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Fault detection and monitoring systems for photovoltaic installations: A review

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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

As any energy production system, photovoltaic (PV) installations have to be monitored to enhance system performances and to early detect failures for more reliability. There are several photovoltaic monitoring strategies based on the output of the plant and its nature. Monitoring can be performed locally on site or remotely. It measures production, focuses also on verification and follow-up of converter and communication devices' effective operation. Up to now, some faults diagnosis methods for PV components and systems have been developed. However, given the evolution of PV installations, more advanced monitoring techniques are continuously under investigation. In this paper, major photovoltaic system failures are addressed. Then techniques for photovoltaic monitoring proposed in recent literature are overviewed and analyzed to point out their differences, advantages and limits.

1. Introduction

An Accurate and consistent performance assessment of photovoltaic systems is essential for a sustainable industry development. On one side, for manufacturers, performance evaluation is a key criterion for their products quality. On the other side, for research investigations, it is a crucial indicator for identifying future challenges.

Further, for end-customers, a reliable performance evaluation can lead them with future decision-making.

Moreover, an effective operation and maintenance (O & M) program enables PV system production to reach its expected level of efficiency; which will consequently strengthen end-users confidence in such systems. However, operation and maintenance costs are significant [1]. Among the solutions proposed in literature to reduce these costs, *O & M best practices* and notably photovoltaic monitoring systems are widely recommended [2,3].

Monitoring PV systems consists in comparing results of the plant with forecasted ones, and providing reports to end users. These systems are mainly composed by sensors (electrical and environmental), a data acquisition system with adapted communication protocols. It also involves algorithms for data analysis.

With the increased interest in monitoring PV plants, more and more papers related to these systems are emerging. Most of them deal with one part of the monitoring system such as sensors, data acquisition… However, at our best knowledge, only few state of art papers are reported in the literature [4–7]. Each paper focuses on one specific issue. First of all, main features of some commercial products are described in [4,5].

Secondly, data measuring devices, data acquisition system, and data storage are overviewed in [5,6] as well as data transmission methods in [6] and dedicated software for monitoring systems in [5].

Furthermore, some of the elements to be used as a starting point for the development of algorithms dedicated to PV module diagnostic and prognostic are proposed in [4]. Moreover, data analysis methods for PV systems are presented in [7] and [6]. Finally, the report [8] states the constructive guidelines, methods and models that may be designed for analytical monitoring of PV systems.

Indeed, new diagnostic techniques and algorithms were proposed to monitor photovoltaic plants, to predict failures and to enhance PV system performance. Some of PV fault detection algorithms are based on electrical circuit simulation of PV generator [9–12]. Other ones use electrical signal approaches [13–32], such as the time domain reflectometry [18,19] or the maximum power point tracking (MPPT) analysis [10–12]. Predictive model approaches for PV system power production based on the comparison between measured and modeled PV system outputs are discussed in [11,13–18] and [33–41] Numerous monitoring systems employ statistical analysis concepts for PV system measurements [42–48] Further methods exploit artificial intelligence [49], particularly neural network [50–55], Bayesian belief network [56], fuzzy logic [57–59], learning method [60] or extension theory

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[61]. Some of these monitoring systems require climate field data or environmental and meteorological data from satellite observations [62,63].

In this paper, we shed some light on few of the numerous remaining questions about the monitoring systems and particularly reviewing all the analysis methods that are not mentioned in papers [3–6]. Also, we point out their differences, advantages and limits. Furthermore, different techniques of diagnosis and supervision in recent literature are exposed. PV system measurements are always required for these data analysis techniques: some of them are based exclusively on electrical and meteorological measurements. Other ones combine measurements and mathematical modeling. In our paper, both of the data analysis techniques are considered.

This paper is organized as follows: Section 1 gives a brief reminder of PV systems and PV generator model. Section 2 presents different failures that can occur in a PV installation. Section 3 details architecture of the diagnostic systems with a focus on sensors and data acquisition systems. Finally, Section 4 details the different monitoring methods presented above.

2. PV system and PV generator model

PV installations can be classified according to power levels i.e. residential, buildings, industrial and utility scale. They are also sorted according to their connection to the utility grid: Stand alone or grid connected systems. This study is limited on grid connected PV systems with or without local load. Fig. 1 illustrates the structure of such systems. They are mainly composed of PV modules connected to DC/AC inverter, generally via a junction box. Blocking diodes are usually included in the construction of each solar panel.

PV module is a combination of PV cells that produce electrical power when exposed to light. They constitute the part responsible on producing energy in a PV generator. Each serie of cells is connected to a by-pass diode. This diode prevents modules from behaving like receivers and consequently avoids from heating up the cells during partial illumination. I-V and P-V curves of PV generator are based on an elementary cell, modeled by the equivalent circuit presented in Fig. 2. Series and parallel resistances (R_s and R_p respectively) take into account the power loss phenomena.

This model is the most used one in literature related to PV monitoring. Moreover, it is the model presented in the EN 50530 standard [64]. Its parameters are detailed below. Various monitoring approaches are based on these parameters, such as series resistance measurement, shunt resistance measurement…However some of references mentioned in this paper relies on the two diode model [12] and [22].

The one diode PV model is expressed by (1).

$$I_{PV} = I_{ph} - I_0\left(e^{\frac{U_{PV} + I_{PV}.\, R_s}{m.\, UT}} - 1\right) - \frac{U_{PV} + I_{PV}.\, R_s}{R_p} \tag{1}$$

$$I_0 = C_0 T_{mod}^3 e^{-\frac{U_{gap}}{U_T}} \tag{2}$$

$$U_T = \frac{k\ T_{mod}}{e_0} \tag{3}$$

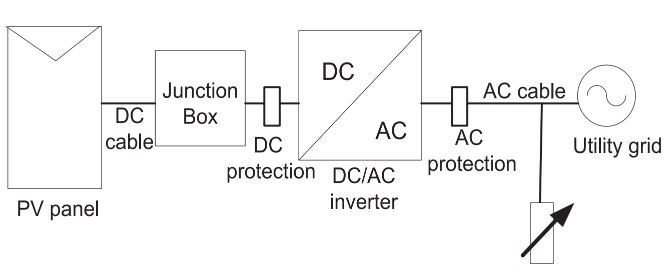

Fig. 1. Schematic diagram of grid connected PV system with local load.

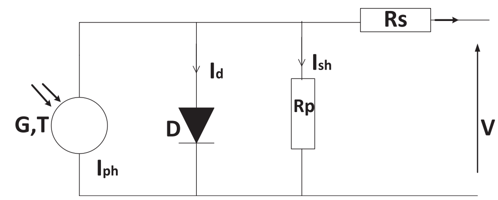

Fig. 2. PV cell equivalent model.

$$T_{mod} = T + \frac{c}{1000\ \frac{W}{m^2}}.\ G \tag{4}$$

With

I_{PV}: Module current (A)
I_0: Diode saturation current (A)
I_{ph}: Photocurrent (A)
U_{PV}: Module voltage (V)
U_T: Temperature voltage (V)
U_{gap}:Bang gap voltage (V)
R_s:Series resistance (Ω)
R_p:Parallel resistance (Ω)
T: Ambient temperature (K)
T_{mod}:Module temperature (K)
G: Irradiance (W/m^2)
C: Temperature model constant
e_0:Elementary charge
k: Boltzmann constant
m: Diode factor

The inverter is equipped by an MPPT that optimizes the match between the solar array and the grid, and therefore enhances the system to reach maximum power P_{mp} which is presented in Fig. 3.

