor of the PV panel's current under the quantum probability model theory [154]. When the current fluctuations are random, the algorithm can differentiate between arc and no-arc states, as it does not need any prior information about the PV system working in progress.

Based on electromagnetic radiation. Electromagnetic radiation signals can detect DC arc faults with the help of a fourth order Hilbert curve fractal antenna, which captures Electro Magnetic Resonance (EMR) signals resulting from DC arcs [161]. As for the detection parameter of a DC arc fault, the characteristic frequency of the EMR signal distinguishes between PV arc fault from switch operation.

Based on joint detection method. To notice series arc faults in PV systems, a joint detection method is provided to an Arc Fault Circuit Interrupter (AFCI). Series PV arc faults are hence recorded by an Intensified Charge Coupled Device (ICCD). The fault definitions and diagnostics are hence derived by a statistic method from the time domain and Short Time Fourier Transform (STFT). For each sub-method a detection variable is proposed for an accurate arc fault identification [158].

Based on frequency spectrum analysis (FSA) of V/I waveforms. PV arc faults are related to frequency contents. Due to signal variations induced by environmental conditions (i.e., irradiance, partial shading, etc.) certain lower frequencies limit ranges are not taken into consideration for false tripping [208]. Also, the upper frequency range is also excluded for its interactions with Radio Frequency (RF) noise. Between lower and upper borderlines, the middle frequency range is partially excluded since converters and charge controllers provide harmonics that affect the frequency [209]. The choice of AFCIs activating frequencies must be well studied according to the FRequency Spectrum Analysis (FRSA), mainly to ignore the disturbances and neglect false tripping [210,211].

Partially shaded modules fault detector (PSMFD). By comparing between reference I–V and measured values, the proposed ANN model can detect faulty conditions on PV modules when being partially shaded. If the residual error between the estimated values developed by the ANN model and the measured ones exceeds thresholds values, this indicates that the PV module is subject to PSC [64].

GISTEL combined with fuzzy logic. Using experimental parameters (i.e., temperature, irradiance, etc.) PV electrical faults are located, by means of a hybrid model, which is created by combining GIsement Solaire par TELedetection (GISTEL) model and fuzzy logic based fabricated algorithm. This system estimates solar radiation data using GISTEL, and has its overall efficiency improved by fuzzy logic algorithm [58]. By estimating on solar radiation, the GISTEL model is introduced to remotely locate and inform about any fault occurring on the level of PV battery bank [245], as revealed in Fig. 15. By comparing the estimated solar irradiance data from satellite images with actual DC power output, failures within a PV system can be identified [190,252]. The detection technique relies on comparing the simulated in verses with real measured DC output power.

ANN based fault locator using electrical attributes. Based on a Field Programmable Gate Array (FPGA), a sum of eight different PV operating faults are detected, using electrical attributes identification. For a set of PV working conditions, such as solar irradiance and working temperature, electrical attributes (i.e., voltage, current, etc.) are simulated first then later on compared with field measurement [60]. Fig. 16 presents the attributes' calculation for a two-layer ANN algorithm. The attributes are calculated by differential comparison between the physical quantities of voltage, and current data, with the simulated ones. Resultant attributes are injected into the double layer ANN algorithm, in order to classify the detected faults.

String current algorithm for OC/SC fault detection. A model for Open Circuit/ Short Circuit (OC/SC) PV fault detection is established using real tabulated data to store backup info in the system. This model relies on Genetic Algorithm, Tabu Search and grey Wolf Optimization algorithms as strategies to program the ANN to be able to detect OC and SC with less needed monitoring parameters [61]. Fig. 17 represents the flowchart for the string current algorithm, where its included error estimation, is the result of comparing between both simulated and actual power received by the solar system, representing hence the fault indicator.

