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Sujet

Study of different diagnosing methods faults in a photovoltaic system

Soutenu publiquement, le 25 / 09 / 2024 , devant le jury composé de :

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Dedication 1

To my family,

With deepest gratitude, this thesis is dedicated to you, the foundation of my life and the stars in my sky. To my parents, your sacrifices have paved the way for my dreams, and your wisdom and love have guided me through every challenge. You have instilled in me the courage to aspire and the strength to achieve.

To my siblings, whose boundless support and infectious laughter have lightened the heaviest days and brightened the darkest nights. Your unwavering belief in me has been a beacon of hope.

This achievement is a reflection of my efforts and a testament to your unconditional love and support. To you, I owe all that I am and all that I strive to be.

With all the love in my heart,

Alaadein ALBAZ
Tlemcen, September 25th, 2024

Dedication 2

The journey wasn't easy , but I made it , despite of breakdowns, hardships and challenges i have faced . So alhamdoulilah , thank you ALLAH for everything you have blessed me with .

I wanna say thank you to the first hero I have ever loved , the fisrt hand I have ever held , my guiding light and source of strength , my dearest father, words cannot fully express the admiration i have for you .

To the woman who sacrificed everything just so her child can have a better life , thank you for lighting up my path when i was lost in the dark , your presence in my life is a constant reminder of the incredible wiman I aspire to be , only god knows how much i love you , mom , your little girl is a graduate now .

My dear sisters , you've been more than siblings you've been my friends and my confidants , you're not just a part pf my family you're a part of my heart . I wanna take a moment to say thank you to my biggest supporter: khawla , I'm so pleased to have a sister like you .

My friends , my forever accomplice in this journey called life , thank you besties .

Asma SACI
Tlemcen, September 25th, 2024

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Alaadein ALBAZ   Asma SACI
Tlemcen, September 25th, 2024

Contents

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List of acronyms

- PID: Potential-Induced Degradation.
- FDD: Fault Detection and Diagnosis.
- PV: Photovoltaic.
- P-V: Power-Voltage.
- I-V: Current-Voltage.
- ISC: Short circuit current.
- VOC: Open Circuit Voltage.
- MPP: Maximum power point.
- FFT: Fast Fourier Transform.
- UV: Ultraviolet
- AI: Artificial Intelligence
- ML: Machine Learning.
- EVA: Ethylene Vinyl Acetate
- SVM: Support Vector Machine
- AML: Advanced Machine Learning.
- DL: Deep Learning.
- CNN: Convolutional neural network.
- LSTM: long short-term memory.
- RNN: recurrent neural network.
- GAN: generative adversarial network.
- NN: Neural Network.

- BM: Boltzmann machine networks.
- FL: Fluorescence Imaging.
- FE: Electroluminescence Imaging.
- NC: Normal Conditions.
- CV: Computer Vision.

General Introduction

Photovoltaic (PV) systems have emerged as a critical component in the global shift towards sustainable energy solutions. As the adoption of solar energy continues to grow, the reliability and efficiency of PV systems have become crucial factors in ensuring their economic viability and energy output. However, PV systems are prone to faults that can significantly impact performance. These faults, from partial shading to line-to-line faults to bypass diode issues, cannot only reduce energy production and damage components but also increase maintenance costs, thereby affecting the economic viability of these systems.

Accurate detection and diagnosis of faults in PV systems are essential to maintaining optimal operation and extending lifespan. Fault detection methods are broadly categorised into signal processing techniques, artificial intelligence (AI), machine learning-based methods, and inference methods. Signal processing methods, particularly those analysing current-voltage (I-V) and power-voltage (P-V) characteristics have gained prominence due to their effectiveness in identifying common PV faults.

This memoir focuses on simulating three faults in PV systems using MATLAB: partial shading, line-to-line faults, and bypass diode issues. It explores the intricacies of each fault and evaluates its impact on the overall system efficiency and health. Additionally, the work delves into different fault detection and diagnosis methods, highlighting their advantages and limitations. Emphasis is placed on signal processing techniques, providing a comprehensive analysis of how I-V and P-V curves can detect and diagnose faults in PV systems.

This memoir is structured into three chapters. The first chapter covers the manufacturing and functioning of PV cells and the history and general information about PV systems. It also provides a classification of the most common faults in PV systems into three main categories.