3. Photovoltaic system failures

3.1. PV module failures modes

The PV array is the main component of the PV installation, any breakdown associated to the module will affect the system performances. The failure modes at the generator level are presented below. All these fails are classified according to their symptoms, their effects and their consequences. Fig. 4 regroups causes classification as proposed in [65] according to events detailed below and resumed in Tables 1–4.

3.1.1. Encapsulation failures

This mode is caused notably by delamination and discoloration that appear frequently in humid and hot conditions. This defect is located between encapsulant and active cells. This default can occur due to salt accumulation, contaminations, moisture penetration or external factors. In one hand, delamination results in reflection and ultimately power loss. In order to detect this anomaly, thermography, ultrasonic

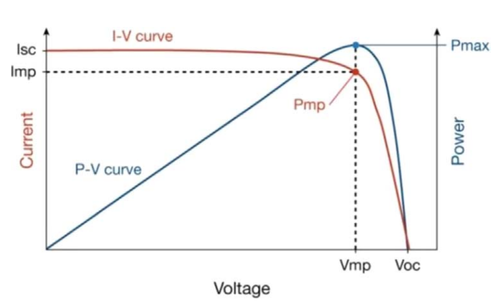

Fig. 3. I–V and P–V characteristics of PV model.

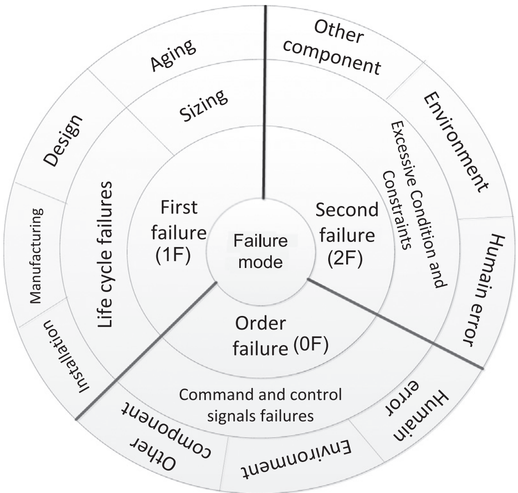

Fig. 4. Failure classification [65].

Table 1
Environmental causes for PV failures [76,77].

Cause		Failure mode
Dust	(2F)	Power loss
Degradation of encapsulation due to ultraviolet, yellowing EVA	(2F)	
Nest of insects	(2F)	
Module degradation due to light	(2F)	Performance loss, overvoltage, diodes destruction
Degradation due to heat	(2F)	Performance loss, heating, deterioration of joints
Rust due to water infiltration	(2F)	Loss of seal, cells deterioration
Lightening	(2F)	Module destruction
storm	(2F)	
Shading	(2F)	Hotspot, cells destruction
Moisture penetration	(2F)	Hotspot, leakage current increase, corrosion, adhesion and insulation loss, DC resistance to ground decrease
Marine air	(2F)	Corrosion

Table 2
Humain error failures [76,77].

Cause		Failure mode
Module stealing	(2F)	Total stop of the installation
Gland plugs missing on junction box	(1F)	Water penetration, connections corrosion
Connection box inversely mounted	(1F)	Water penetration
Incorrection module inclination	(1F)	Performance loss, shading
Module degradation by vandalism	(2F)	Performance loss, total stop of the installation
Non connected module	(0F)	Performance loss
Inversion of output links	(0F)	
Badly fixed module	(1F)	

Table 3
Life cycle failure [76,77].

Cause		Failure mode
Inaccessible panels	(1F)	Cannot be cleaned: Dust accumulation
Poor isolation between module and inverter	(1F)	Short circuit, module destruction, fire
Weakness of structures	(2F)	Module snatched, broken
Poor mechanical strength of module supports	(1F)	Support deformation
Inadequate, improperly installed support	(1F)	Significant mechanical stress on modules
Module badly or not ventilated	(1F)	Heating
Module producing less than expected	(1F)	Performance loss

Table 4
Other causes for PV failures [76,77].

Cause		Failure mode
Increase in series resistance due to thermal cycle	(0F)	Performance loss
Antireflection layer deterioration	(2F)	
Different performance module		
Module producing less than expected		
Cracks	(2F)	Performance loss, seal loss, calls or module deterioration
Damages of seals	(2F)	Seal loss, cells degradation
Module frame corrosion	(2F)	
Phosphorus diffusion to the surface	(2F)	Loss of encapsulant adhesion
Important leakage current	(0F)	Heating
Interconnection degradation	(2F)	Joint deterioration, performance decrease, series resistance increase, heating.

scanner and X-Ray tomography are recommended. The irregularity can be quantified by a reflectometer. On the other hand, discoloration results in corrosion that leads to a reduction of series resistance, which is considered as the most frequent degradation mode of PV panels [66–69].

3.1.2. Back sheet adhesion loss

A back sheet of a panel is a protection of electronic components from external factors and a safety from high DC voltages. Back sheet failures can be caused by delamination. If it occurs, active electrical components will be exposed. This would result in an isolation default which presents safety concerns. The form and the composition of back sheet materials can determine this fail [68–70].

3.1.3. Cells cracking

It can occur at any lifetime level of the PV module. It can be caused during essential manufacturing process or during packaging and transportation by mishandling and vibration. Installation process is also a source of this default; same as bouncing hard object against modules after installation [66,68].

3.1.4. Broken interconnection

Poor soldering between string interconnect and cell interconnect ribbon is the main reason for this disconnections. Stresses during transportation, hot spots, thermal cycle or repeated mechanical stress forces weak ribbon interconnect to break. Short distance between cells develops this kind of failure. It can result in short circuited or open circuited cells and resistance increase [32],[68–70].

3.1.5. Shading and soiling

Two types of shading exist [32]. The first type is hard shading; which occurs if PV panels are shaded by a solid material, e.g. buildings or dust. The second type is soft shading; it can be caused by smog in the air. The first one results in a voltage decrease. The second one affects the current and not the voltage. Both affect PV module performance. The performance and power loss are related to soiled or shaded surfaces [71]. In fact, shaded cells behave as a resistance to generated current [32]. They heat up and result into hot spot.

3.1.6. Hot spots

This phenomenon occurs when cells operate at reverse bias: instead of producing power they dissipate it. Cells can operate abnormally and this can cause serious damages. Therefore, it is important to detect it before damage occurs [32]. Hot spots degrade PV panel and reduce performances of PV plant. Shading, bypass diode failure and mismatch between electrical characteristics; all these factors contribute in the development of hotspots [67–69].

3.1.7. Module corrosion

Laminate edge lets moisture invade the module and causes corrosion. Moisture retention increases the material electrical conductivity. In fact, the corrosion attacks PV cells metallic connections, causing a leakage current and performance degradation. Corrosion affects the adhesion between metallic frame and cells [67,70].

3.1.8. Potential induced degradation (PID)

It occurs only in crystalline silicon modules [72] and leads to gradual deterioration of the module performance. It is caused by stray currents in most ungrounded PV systems; the PV modules with a positive or negative voltage to the ground are exposed to PID. It occurs mostly at negative voltage with respect to the ground potential and is accelerated by high system voltages, high temperatures and high humidity.

3.1.9. Light induced power degradation (LID)

The LID is a natural degradation caused by physical reaction as a result of the p-n junction of a PV cell. It is reflected as a loss in the silicone solar cell efficiency, and seen as a shrinkage on the short circuit current and open circuit voltage of the solar cell [73,74].

All these failures are summarized in Fig. 5. It indicates principle PV module aging and failure mechanisms that are classified as infant-failures, midlife-failure and wear-out-failure [73].