Mamdani–Sugeno fuzzy logic. By taking advantages from the ANN

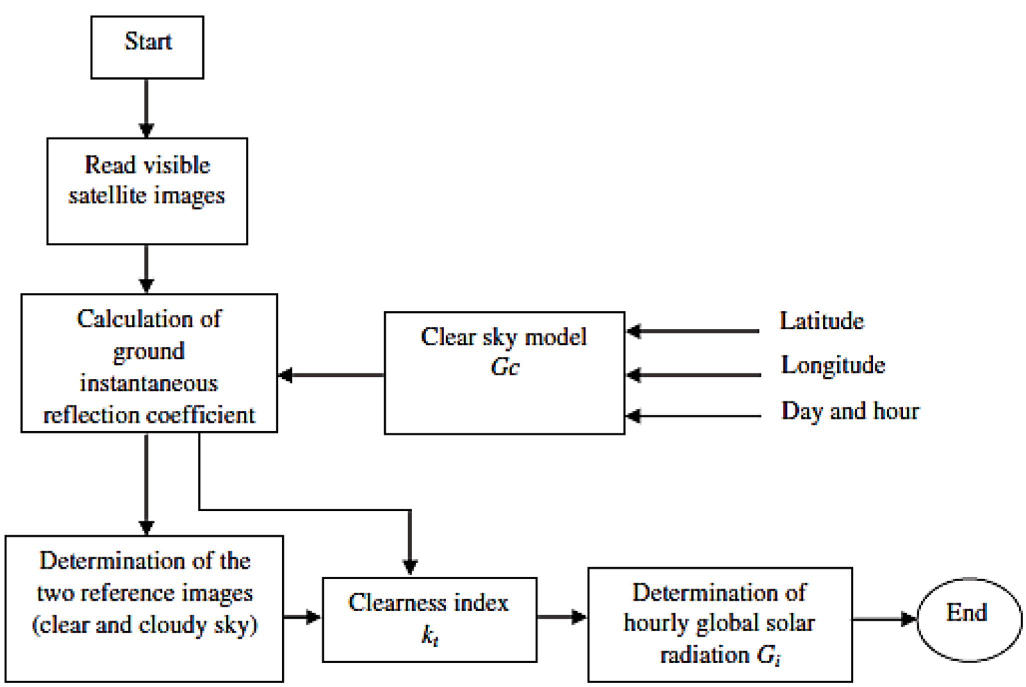

Fig. 15. GISTEL steps [245].

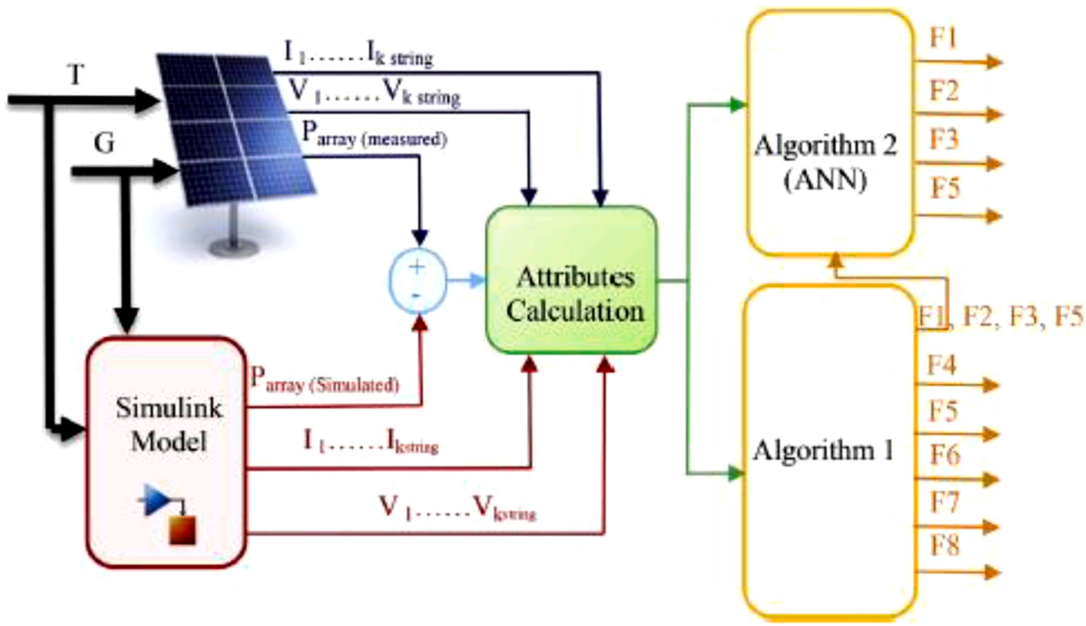

Fig. 16. Two-algorithm ANN proposed fault classifier [60].

topology and fuzzy logic system interface combination, an environmental as well as electrical PV fault detector is created. The method begins by data acquisition from the PV plant, modeling the DC side of the PV system using five-parameter model, creation of power and voltage ratios, to finally implement the ANN model. The suggested algorithm is able to detect different PV faults such as faulty PV modules and PSC with a maximum detection accuracy of 92.1 % [65].

Electrical and partial shading faults based on kNN rule. A Fault Detection and Classification (FDC) technique relies on machine learning, dictated by the k-Nearest Neighbors (kNN) rule, traces the abnormalities within the I–V characteristic curve. The FDC models and simulates the PV system using STCs and NOCT, yielding in PV fault localization and characterization. The absolute error between the measured data and the developed in the range 0.61–6.5 % with an average fault classification's accuracy of 98.70 % [67].