The second chapter focuses on fault detection and diagnosis methods in PV systems. These methods are divided into three groups: signal-processing methods, AI-based methods, and inference methods. Each category is presented with relevant examples and its advantages and disadvantages.

The third chapter presents the validation and simulation of a 4x4 PV farm. Through I-

V and P-V curve analysis, the farm's maximum power point (PMPP), open-circuit voltage (UOC), and short-circuit current (ISC) are compared between normal conditions and under six simulated faults: partial shading (cases 1 and 2), bypass diode failure (cases 1 and 2), and line-to-line fault (cases 1 and 2). The chapter concludes with recommendations derived from the results at the end of the chapter, along with the general conclusion.

Chapter I

Generalities on the PV

Contents

I.1 Introduction

The past ten years have seen a significant increase in interest in photovoltaic (PV) energy systems because of their many benefits. These benefits include being globally accessible, not generating pollution, operating silently, being modular, being simple to install, converting energy reliably, and being adaptable enough to be integrated into structures. As a result, PV systems (PVs) have rapidly increased in both number and scale around the globe. The PV market grew by 75 GW in 2018 alone, reaching a 402.5 GW worldwide capacity [1]. The International Renewable Energy Agency (IRENA) [2] reports that from 2010 to 2017, the price of solar modules fell by 83 %, and they are currently less expensive than $1 USD/W [2, 3].

External atmospheric conditions or internal system failures can disrupt the cells during photovoltaic (PV) system operation. This compromises system stability and reduces efficiency, lowering output yield. In the next part, we shall discuss these faults as the main step.

I.2 What is photovoltaics?

The scientific method of using semiconductors exposed to photons to produce direct current (DC) electrical power, expressed in Watts (W) or kilowatts (kW), is known as photovoltaics. This method produces electricity constantly as long as the solar cell is exposed to light. When the light goes out, so does the electrical output. Interestingly, unlike batteries, solar cells don't need to be recharged. Some solar cells have proven to work continuously in space or outdoors for longer than 30 years [4].

I.3 History of photovoltaics

Antoine Becquerel established the theory of the photovoltaic effect in 1839. It includes using semiconductor technology to convert light energy into electricity. In order to create a potential difference between the cell terminals and produce a direct electrical current, this approach uses photons to liberate electrons. With the development of selenium and cuprous oxide cells, the first uses of solar power appeared in the 1930s. But the viability of energy provision was not understood until 1954, when Bell Telephone Laboratories developed the first silicon solar cells. In the 1960s, this technique became widely used to power spacecraft, especially satellite hardware. Terrestrial applications began to concentrate on energizing remote locations in the 1970s.

During the 1980s, there was a steady advancement in terrestrial photovoltaic technology, demonstrated by the installation of multiple megawatt-scale power plants. Additionally, consumers were introduced to low-power products like watches, calculators, radio beacons, weather stations, pumps, and solar refrigerators. From the 1990s forward, prices decreased as a result of improvements in solar cell production processes and greater production quantities. Major firms like Yingli Green Energy, First Solar, and Sentech Power manufacture modules in nations including China, Japan, the United States, Germany, and

England. From 5 MW in 1982 to over 18 GW in 2013, solar module output increased dramatically worldwide. In July 2013, Condor Electronics began producing solar panels in Algeria with power outputs ranging from 70 W to 285 W at competitive costs.

A 400 MW photovoltaic project was started as part of Algeria's national renewable energy policy in expectation of increased power output in the summer of 2014. 23 photovoltaic solar power plants will be established as part of this initiative throughout Algeria's southwest, southern, and Highland regions. There are plans to create a 5539 MW renewable energy park within the next ten years. Achieving 12,000 MW of renewable energy for domestic power use is the goal for 2030. By the end of 2013, installed photovoltaic capacity was 138.9 GW globally [5].

I.4 Functioning of the photovoltaic cells

A photovoltaic (PV) cell, commonly called a solar cell, is a nonmechanical device that converts sunlight directly into electricity. Some PV cells can convert artificial light into electricity.

Sunlight is composed of photons, or particles of solar energy. These photons contain varying amounts of energy that correspond to the different wavelengths of the solar spectrum.

The definition of solar spectrum: The sun emits electromagnetic radiation across a broad spectrum. The solar spectrum is divided into different regions based on wavelength. The visible light region spans from approximately 390 to 780 nanometres (one nanometre is one billionth of a meter). Around 99 percent of solar radiation falls within the wavelength range of 300 nanometres (ultraviolet) to 3,000 nanometres (near-infrared). The radiation spanning from 280 nanometres to 4,000 nanometres is collectively known as broadband or total solar radiation.