In [75], authors summarize the observed degradation mode trends over the last 10 years. Modules in hot and humid climates were reported with a sensitively larger variety of degradation modes than modules in desert and normal climates. Delamination and diode/junction box issues are also more widespread in hot and humid climates. The most important problems of installed systems during the last 10 years are hot spots followed by discoloration. Because hot-spots have multiple fundamental mechanisms, more investigations into those causes could help dealing with this issue for future module generations. Encapsulant discoloration is the most common degradation mode, particularly in older systems. In newer ones it appears in hotter climates, but to a lesser degree. Fig. 6 presents a pareto chart of the most significant degradation mode sorted according to their severity level. It was obtained by considering modules affected by specific degradation modes.

3.2. Inverter failure modes

PV inverter is considered as the brain of the PV system. Studies have demonstrated that it is the most vulnerable component [66]. Inverter failures are classified into different categories:

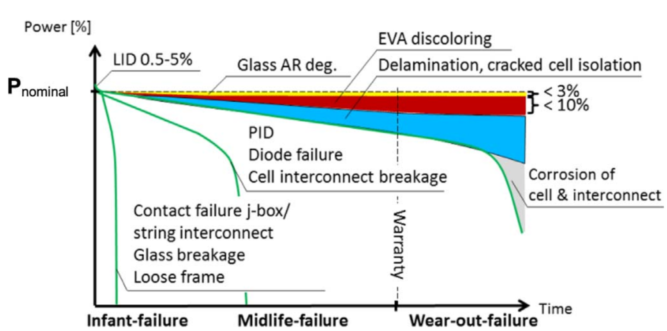

Fig. 5. Aging mechanisms leading to PV module degradation [73].

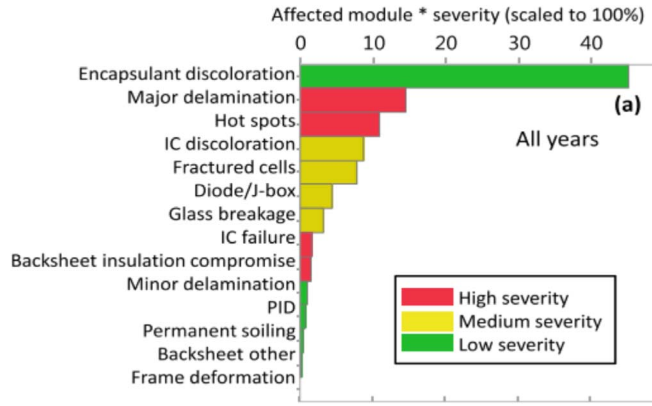

Fig. 6. Pareto chart of significant degradation mode [75].

- Manufacturing and design problems: PV inverter performance depends on operating conditions and the system lightening. Indeed, thermal management, and mechanisms of heat extraction of commutating components and capacitors are classified in this category.
- Control problems: They are related to the inverter interaction and behavior regarding the grid at AC side and the panel on DC side.
- Electrical components failures: They occur when PV inverter components are exposed to thermal and electrical stress during operation.

Actually PV inverter lifecycle depends highly on its critical components activity which is presented in the Fig. 7. Authors in [78] studied IGBT and showed that it is considered as root cause of PV inverter failure. In fact, the IGBT is considered as the main part of the inverter [79]. Potential failure modes in PV inverter are summarized in Table 5.

3.3. Other failure modes

3.3.1. Balance of system (BOS) failures

BOS components failures are considered as main reason behind the existence of non-producing modules in PV field. A failure of one BOS component can lead to reduce production. For example a faulty fuse, the entire string would be out of service [66].

3.3.2. Junction box failures

A junction box is a protection for wiring from strings to external terminals This failure mode could be caused by poor fixation of junction box to the back sheet, moisture penetration, corrosion of connections, poor wiring leading to internal arcing, poor mounting or because of thermal degradation [68]. Some examples of these failures are presented in Fig. 8.

3.3.3. Bypass diode failures

A bypass diode compensate power losses and performance reduction resulting from module shading. It avoids reverse bias heating phenomenon, hot spot and module destruction. Their detection is difficult because they appear when mismatch in I-V characteristics of cell is occurring. They can be caused by diode disconnection or a reverse mounting of the diode [68]. When temperature rises in diodes, it means

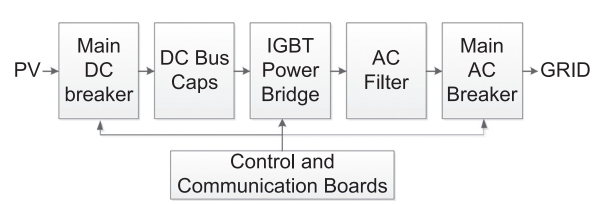

Fig. 7. PV inverter diagram [79].

Table 5
Failure modes in PV inverter component.

Component	Role	Failure mode
IGBT	Conversion DC to AC	Thermal runaway Ceramic substrate to base hob solders fatigue Emitter wire bond fatigue
DC bus capacitor	Supply ripple current source sink for the PV inverter DC inputs	Overvoltage, overheating pollution, humidity, radiation, and vibrations.
Cooling and circulating fans	Cooling the IGBT module and main conductors	Overheating

that they are functioning correctly [69].

3.3.4. *Mismatch fault*

it occurs if the module electrical parameters change compared to the initial state. [39]. It can be temporary, such as shading cells leading to a hotspot. Or permanent, due to the presence of an open circuit or defective cell producing less current leading to a power dissipation [69].

3.3.5. *Ground fault*

It occurs accidentally by an electrical short circuit [39]. Indeed, it is an unintentional low impedance path among one of current carrying conductor and the ground. Majority of PV systems are equipped by ground fault detection and fault current interruption [80].

3.3.6. *Line-line fault*

It is an unintentional short circuit connection between two different potential points in PV panel. This failure takes place between two points belonging to the same string or among two adjacent strings. It may be undetected and presents important loss [39,80].

3.3.7. *Arc fault*

It occurs due to discontinuities and insulation breakdown in current carrying conductors or adjacent ones. Series and parallel arc-faults produce high frequency noise in DC current of PV string, and parallel arc fault results in additional sudden voltage/current drop inside PV array [80]. This type of failure is very dangerous for the plant, and may produce fire.

4. Diagnostic architecture for fault detection and data acquisition

4.1. *Diagnostic architecture*

The main objectives of PV system monitoring are failure detection, performance evaluation and insurance of system proper operation. This requires both electrical and environmental data at PV panels. To reach these objectives, dedicated components, such as sensors, data acquisition systems, data communication systems and devoted software and algorithms for data analysis are used.

According to [66], plant size, system criticality and operation and maintenance costs determine the adequate monitoring system. On the other hand, plant size is important for monitoring system design. Adopting wired sensors in small plants is economic and less complex. However, wireless networks are more convenient for medium and big sized plants.

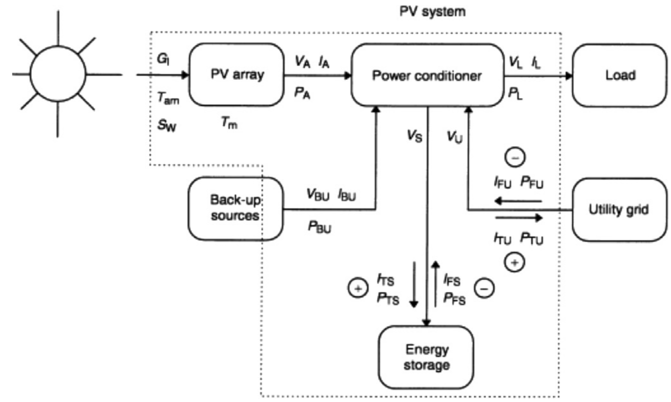

Fig. 9. Diagram of parameters to be measured in real time [3].