Neuro-fuzzy bypass/blocking diodes faults classifier. A neuro-fuzzy classifier detects faults at the PV cells' level, such as series losses, bypass and blocking diode faults, basing on electrical parameters such as maximum power, and open circuit voltage deviations. The corresponding fault identification/discrimination processes take into consideration four electrical parameters, where the classifier has shown an ability to work with different irradiance/temperature levels [198].

Third-order polynomial function samples with fuzzy logic classification. After that different attributes are measured, a third-order polynomial function is used to classify higher and lower detection limits for PV voltage and power ratios faults. Samples are aftermath processed by a fuzzy logic classification to gain one output membership function. The correspondent maximum detection accuracy for this algorithm is equal to 95.27 % [202].

Multiresolution signal decomposition. In a cascaded PV system, a fuzzy inference system indicates if a fault has occurred by giving an order decision to a multiresolution signal decomposition technique which in turns extracts the needed necessary features. Such method is based on a pattern recognition approach. The system uses fuzzy logic to interpret the monitored data and an online resource to acknowledge the faults. The suggested fault detection scheme is able to detect the DC-sided short circuit fault of a PV system, which are generally undetectable under low irradiance conditions [157].

Multi-resolution signal decomposition with two-stage support vector machine. To reduce the fire hazards due to faulty PV currents (being undetected in low irradiance conditions) with the presence of a MPPT, the multi-resolution signal decomposition for fault extraction is combined with two-stage Support Vector Machine (SVM) classifiers to detect the occurrence of Line-to-Line (L-L) faults. The required data for the algorithm is obtained from the total voltage and current from a PV array, with other labeled data to train the SVM. This method is found to be economical for requiring a smaller number of sensors, yet effective in detecting L-L faults under various operating conditions [186].

Logistic regression. Based on ML, all of open-circuit, short-circuit, and mismatch faults can be predictively (i.e., during early stages of formation) identified by means of an algorithm relying on logistic regression with cross validation. Trained with a yearly data of irradiance and temperature, the suggested algorithm shows an accuracy of 97.11 % in detecting the specified types of PV faults, with a fast operational speed [298].

Insulation monitoring relays (IMR)

A continuous monitoring measurement is held between Current Carrying Conductor (CCC) and ground: whenever the resulting resistance value is smaller than a threshold, an alarm is set, thus informing that a short circuit exists in the PV system. Such instrumentation is effective in detecting short circuited paths in PV systems, preventing further electrical complications [212].

Heat exchange and temperature based model (HET)

The Heat Exchange and Temperature based model (HET) detects a PV fault according to the change in the PV module temperature, due to the correlation between a PV fault and its temperature changing like in the case of hotspots. All heat exchange is scheduled within the fault detection technique. Using a finite element method, the physical defects of different types of PV cells are modeled [219,220].

Climatic data independent technique (CDIT)