Diagnostic system architecture can be divided into three levels:

In the first level there are the sensors, which are the main components for achieving an accurate and reliable database. The second level is the data acquisition, which includes measurements and pre-processing application. It requires specific hardware and communication networks. The final level is the most flexible one, which consists in analytic techniques implementation that leads to evaluate and estimate PV performances [81]. Major aspects of monitoring systems such as sensors and their operation principles, data acquisition and controllers, data transmission, and data storage are described and analysed in [82].

4.2. *Sensors and measured parameters*

International standards set the parameters for PV systems measurements and monitoring. The IEC 61724 presents guidelines for analysis and monitoring PV systems performances [83]. Fig. 9. presents an example for IEC standard application on PV system and illustrates the electrical and environmental data to measure. These data are listed in the Table 6. Other parameters can be calculated from these measurements in real time, using data acquisition system. Monitored parameters are classified under two groups, environmental and meteorological parameters and electrical parameters.

4.2.1. *Irradiance G_I*

In plane irradiance, recorded at the same plane as the PV array, which is measured using pyranometers or calibrated reference device. Horizontal irradiance data may be measured, in order to compare with standard meteorological information from other locations. If reference cells or modules are used, they should be calibrated and maintained following IEC 60904-2 or IEC 60904-6 standard. Sensors location should be representative of the array irradiance conditions [83]. Irradiance sensors accuracy, including signal conditioning, should be better

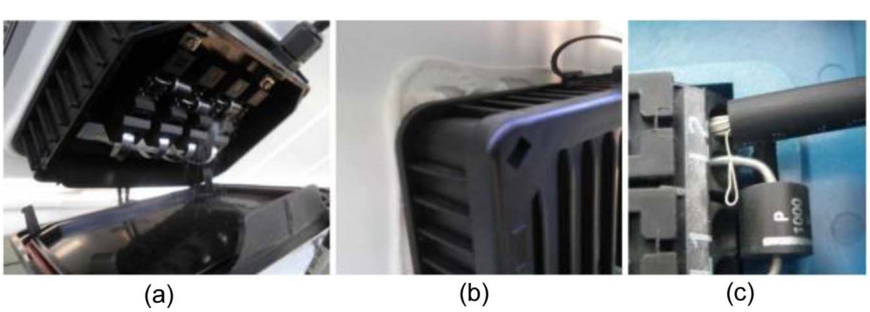

Fig. 8. Example of Junction box failures: (a) an open junction box in the field, (b) a poorly bonded junction box on the back sheet, (c) a junction box with poor wiring [68].

Table 6
Parameters to be measured according to IEC 61724.

General parameter	Specific parameter	
Meteorology	Total irradiance	G_I
	Ambient temperature	T_{am}
	Air speed and direction	S_w
Photovoltaic array	Output voltage	V_A
	Output current	I_A
	Output power	P_A
	Module temperature	T_m
Energy storage	Operating voltage	V_S
	Current to storage	I_{rs}
	Current from storage	I_{FS}
	Power to storage	P_{rs}
	Current from storage	P_{FS}
Load	Load voltage	V_L
	Load current	I_L
	Load power	P_L
Utility grid	Utility voltage	V_U
	Current to utility grid	I_{ru}
	Current from utility grid	I_{FU}
	Power to utility grid	P_{ru}
	Power from utility grid	P_{FU}
Back up sources	Output voltage	V_{BU}
	Output current	I_{BU}
	Output power	P_{BU}

than 5% of the reading.

For small scales PV arrays, the high cost of pyranometer incites the use of other devices. Studies on different small scale PV systems [84] requires the use of a pyranometer and modules in short circuit condition, in order to evaluate impacts of standard PV modules used as irradiance sensors in performance modeling. Results have shown better accuracy when using Cadmium telluride[1] "CdTe" modules in short circuit as irradiance sensor which can be an interesting choice for small scale PV arrays.

4.2.2. Ambient and module temperature

(T_{am} and T_m)*:* They are recorded at a location representing the panel conditions. Ambient temperature data is measured using temperature sensors, situated in solar radiation direction. For ambient temperature measurement, dedicated sensors are located on the back surface of the PV array [83]. These sensors accuracy, including signal conditioning, should be higher than 1 K.

4.2.3. Wind speed S_w

Wind speed should be measured at the same array conditions. [83]. Wind speed sensors accuracy should be higher than 0,5 m s^{-1} for values measured for less than 5 m s^{-1}. And should be higher than 10% of reading for wind speed values greater than 5 m s^{-1}.

4.2.4. Voltage and current

(V_A, V_S, V_U and V_{BU}) and (I_A, I_{rs}, I_{FS},I_L, I_{ru}, I_{FU} and I_{BU})*:* Voltage and current values may be measured either on DC or AC side. Voltage and current sensors accuracy, including signal conditioning, should be higher than 1% of the reading [83]. They can be recorded by means of shunts or current transducers [85] or voltage transducers. Using shunts is quietly simple and does not require extra power supply unlike current transducers. But, it requires an important sample rate monitoring in order to measure AC Current. Current transducers have excellent accuracy, low temperature drift, good linearity, optimized response time, good immunity to external interference, no insertion loss and current overload loss [86]. Voltage transducers have also excellent accuracy, low thermal drift, low common mode disturbance, good linearity and good immunity to external interferences.

[1] Stable crystalline compound formed from cadmium and tellurium.

4.2.5. Power

(P_A, P_{rs}, P_{FS}, P_{ru}, P_{FU},P_{BU})*:* Power data can be on DC or AC side or both sides. It can be measured directly by means of power sensors or calculated in real time as sampled voltage and current values [83,85]. The power sensors at the AC side takes into consideration the power factor and harmonic distortion. DC input power on stand-alone systems may have considerable AC ripple impressed, so a DC wattmeter is more eligible to measure DC power. Power sensors accuracy, including signal conditioning, should be greater than 2% of the reading.

4.3. Data acquisition system

Data acquisition systems are implemented to collect and store data for phenomenon analysis. These systems are currently used in PV systems for monitoring performances and controlling operations.

Data acquisition systems differ according to five parameters, which are: data transfer mechanism, monitored data, controllers, sampling intervals and program development software. Data transfer mechanisms, wired, wireless, and power line communication systems are introduced in [82] and [86].

4.3.1. Wired communication

To start with, coaxial cables have low resistance, low error rate and good data transmission rate of 10 Gbps. Their limitations are covered distance and deployment [82]. Secondly, the protocol MODBUS rtu RS 232 or RS 485 used in [87–90] have some limitations such as covered distance and are less favorable than wireless systems for monitoring large PV plant. Third, fiber optic cables can be used for long distance and offer high data transmission rate from 100Mbps to 200Mbps [82]. But, it is an expensive solution.

4.3.2. Wireless communication

There is a wide variety of wireless data transmission technologies presented in literature.

Transfer mechanisms using satellite presented in [62,63] were described as slow and expensive mechanisms. Another data transmission mechanism which is more reliable and accurate is presented in [88–90]. This type is based on GSM where data are transmitted via SMS or GPRS that allows high speed data transmission and big volumes of data. It presents low retransmission and low data loss rates. However, this exhibits a high operating cost, because users have to pay for this service. High speed of data transmission is possible with GPRS devices.

The third type of wireless transfer mechanism is the radio frequency data transmission that allows sending and receiving information at low cost. It is a great alternative in areas without telephone lines. However, it is difficult to be implemented because of transmission frequency permission and its cost.