The Climatic Data Independent Technique (CDIT) is attributes-

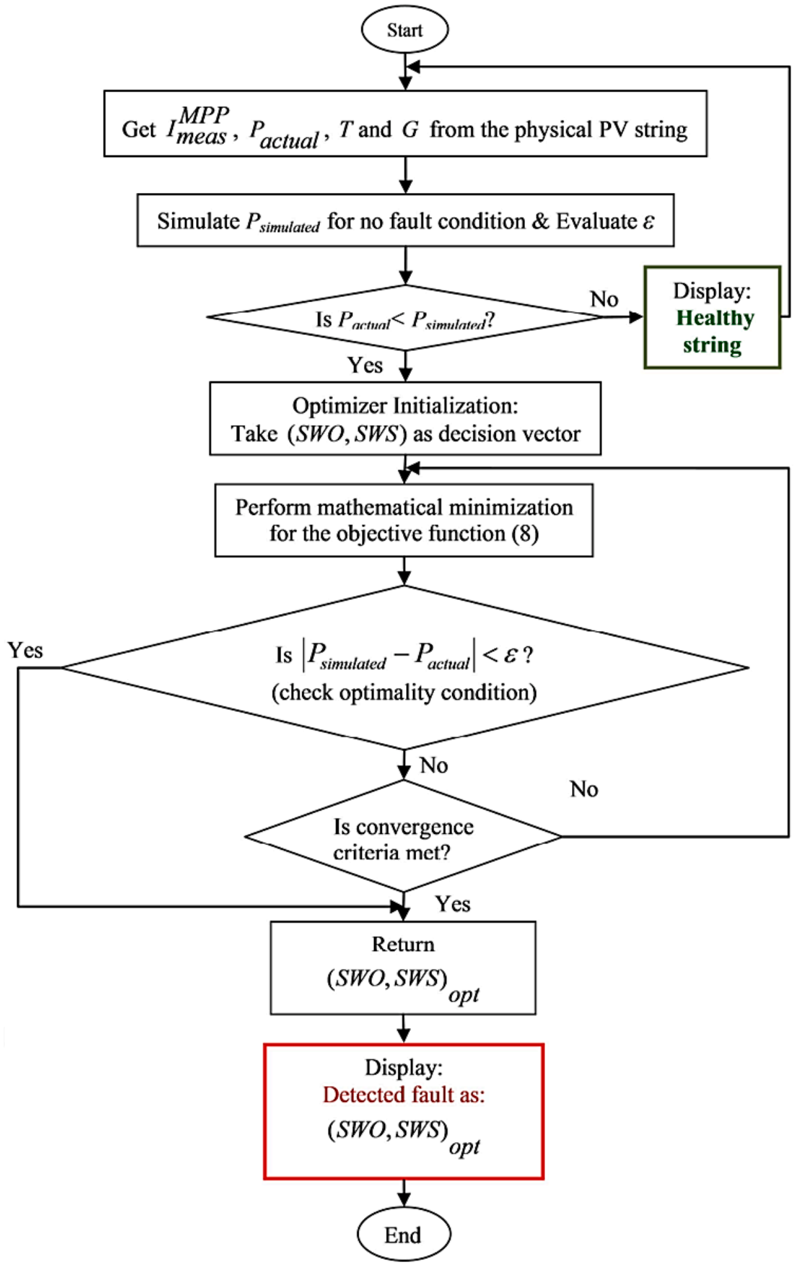

Fig. 17. Solution flowchart [61].

independent, where it does not need any solar irradiance, temperature, humidity, and other climatic data. It relies coarsely on external meters as Inductance Capacitance Resistance (ICR) meters, Earth Capacitance Measurement (ECM) [265], Time Domain Reflectometery (TDR) [266], and ANalysis Of VAriance (ANOVA) [267] techniques. Fault detection is hence accomplished after analyzing the different effects of signal generators on the PV system, without any dependability on climatic factors, such as irradiance and temperature.

Infrared/thermal imaging (In/ThI)

Across a resistor, any power loss is noted as joule loss, where current passed is transformed into heat. Similarly, any loose contact shortening across PV cells can result to the same effect: loss in terms of overheating where affected cells produce less current as compared with normal ones and become reverse biased. Through temperature monitoring, the fault can be identified, in two ways: Forward Bias Imaging/Reverse Bias Imaging (FBI/RBI). Each of FBI/RBI techniques has its private method for calculating the shorted/faulty current in order to identify hotspots creation. This can be done in both methods by using Infra-Red (IR) cameras to record IR images, then performing image processing which results in identifying the PV fault nature and locating it within the PV system [268].

As a first approach, to identify the PV fault's type, and its frequency of occurrence, an IR thermography considers the panels' attributes under investigation, leading to fault identification [269], with the ability to investigate the existence of dust accumulated particles [261].

For hotspot cells exerting a reverse voltage with opened bypass diode, the inability to identify which PV module is defected, is solved by a technique described in the reference [270]. PV modules correspondingly do not need to be tested individually, where the detection relies on the observation of the total modules' surface temperature changes. Hence, the abnormal PV modules with open bypass diodes are identified using DC power supply and an IR camera [270].

To acknowledge the PV modules' actual temperature values, a thermal camera is connected in cascade with electrical sensor which measure different V-I values. Therefore, a diagnostic model can identify different PV faults using the established parameter based model, which in turn is composed of an electrical model expressed by an energy balance equation of a PV module [271]. The measured parameters are compared to a reference performance estimation model, and the derived error can indicate the occurrence of a PV fault. Fig. 18 exposes the process of fault identification using a thermal camera over a PV module. A model parameter calculation is thus achieved by combining the data captured from the electrical sensors with the values captured from the thermal camera. Fault diagnosis is hence completed after evaluating the performance estimation model [271].

Electroluminescence imaging (EI)

To detect the aging process of PV modules, related to time entropy or reactions with the front glass cover, 2D-luminescence imaging can detect any defected PV modules by reflecting inhomogeneous luminescence patterns [272]. This type of detection reveals the degradation pattern of the encapsulation material, which gives a clear idea about the modules' lifetime energy output efficiency. The amount of light harvested by the PV modules, and its translation into DC power generation, reflects an indicator upon the health of PV modules [273].

When the excited carriers recombine within a PV cell, their emitted photons retrieve the EI imaging. An EI effect happens then by means of an injected current, which in turn yields to the carriers' excitation [275]. The Photo Luminescence (PL) effect can also give a clear idea about the amount of light beam being absorbed by the PV modules [276]. The emission intensity of EI images is proportional to the PV current density and carrier lifetime, hence the ability to detect non-uniform currents sourced from poor PV inter-connections.

Ultrasonic inspection method (UIM)

When cracks/micro-cracks are present in the cells of a PV module, their response to ultrasonic vibrations followed by an excitation, is different from healthy cells. There are two modes to detect cracked PV cells by Ultrasonic Inspection Method (UIM): pulse-echo and transmission [274]. An ultrasonic transducer is present in both techniques to

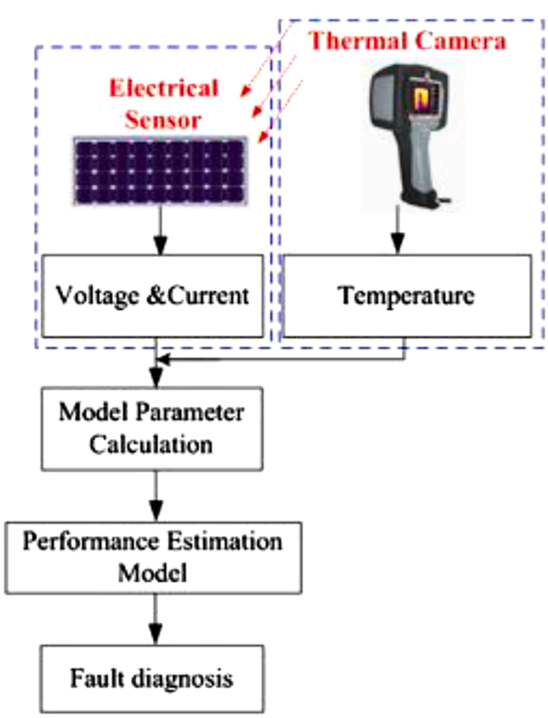

Fig. 18. Thermal imaging [271].

generate and distribute the pulses. In the first mode, the pulses are passed through a PV module to record the reflected pulses from the defected cells. In the second mode, the attenuated signals are recorded, yielding in locating the defected PV cells [200].

Lock in thermography (LIT)

Lateral PV power loss is found using the Lock In Thermography (LIT) after injection of discontinuous pulsed currents into solar cells. Corrupted cells respond to these pulsed currents by appearing as local temperature generators, where by using different modulations, the defected PV cells appear. The pre-breakdown sites' visibility in LIT was better than that in reverse-bias EI [277].

The different fault detection methods of IMR, HET, CDIT, In/ThI, UIM, EI and LIT share all in common the need for external devices (transducers, cameras, etc.) in order to detect a fault. This fact could add extra financial burden on the fault detection prototype what decreases the cost efficiency of the PV system.

Discussion and recommendation

The surveyed types of PV faults would present a rich background to be fed into any PV fault detector database. As compared to other PV faults recurrence dataset, as in the work of [295], this paper did not estimate/record the frequency of occurrence of different PV faults, as posted in Table 8: the recorded data from real PV systems under operation, concerning the frequency of occurrence of PV faults would be treasurable for PV fault detection methods' databases, especially the ones classified under the AIT. The presented data in Table 8 for instance [295], would accelerate the learning paths for ML based PV fault detection methods, requiring the last for less self-learning processes. On the other side, however, the work in [295] focused only on specific PV faults and did not take into consideration broader types of faults, such as MPPT and inverter failures, contrarily to the surveyed PV faults in this paper.

Concerning the fault detection methods, not a set of techniques can replace the other. For instance, AC faulty scenarios cannot be detected by means of DC sensors, transducers, or any form of DC data capturers. Likewise, for DC faulty conditions, CBs, RCDs and GFDIs for example cannot trip or declare any form of fault detection based on continuous signals. From another side, online (real-time) PV fault diagnosis offers a higher fault detection accuracy than offline diagnosis, but in turns require extra hardware equipment in order to be able to cope with the larger amount of instantaneous operational data from the PV system. To only implement one form of fault detection techniques leaves a full region within the PV system (whether it was the AC zone or DC zone) unmonitored with a probability to excessively have repeated faulty scripts.