Other options for wireless communication are presented in [82]. Such as wireless local Area Networking (WLAN) and File Transfer Protocol (FTP). WLAN covers large area; it is flexible in data transmission and can communicate without future restriction. However, it has lower bandwidth and lower quality of service due to interference. FTP server is an option for data transmission via GSM-GPRS. It is in the form of a PC card that can be connected via USB or serial cable.

Bluetooth and Wi-Fi were also used for data transmission. Bluetooth [91] is a simple networking but does not cover long distances, at maximum 100 m. In the other hand, Wi-Fi [92] has great data transmission rate but is more expensive than other technologies such as Bluetooth or Zigbee.

Zigbee device is considered as the best solution and the cheapest alternative for monitoring systems. It allocates special time slot to avoid data collision. In addition, its topology enables integration of other wireless nodes which makes it upgradeable to support large network capacity. Last but not least, the internet / Ethernet protocol known commonly as TCP/IP is considered as the most convenient especially for real time monitoring systems. A non-intrusive monitoring system using this type of communication is presented in [93].

4.3.3. Power Line communication

(PLC): PLC is considered a better choice for monitoring the status of PV module compared to Zigbee, WiFi, Bluetooth, and RS 485 [94] It has a data transmission speed around 200Mbps.

The second important parameter for data acquisition systems is the controller. It has an important role in handling data from sensors to the end users. Some monitoring systems use microcontroller or data acquisition cards or modules [87,95]. Cards and modules are more expensive than microcontrollers but they are easier to program. In the other hand, a microcontroller is characterized by analog digital converter (ADC) resolution which represents the most important factor for monitored data accuracy. This problem is reduced with recent high resolution ADC.

The third parameter is the program development software. For programming microcontroller C language is commonly used. For calculation and analysis, generally MATLAB is the most popular choice. LABVIEW is usually used as system design software [87,95] and it provides comprehensive measurement and control tools.

Fourth, in literature, various sampling intervals were proposed from seconds up to one hour. Nevertheless, basing on the IEC 61724 standard, this interval should be selected based on parameter types. For example, for parameters that depend on irradiance, sampling period should be 1 min or less, and for parameters with high time sample, it should be between 1 and 5 min.

Finally, monitored data choice is important. Solar irradiance, temperature, voltage and current are essential for PV monitoring systems. Then, it depends on whether the PV system is grid connected or not.

5. Data analysis methods

5.1. Electrical circuit simulation

Monitoring method based on PV panels circuit simulation developed under PSIM software is presented in [9]. The proposed model was applied on a 3 kW PV array system, in order to explore P–V and I–V characteristics, environmental parameters and load variations effect. An extension diagnostic approach based on extended correlation function and matter element model is proposed in order to identify failures types. The advantages of this method are: The high precision of electrical parameters and the aptitude to detect faults with less memory consumption and less simulation time.

Authors in [10] introduce an automatic PV failure detection based on statistical correspondence between potential causes of failures, results of simulation and the extraction of parameters of the PV system model using Matlab/Simulink. The combination of the PV system obtained data with the extracted parameters in Matlab, allows failures diagnostic in real time.

Another study adopts Matlab/Simulink in order to evaluate PV system power is presented in [11]. The proposed method is divided into two parts: The first part is dedicated to carry out the PV modules characterization under different weather conditions, in order to follow the performances degradation of the solar panels. In the second part, the monitoring system compare in real-time the power produced by the PV generator to the obtained one from simulation model developed under Matlab/simulink software.

In [12] an intelligent monitoring system is set up for detecting automatically the PV fails. The proposed algorithm compares actual and expected electrical parameters. Accurate reference data are computed by a detailed PV circuit simulation program. The model used for this simulation is the two diode model. This procedure could be integrated within a data acquisition system installed in the PV plant.

5.2. Statistical analysis

Specific procedures have been implemented to obtain accurate information about PV system different parts. In [42] a simple real time monitoring system was presented. It provides operating parameters that are not enough to evaluate plant performance and detect failures. For this purpose, a daily corrected performance ratio that considers weather conditions was evaluated. Then, a physical approach and two fitting approaches were proposed in order to estimate P_{DC}[2] and $P_{AC,}$[3] and compare them to reference values. Based on variation between measured and estimated power, a statistical approach was proposed. It allows establishing thresholds that can be used for locating defects in the PV system. This method was applied on a 1 MW PV plant located in Agrigento, Italy, that allows distinguishing faults on DC or AC side, or measurement problems at inverter level only.

Other procedures based on statistical tools for diagnosing PV plant are presented in [43] and [44]. The proposed approaches are based on descriptive and inferential statistics. They are divided into two steps. First step is an off-line supervision that is able to select installation performance benchmarks. They deliver information about total PV plant behaviour and its constitutive parts. Second step is a real time monitoring implemented for failure detection in order to check if the PV plant operation respects the evaluated benchmarks. This approach is grounded on two different statistical tests that are the ANalysis Of VAriance (ANOVA) test and the non-parametric Krusal-Wallis test. They present a great level of accuracy. This method was tested on 20 kWp PV grid connected system in Bari, Italy in 2003. Results have shown that it is possible to characterize anomalies until they turn into failures. However, the algorithm does not give any information regarding anomaly typology and causes.

Another statistical fault detection approach in photovoltaic systems is developed in [45] for monitoring performances of the PV installation, by detecting failures on DC side and diagnosing their types. This approach uses a simulation model based on the extracted one diode model parameters, in order to predict the maximum voltage, current and power generated. The difference between measured and predicted values is used as input for the EWMA[4] chart. Thereupon, the EWMA based on residuals of output DC power is used to identify, in real time, the presence of failures. Voltage and current residuals are used to differentiate between open-circuit faults, short-circuit faults and partial shading in a PV system. The effectiveness of ODM-EWMA[5] to detect and identify faults in an actual PV system has been demonstrated. Despite the promising results for fault detection and diagnosis obtained using the ODM-EWMA approach, the work carried out in this paper raises a number of questions and provides guidance for future works.

Unlike methods presented above, outlier detection rules presented in [46] do not require weather data or model training. Statistical outlier detection methods that are 3-sigma, Hampel identifier and box plot are used in order to identify PV string normal operation based on individual string current measurements; The 3-Sigma rule states that nearly all values lie within 3 standard deviations of the mean. 3-sigma limits are used to set the upper and lower control limits in statistical quality control charts. For Hampel identifier, it is an outlier identification method designed for location-scale models. It is modified to account for the special structure of the data. Instead of the sample mean, Hampel identifier adopts the sample median as reference value.

Fig. 10 is an illustrative example of outlier detection rules described in [46]. The leftmost axis represents samples and distribution parameters. This figure demonstrates the deviation of the sample mean from

[2] DC side power.

[3] AC side power.

[4] Exponentially weighted moving average: a statistic for monitoring the process averages the data in a way that gives less and less weight to data as they are further removed in time.

[5] Oracle data mining.

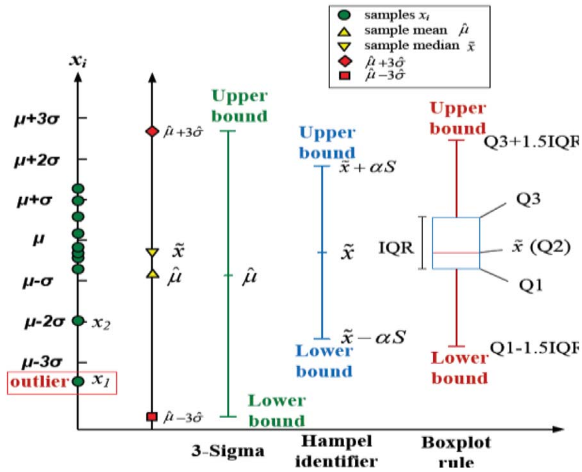

Fig. 10. Illustrative example of outlier rules [46].

the true mean because of the outlier ×1. From one side, ×1 lies within the normal range of the 3-signa rule. This results in the failure of the outlier detection. On the other side, Boxplot rule and Hample identifier consider ×1 as an outlier, since it is below the lower bound of these rules. In the meantime, ×2 value is considered a normal sample by all the rules.