Recent research in the field of PV faults detection methods emphasize on identifying untraditional PV faults. For example, by means of a wave shape based statistical algorithm, which analyzes the superimposed PV array power curve shape using the kurtosis function, short-circuit faults (i.e., electrical) of low values can be detected. Other types of faults (i.e., internal, external) can be as well detected, such as partial shading, blocking diodes, and others [282]. By following the same concern of detecting PV faults with small magnitudes, the triple exponentially weighted moving average statistical monitoring technique, when fused with other latent variable regression methods shows a good efficiency. Such incorporated method can detect string faults, inverter disconnection, circuit breakers faults, short circuit faults and others, from an actual 9,54 kW PV plant [283]. As a form of PV preventive maintenance, the statistical monitoring approach, initiated by a Hartigan's dip test, can identify any PV abnormal operating conditions, priorly than becoming actual failures [284], as similar is the case for the work in [285] where the suggested models offer quick and accurate prediction of different fault conditions. From another perspective, both DC and AC parts of a PV system can be monitored through a

Table 8
PV faults occurrence recording data [295].

Frequency of occurrence (number of times)	Time *t* (in years: duration of the PV system installation)									
	1	2	3	4	5	6	7	8	9	10
1	Corrosion	Degradation, burn marks, defective backsheet	Discoloration, corrosion	Delamination, cell cracks, burn marks	Disconnections, discoloration	Corrosion, disconnections, degradation, burn, delamination	Corrosion	Discoloration, delamination	–	Defective bypass diode
1.5	–	–	–	–	degradation	–	Burn marks	–	–	–
2	Potential induced shunts	Defective bypass diode, Corrosion	Cell cracks, bypass diode	Bypass diode	–	–	–	–	–	–
2.5	Glass breakage,	–	–	–	–	–	–	–	–	–
3	–	–	–	Disconnections	–	–	–	–	–	–
3.5	–	–	–	–	Cell cracks	–	–	–	–	–
4	Cell cracks	Cell cracks	Degradation	Degradation	–	–	Glass breakage, bypass diode	–	–	–

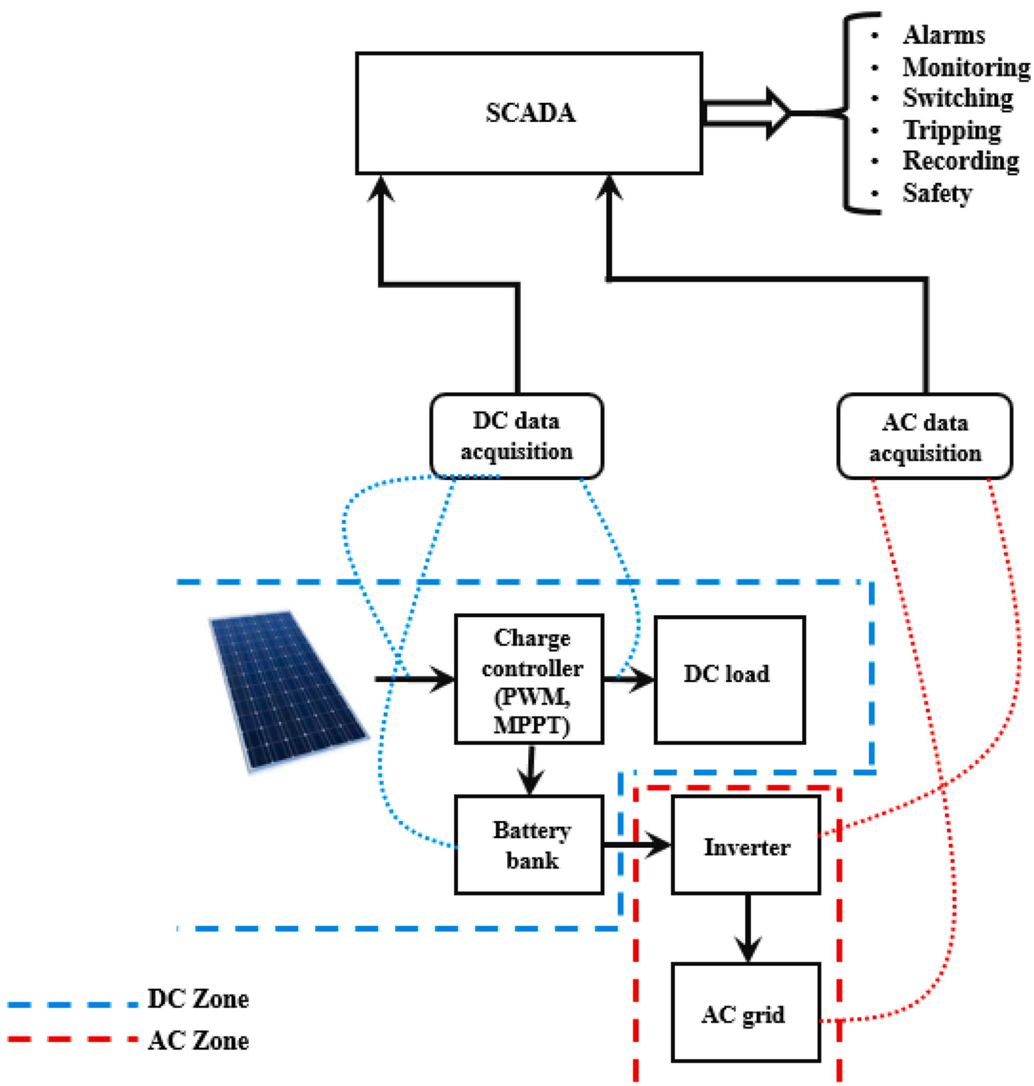

Fig. 19. The suggested AC-DC fault detection general overview.

nonparametric approach using kernel density estimation, where different types of faults can be detected, such as string fault, partial shading, and loss of energy due to an inverter's disconnection [286]. Similarly, faults at both the DC side of the PV system, such as soiling and partial shading, as well as on its AC side, such as circuit breaker faults and inverter disconnection, can be detected via parametric models with double exponentially smoothing based scheme [287]. Contrarily, in order to have better focused PV faults detection on the DC side of a PV system (e.g., short circuit, open circuit, and shading faults), the generated residuals of current, voltage, and power, capture the difference between the actual and maximum power point of the same quantities. Successively, when the resulting fault indicators are subjected to an exponentially weighted moving average algorithm, the stated DC faults are identified [169], and better acknowledged due to the reduced measurement noise after the usage of a multiscale representation [289].

Despite the numerous advantages presented by the recent PV faults detection research field, very few methods from the massive presented literature review, present any solution in troubleshooting the PV system from its both AC and DC sides. Under working conditions, a PV system may encounter having multiple faults in both AC as well in DC regions. Accordingly, and for an efficient fault tracking process, a dual AC-DC fault detector is recommended to be installed in the PV system as shown in Fig. 19.

The dual fault detector shown in Fig. 19, implies some sensors/transducers installation at the DC side of the PV system in order to capture various DC faults. On the other hand, RCBOs and different AC switchgear can be coordinated with remoted applications, IoT-based (Internet of Things) to remotely access to AC-sided faults. In other terms, future directions are recommended based on the utilization of addressable protective switchgear for both sides of the PV systems, that can be remotely networked, controlled, and current-state acknowledged. Such protective devices can for example be assigned to a local area network, and accessed via internet protocol addressing (as an example), with an ability for a remote access through a virtual private network certification. A registered user can hence configure and read the different states of the AC as well as the DC protective switchgear. Therefore, the actual states of these tripping devices can hence be network sent to a SCADA, over the same local area network, through a data block messenger that actually carries the "status" of the tripping devices (i.e., open contacts reflect the presence of a fault through a logic TRUE; closed contacts reflect normal working conditions through a logic FALSE). Other information (i.e., integer data type) can be as well carried to the SCADA from other protective devices, such as under/over-voltage sensors, temperature sensors (i.e., to acknowledge the states of electrical cables overheating), and power factor recorders.

The SCADA in turns gather the processed acquainted data with a distinguishing algorithm between the two-sided faults zones in the PV system's regions, and set accordingly the corresponding needed fault alarms, signals, and switching mechanisms to declare the detected fault. The obtained fault type can be graphically represented on a Liquid Crystal Display (LCD) or any Human Machine Interface (HMI), with an ability to set sirens for heavy/risky faults. Accordingly, the bottom line of the suggested AC–DC dual fault diagnostic tool for PV systems consists of network addressable protective switchgear for both sides of the PV systems, connected (database-wise) to a SCADA (that can be programmed via visual basic application for example) through a data block carrier over the same network. Each zone of the PV system can be uniquely graphed, where each protective device would have its own representative graphical images, that is to be animated according to the real-time status of the device (i.e., intermittent red colored animations denote the presence of a short circuit, where static green colors indicate a non-tripping mechanism, for example). With the aforementioned suggested architecture, such fault diagnostic tool can be set to be controlled by means of programmable logic controllers, which in turn can be remotely accessed via webservers, thus enabling the ability for PV system fault detection/monitoring from smartphones.

The proceeding step which comes after the fault identification and detection is the corresponding fault maintenance technique, that is classified under four different topologies [280], for different types of PV cell raw materials [281]:

- Corrective maintenance
- Urgent case maintenance
- Preventive maintenance
- Predictive maintenance

Table 9 encapsulates a comparative characterization of different PV maintenance techniques. The different PV faults acknowledgement, with various fault detection methods, and fault maintenance represent a complete package, which yields in a more robust performance for PV systems.