Studies in [46] reveal that Box plot rules and Hampel identifier can be recommended for fault detection. Moreover, outlier detection rules are more reliable as PV measurement number is higher.

An interesting monitoring system founded on power loss analysis using statistical signal processing, was proposed in [48]. Authors compared measured power with obtained one under MATLAB/Simulink environment in real time. From this comparison, a residual signal is generated. Then a Wald test is applied on this signal in order to detect alarm signals from data captured randomly and consequently facilitate the decision making. The general structure of this diagnostic system is presented in Fig. 11.

5.3. Electrical signal approaches

Between thermal methods, visual methods, and electrical methods for failure detection, the last stated method is the most appropriate to integrate into power conditioner [32]. Some methods rely on power measurements, such the one proposed in [13] generating a diagnostic signal which indicates potential faults in GCPV plant. A ratio between P_{DC} and P_{AC} is supervised in order to locate the fail. This method is simple, fast and automatic: it allows a correct detection and localisation of failures in both DC and AC sides using software designed on Matlab/GUI.

Another PV fault detection algorithm operating on power conditioning system using multilevel decomposition wavelet transformation was proposed in [14]. This method is efficient in detecting failures and determining their locations. Moreover, it does not require any additional hardware and has simple structure. However, it is an expensive method and has the disadvantage that once the inverter changes the problem is re-designed.

An automatic supervision and diagnosis of power loss failures is presented in [6–9]. For loss analysis, the methodology is based on a comparison of simulated and measured yields. Defects identification is based on error deviation value analysis in both DC current and voltage, respecting reference. Thresholds are evaluated on the basis of a healthy system. This approach is designed under LABVIEW software which allows PV module parameters extraction, simulation and modeling of dynamic systems, monitoring of electrical and environmental parameters, and finally diagnosis and fault detection.

In some other electrical methods for PV systems monitoring, usually I–V measurements are used for PV characteristics check. Besides I–V measurement, it shows characteristics variations. In fact, works in [19] present an automatic fail detection approach which consists in static characteristic analysis. It studies malfunctions impact in PV generator on PV field performance, and therefore on I–V characteristic. This method aims to avoid current suspension by means of simple diagnostic function. A power conditioner monitors its voltage at the beginning and at the end of the day. This method allows I–V curve acquisition of the installation for low irradiation. Each curve is divided into two zones: one for the tension area, and the other for the current area. If a fail is detected, a curve deviation is created as illustrated in Fig. 12. According to this detection method, three characteristic parameters can be identified as the series resistance, shunt resistance and diode factor. The method was designed to minimize DC power capacity to measure the I-V curve.

Another PV array diagnostic approach based on I-V curve analysis is presented in [20]. The dI/dV-V acquired from the I-V curve of a normal operating PV subarray is considered as standard characteristic. This parameter is compared with dI/dV-V of an abnormal I-V curve. The variance value is calculated in order to evaluate mismatches between the two curves and detect failures. When the resulted value is higher than a normal operation system value, the PV subarray is faulty

In the same methodology, authors in [21] present a new method based on PV module series resistance inspection that measures its I–V characteristics and compares it to the series resistance provided by the manufacturer. This approach aims to detect the disconnections between PV modules or cells in a string, and is based on complex measurements that determine series resistance. However, it is not accurate for large scale PV plants.

Another approach based on a comparison between I–V curve of faulty module performances and its accurate model is presented in [22]. An electrical signature of a failure is established by considering I-V deformations. The fault diagnosis is determined by choosing both normal and faulty thresholds for each failure. The proposed approach provides identification of failures by calculating their threshold ranges. This method allows the instantaneous monitoring of PV system electrical power delivery.

An experimentally demonstrated PV system monitoring using I-V curve measurement capability is presented in [23]. A first method for monitoring single or independent strings is based on the evaluation of the ratio of some operation points on the I-V curve. The second method

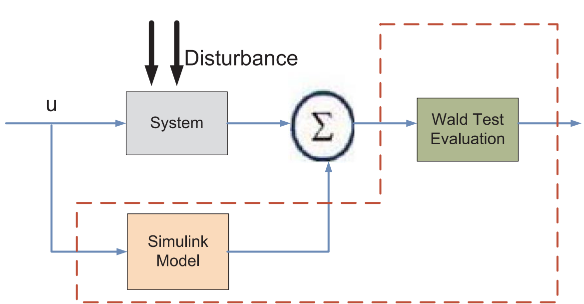

Fig. 11. General structure of a diagnostic system using model based approach [48].

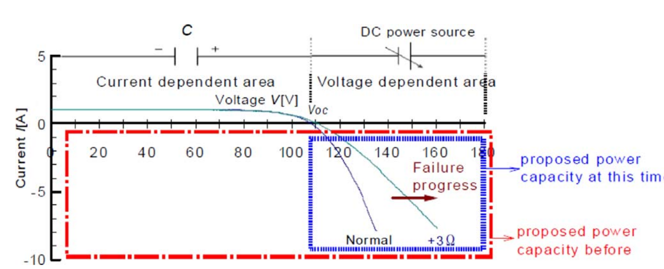

Fig. 12. Concept of acquiring characteristic in two kinds dependent area [19].

is suitable for PV systems with identical strings, and is based on inter-comparison of I-V curve strings. For PV systems with non-identical strings, the irradiance and module temperature are measured. A performance model of PV strings is set in order to predict optimal string I-V curve; it is then compared with the measured values, to identify failure root causes.

A new current and voltage detection method which analyzes power performance was exposed in [24]. Current and voltage do not consider environmental factors, thus causes power generation capacity decrease. The proposed method overcomes these problems and allows locating faulty cell array. This approach is used in real time fault detection

Work in [25] presents a fault detection system that monitors current and power value, in order to get a string data sensitivity comparison with a power conversion system data. It detects output reduction due to failures. Then, an effective failure detection method is detailed; it consists in a current comparison between strings and has no influence from external factors. Finally, in order to improve accuracy of the method mentioned above, it is combined with another diagnosis technique using other criteria, which is performance ratio PR. The procedure consists in creating a regression line based on previous data and comparing the measured PR value with the expected one. Thanks to the combined diagnostic methods, it is possible to detect failures occurring in multiple strings.

A method based essentially on output voltage and temperature measurement is developed in [26]. It allows the detection of the open and short circuit faults quantity and the differentiation between these fails and the partial shading. The proposed method considers partial shading conditions affecting the PV plant. So, obtained probabilities give indications about the failure type under different irradiance conditions. This algorithm can be easily applied for small and medium size PV installation. It can also be extended for application in large scale PV plant, if voltage interval number is reduced due to effort when collecting data, and can be adapted for any PV technology type.

Authors in [27] propose a procedure that analyses failures effect on power, current and voltage with distributed MPPT. This approach determines exact failures and power loss. It also allows module parameters monitoring at the working power point. As the monitoring system requires only operating current and voltage parameters, it does not require temperature and irradiance sensors which reduce its costs. Otherwise, it is necessary to provide communication module and power line signal in order to collect data of overall modules' working point. The diagnosis tool is developed under Matlab that informs user about power reduction, failure severity and priority. Failures that can be detected are mainly shading, soiling, hot spots, DC cable interconnection or loss, and module degradation. This monitoring system is ideal for users without technical background or for maintenance companies owners of systems dispersed over a large area. However, it is limited to detect only a lower power production in a module.

In [29], a simple and economic performance monitoring approach based on reference cells and electronic subsystem for processing is proposed. Reference cells are used to collect real time data and to estimate module output power and has the following advantages. First, measured voltage and current values are lower than the total module array values. Also, it does not require disconnection of load while measuring array or module current. Finally, it proposes simpler electronic circuits used to collect and process data. For more accuracy in module output estimation, reference cells should be distributed around modules, in order to collect variations caused by irradiation, temperature or shading. Experiments show a great correlation between reference cells and array, also accurate output power estimation.

Mismatch based diagnosis of PV fields relying on monitored string currents is presented in [30]. It shows a DC side diagnostic approach for PV plants operating on string currents, supplied previously by an appropriate supervision system. The relevance of this method is the definition of effective and reliable day-by-day target power normally produced by a string.

Two diagnostic techniques are reviewed for possible faults detection in PV module string in [31]. The first method, earth capacitance measurement (ECM), and the second is time domain reflectometry (TDR). In one hand, ECM is an electrical method that detects disconnection positions between modules in a single string and does not require any climate data. In the other hand, the TDR is used to detect degradation and its position in a string, based on response waveform change. It measures electrical characteristics of transmission line [32] and compares inputted signal into PV generator and reflected one from the circuit. Reflected signal analysis deduces information about the system. It can detect not only string disconnections but also impedance change caused by degradation. This method is easily affected by installation circumstances. Thus, it is necessary to measure basic features about PV array signal reflection. However, this approach is limited by the quantity of localized defects. In addition, signal injection requires a system interruption. The use of these methods depends on the following situations: ECM must be used during PV system completion inspection or some accidents such as earthquakes. And TDR should be used during periodic inspections to find system degradations.

5.4. Artificial intelligence

Artificial intelligence is used for automatic fault detection in [50] using combined artificial network (ANN) and conventional analytical methods. A two-layer ANN is applied to forecast power based on module irradiance and temperature. Then the predicted power is compared with real measured power in order to detect fault occurrence and type. Afterwards, comparison between calculated open circuit voltage and short circuit value using analytical equation with measured values is applied. Moreover, it presents a compact structure, great accuracy, fast detection response and does not require any complicated devices or system knowledge.

Another approach based on Artificial Neural Network Based Model (ANNBM) to detect loss in PV panel caused by partial shading is interpreted in [51]. A Multilayer Perceptron is used in order to estimate electrical output based on environmental data. Monitoring system interpreted in Fig. 13, allows an early system faults detection by calculating and analysing residual errors between predicted performances by the ANNBM and measured ones. The ANNBM approach does not require any complex system for output power estimation, neither mathematical model.

A healthy monitoring approach that uses probabilistic neural network is introduced in [52], in order to detect and classify failures and locate faulty string in PV array. For this purpose, the proposed approach uses environmental and electrical data. Additionally, to validate the method a new approach for modeling PV system is introduced taking into account manufacturer's datasheet information.

In [53] a hybrid model for monitoring and estimating PV module maximum power output taking into account nonlinear features of the system which is called Estimation model (EM) is introduced. The objective of this method is to get a better estimation approach of system real behavior. A supervised adaptive resonance theory neural network

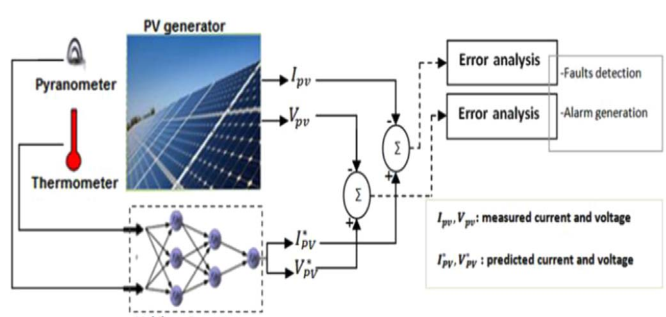

Fig. 13. PV generator monitoring using artificial network [53].

is used in order to correct one diode model power estimate. This monitoring system is applied via Matlab and assessed on a sample data. The proposed model is convenient for any PV module technology because it evaluates input and output relationships.

Since simple layer ANN is less suitable to provide accurate solution for PV modules failures, another fault diagnosis technique, especially for short circuit defaults, that uses a three layer artificial neural network is exposed in [54]. The method enables short circuited PV module localisation in a string. In order to multiply fault localisation between strings, the system has to increase the number of data training and to update control rule. The proposed approach is simple and accurate and may be difficult to be implemented in large scale PV systems. It requires a large memory because a significant number of ANN classifiers are used.

PV prognostic and health management (PHM) system is presented in [55]. This model aims for PV system health monitoring, degradation assessment and maintenance plans elaboration. This method is based on artificial neural network model with environmental and power input data, in order to alert users about the performance loss. The model predicts system's output based on meteorological parameters. According to the difference between measured and predicted AC power, failures which cause power loss are detected.

ANN health monitoring system does not require information about components or system topology to model output power. Additionally, the system can indicate catastrophic failures when monitoring the degradation rate. Finally, a PHM system is able to predict PV failure based on fault precursors. The ANN is used to predict power output from the PV array based on monitored irradiance compared to the measured power. However, it is not able to identify faults causes.

A second artificial intelligence technique which is called Bayesian Belief Networks (BBN) is used for monitoring PV system in [56]. The authors' approach is similar to method presented in [62] for identifying faults sources. In this work, BBN is built to reflect dependencies among measurement variables representing specific devices. The measurements received by a BBN leads to automatic derivation of a decision regarding a failure potential cause. Algorithms based on fuzzy logic were introduced in [57–59].

Authors represent in [57] an algorithm based on the evidence theory and fuzzy mathematics theory. The proposed work designs new and accurate type of framework of fault diagnosis structure. Then, based on data fusion technique and fuzzy mathematics, the difference between measured and predicted value is consolidated. Experiments show that data fusion is able to deal with uncertainties caused by PV arrays interaction, and can enhance faults localisation for large scale PV arrays.

In [59] a method based on calculation of PV module parameters in different operation conditions, by means of Neuro-Fuzzy approach is proposed. The PV system status is determined by norms of evaluation and comparison. This intelligent system is developed in Matlab & Simulink environment. Results show that the diagnosis system is able to discern between normal and faulty operation conditions with the same defective existence of noise and disturbances.

Another expert system for PV monitoring is proposed in [60]. It explores the system data base, detects the energy loss caused by inverter defaults. The method consists in the comparison between the real time output and the stored value in the database in a free faulty functioning. The method should be updated monthly. Its drawback is that it cannot be used for real time monitoring. As a result, the system does not detect power decreasing if there is shading. This technique is based on learning method and takes into account specific conditions of monitored system. It simplifies operation and maintenance of PV plants, even though it requires many measurement sensors. It uses criteria of database, analyses the obtained data from the PV system and determines if the plant functions correctly. Two types of faults were identified by this method which are shading and inverter failure

In [61] authors present a two-stage diagnosis system using the extension theory for PV systems. This method is able to diagnosis fails and also locates them. The main strategy is the fault array identification during daylight, and the use of light scanning approach to detect faulty module by night. It is based on wireless network, the output data is transmitted to the diagnosis system. It tends to reduce test time, to locate faulty module and enhance maintenance efficiency. The diagnosis system is established under LabVIEW to know system conditions and under PSIM to simulate normal operation and faulty conditions. The proposed method can be used in large scale PV plant.