Conclusions

PV systems are a lifetime investment with a great cost of installation. In order to grant the predicted energy saving during a PV system's lifecycle, and to ensure a reliable payback period, the PV system is assumed to work optimally, with no faults occurrence. However, PV systems often interact with various faulty scenarios that reduce their competencies and prohibit their cost effectiveness.

Throughout this paper, the different PV faults were classified as either internal, external, or electrical faults. Internal faults are mainly due to the manufacturer's defects: the impurities in the PV cells raw material, as well as the low semiconductor's quality used during the fabrication process, yield eventually to further complications under the operation of the PV system. With that being said, their probability of occurrence is indirectly proportional to the fabrication's quality class (i.e., higher PV raw materials reflect lower probability of internal faults occurrence), where they affect the performance of the PV system from its DC side. On the other hand, external faults are directly related to undesired environmental conditions: weather fluctuations, accumulation of dust, soil, and snow, for example, affect the proper functioning of PV system also from its DC side: the PV cells are not able as supposedly to convert light into a DC voltage, due either to the presence of physical obstacles (i.e., temporary mismatch faults), or to the damage induced on the level of the PV modules (i.e., permanent mismatch faults). External faults are the most common for PV systems, mainly due to the chaotic and random aspects of the PV systems' environmental surroundings In addition, electrical fault can affect both the DC and the AC sides of the PV system: possessing a spontaneous criteria, electrical faults provoke abnormal quantities of currents (i.e., in the events of short circuits) and voltages (i.e., in the event of open circuits, voltage superimposing, etc.), thus affecting furtherly the load dissipation, as well as the safety of the

Table 9
Overview of different maintenance methods [280].

Maintenance strategy	Description	Goals
Corrective	Takes place after a failure event, and includes fixing, repairing, replacing and other correction tasks	Make corrections to avoid major equipment damaging
Urgent case	Takes places after a major force event, and requires fixing, replacing and other correction tasks	Make corrections in a hurry, prior to anything else to prevent bigger damages
Predictive	Evaluates the conditions of the system by performing scheduled/continuous real-time monitoring	Predict the optimal time to perform maintenance and hence elevating the equipment uptime
Preventive	Performs maintenance on a pre-scheduled time interval regardless of the condition	Reduce the possibility of any failure

wiring circuits.

The presented PV fault characterization helped in investigating the applicability of a corresponding fault detection system on both sides of a PV system. The DC-sided fault detection methods, on the first hand, in majority rely on sensory data acquisition- the statistical monitoring methods for example collect the PV performance data, that when compared to a reference, a fault can be detected. Electrical based methods are the most abundant in the literature, where such methods can detect each of the three major types of faults. Signal processing and ML based techniques are the most complex, since they imply on waveforms interpretation and data mining respectively. The easiest DC detection methods correspond to IMR, HET, CDIT, In/ThI, EI, UIM, LIT, since they are based only on installing readily available hardware. For that, such techniques, when incorporated with a SCADA, would present the most efficient and reliable PV fault detection method at the DC side of a PV system. .

As concerning the PV fault detection methods at the AC side of the PV system, unlike AIT and RDM based methods that are complex to implement and require heavy computational facilities respectively, the IDT, RCD, GFDI have more priority for installation in a PV system, while at the same time being the easiest to adapt: higher reliability is presented using these techniques, since they rely only on ready equipment. The keynote is that newer RCD and GFDI and other relevant equipment are fabricated with a small embedded system in each, where they can be address assigned and remote controlled (i.e., networked). With that being said, such devices can be graphically assigned to the SCADA, in a way that when an RCD trips for example, a site operator can graphically visualize this issue, directly locate the source of error, and be able to send remote alarms for further fault acknowledgement. Therefore, through this paper, it has been seen that a dual AC-DC fault detection system can be easily applied to a PV system, simply by the usage of fault indicator devices (e.g., RCD, RCBO, MCB, LIT, etc.) that possess the feature of remote addressing (e.g., through local area network, peer-to-peer communication, etc.). Such devices, hence, serving on both sides of the PV system, can be thus reflected to a visual SCADA which also have its own set of data blocks to be networked with. The tripping mechanisms can be hence inspected remotely, while directly localizing the source of error, for further on-site commissioning.

The reliability, durability, and sustainability of PV systems are greatly improved by continuous monitoring, and faults' identification processes. When equipped with fault detecting tools, like the one suggested in this paper, PV systems ensure robust power production, and a safer performance.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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