5.5. Predictive models and comparison with real models

Some PV monitoring systems are based on predictive models for PV system power production. Various works in literature follow this approach.

A PV array conditions monitoring system using Sandia Array Performance Model which can predict PV array power production and energy production accurately is presented in [33]. The system is configured online based on regression modeling from PV array data (Production, plane irradiance, module temperature) collected during a first learning test of the system. After configuration, the condition monitoring system introduces normal operation phase; where PV panel power output is predicted using performance model. Based on the predicted and measured output power values, condition monitoring system allows the detection of power loss above 5% in the PV panel.

An analytical model that uses equations for the relative power is implemented in [34] for fault detection especially under short and open circuit conditions. Based on these equations, the diagnosis of fault condition gets easy. However, coefficients identification is very difficult and can be influenced by weather conditions.

Also in [11] authors, first, carry out characterization of PV module under different weather conditions to follow PV module performance degradation. Secondly, real time produced power is compared with model developed under Matlab/Simulink environment. However in [35] system in normal conditions is measured, then real faults events are created and effects are analyzed to get correlation between a known failure and output signal.

Another PV fault detection approach based on data analysis from real PV installation, on language theory and Petri Nets is developed in [36]. The proposed method does not require any faults models, so it could detect any abnormal behavior. The idea is to identify a normal operating model of the PV installation and to compare real time data with the identified model change. Any deviation between predicted and observation means a failure in the system.

The identification algorithm involves normal behaviour signals and statistical stopping criteria to model stochastic process. This method doesn't require the previous behaviour mode. Moreover, it is capable to detect all types of faults; and it is a low cost, complete and accurate method.

Authors in [37] present a simple fault detection approach based on a self-adaptive PV model that requires only two inputs, PV power production at two different points in the same string. This model does not require any input concerning model parameters. The main idea of the algorithm is to compare measured and predicted power. A model compares the two powers and informs user if a mismatch is detected.

Another online fault detection approach based on comparison between measured AC power production and the predictive model is presented in [38]. A significant variance between those two parameters is considered as a fail. The model evaluates the AC power production taking into account environmental parameters such as solar irradiance and module temperature, and it is represented at various irradiance levels in order to get a better PV system representation. The predictive model and fault detection algorithm is site specific, meaning that they are based on historical measurements of monitored PV system.

A new fault detection and classification method based on decision trees (DT) is developed in [39]. This model can detect the fault and

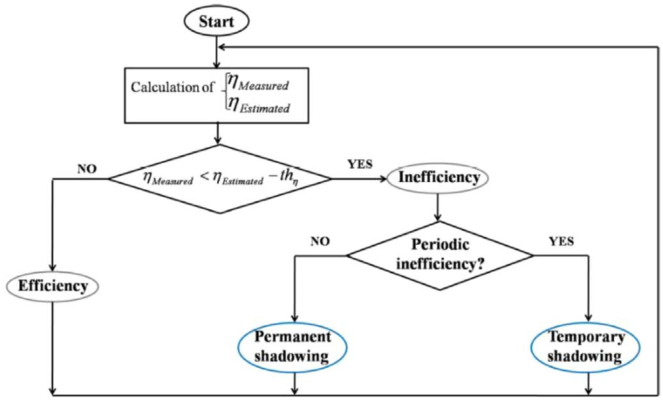

Fig. 14. Approach for the detection of causes of efficiency losses, based on the estimation time of the panel efficiency [29].

classify its specific type. The proposed DT model can identify faults in real-time, with great prediction accuracy. For DT model development, data is collected from experimental PV installation in normal and faulty conditions. All of collected and preprocessed raining are randomly selected from the experimental data and used to build the model. DT model has various advantages, fast action of training and classification, easy implementation, and explicit interpretation. However, it has limitations, such as high cost for training or abnormal operation at unknown data from the training. While PV arrays operation depends on meteorological conditions, and large number of faults conditions may appear. It is difficult to get sufficient training and dataset covering possible fault scenarios.

Low-cost multi sensor architecture is developed to detect efficiency loss of PV system and correlated causes. The adopted methodology in [40] is to compare PV module measured efficiency with nominal value estimated in real functioning conditions. Fig. 14 presents the methodology for efficiency loss detection. Additionally, the aging estimation uses five parameter model that exploits a minimization paradigm to analyse mismatch between modelled I–V characteristic and measured one of the PV model. The major advantage of this method is the continuous monitoring of the PV system and the assessment of potential causes of power inefficiency.

The EU project PVSAT-2 presented in [62,63] develops an automated performance check to assure maximum energy yields and to optimize PV system maintenance. The objective is the early fault detection and the identification of any changing operation conditions to prevent energy and financial loss. The method developed is based on solar irradiance derived from satellite information that replaces the onsite measurements. The expected energy yield of the system is calculated based on a simulation model. The difference between the simulated energy yield and the real value is calculated. An automated failure detection routine search for the most probable failure sources and notifies the operator.

The accuracy of three different methods of PV module failure detection based on AC output parameters is assessed in [41]. These methods are the following

- Comparison of measures output parameters and estimated ones.
- Comparison of the actual and previous performance ratio.
- Comparison between actual and previous output differences in the intersystem.

Studies show that the first method can make erroneous results under conditions in which only two PV panel faults may occur in one string. It also shows that the second and the third method can correctly evaluate one PV module fault in one string.

In [81], authors summarize the principal failure modes and their detection as presented in the Table 7.

Table 7
Examples of failures modes and their detection.

Object	Failure mode	Detectability
PV panel	Encapsulation	MPP analysis
	Module corrosion	Model approach: series resistance
	Cells cracking	Model approach: analysis of the open circuit voltage
	Dust	MPP analysis and comparison between panels
	Hot spot	Overheating
BOS	Connection box defective	Lower production
	Open circuit/ short circuit	Lower production
	Broken fuse/ cable / Theft	No string current

6. Discussion

This paper describes the instrumentation equipment and the methods used for fault detection in PV systems. This section focuses on the algorithms proposed by literature for PV data analysis and points out their advantages and limits.

Indeed, most of these methods use recorded on-site measurement electrical and meteorological parameters. Consequently, depending on the needed sensors and the plant size, the investment cost can sensitively vary from one fault detection method to another.

Furthermore, the numerical approaches exposed in Section 5.4, such as algorithm based on artificial intelligence and especially artificial neural network (ANN), can be implemented for multiple failure detection. Some of them can also identify the failure types. From maintenance cost minimization point of view, the best ones are those which identify and localize PV failure. This is because fault localisation is the most difficult and time consuming process, especially with large scale PV plants.

Unlike these numerical methods, the statistical ones, such as the outlier detection rules, do not require knowledge of previous data. However, they cannot identify the PV system failure type and some of these methods require an off-line supervision.

From another point of view, the performances of the methods based on electrical parameters and electrical signal comparisons, such as reflectometry (TDR) and earth capacitance measurement (ECM), do not depend on solar irradiance and are sensitive to connection degradation. However, they require external signal function generator which increase considerably the installation cost and size.

Knowledge model based methods using residual current, voltage or power measurement have the following advantages: they provide fault detection and identification, are easy to implement and could be conducted during PV plant operation. However, they require knowledge of previous data and need electrical and meteorological sensors.

7. Conclusion

In this paperwork, sources of PV module defaults at generator or inverter level are presented and different parts of diagnostic architecture were detailed. An overview of different fails detection methods in a PV system existing in the recent literature is exposed. These techniques are not based on the simple analysis of PV module productivity, but different other measurements, methodology and simulations that detect certain failures.

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