A PV cell is made of semiconductor material. When photons strike a PV cell, they may reflect off the cell, pass through the cell, or be absorbed by the semiconductor material. Only the absorbed photons provide energy to generate electricity. When the semiconductor material absorbs enough sunlight (solar energy), electrons are dislodged from the material's atoms. Special treatment of the material surface during manufacturing makes the front surface of the cell more receptive to the dislodged, or free, electrons so that the electrons naturally migrate to the surface of the cell.

When a solar spectrum hits the PV cell, it gives the energy to move the electrons freely put not directed yet, so that means you need a driving force to make a current flow, the driving force here is the P-N junction.

The n side is the side which faces directly the solar irradiance holding a negative charge from a free electron (a silicon (Si14) atom with a phosphorus (P15) atom makes the spare electron), the P side is the side which holds a positive charge due to a (hole) due to (B5) or (Al13) atom with a Silicon making a P-N junction, the n is negatively charged and the P considered positively charged.

The area between the two sides is called a depletion region making a barrier with a slightly negatively charged region on the P side and slightly positively charged region on the N side, this makes an electric field preventing electrons or holes to move from one side to another , the irradiance that has enough energy will knock an electron on the depletion region making a hole and a free electron , the electron heads to the N side , the hole is filled with an electron from the P side leaving another hole behind it , the differential charge between the two sides is the voltage , and this allow a current to flow throw if we connect the two side, producing electricity[6,7].

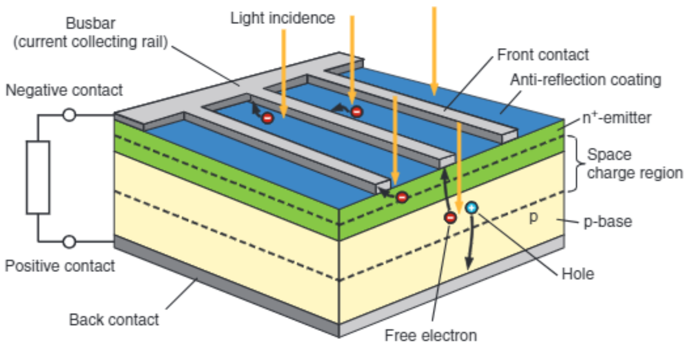


Figure I.1: Typical solar cell [8]

Essentially, the photovoltaic (PV) phenomenon encompasses the absorption of solar radiation, generating and transporting free carriers at the P–N junction, and the accumulation of these electric charges at the PV device's terminals [9,10]. The rate of electric carrier generation is contingent upon the incident light flux and the semiconductor's absorption capacity, which is primarily influenced by factors such as the semiconductor bandgap, cell surface reflectance (affected by surface shape and treatment), intrinsic carrier concentration, electronic mobility, recombination rate, temperature, and various other factors. Solar radiation consists of photons with different energies. Photons with energies lower than the bandgap of the PV cell do not contribute to voltage or electric current generation.

Conversely, photons with energies exceeding the bandgap generate electricity, with only energy corresponding to the bandgap being utilised; excess energy is dissipated as heat within the PV cell. While silicon is the predominant semiconductor material for PV cells due to its economically feasible fabrication process at a large scale, other materials may offer superior conversion efficiency at higher, commercially unviable costs [11].

I.5 Types of solar photovoltaic cells

As previously mentioned, solar cells generate electricity by assembling many layers of semiconductive material. The electromotive force between these layers is formed when the sun's rays strike the solar cells, causing electricity to flow. The flow of electricity increases with increasing solar radiation intensity.

Silicon is the most often used material in the manufacture of solar cells. The supply of raw materials is infinite as silicon is one of the most prevalent elements in the earth's crust and can be extracted from sand.

I.5.1 Monocrystalline

Silicon cells have a conversion efficiency of between 13 % and 17 %, making them usually considered to be in widespread commercial usage. It is the most efficient photovoltaic cell when the light is good. With a $1m^2$ cell surface, this kind of cell can convert $1.000W/m^2$ of solar energy into 140 W of electricity.

Pure semiconducting material is necessary for the fabrication of monocrystalline Si cells. From the molten silicon, monocrystalline rods are removed and cut into thin chips, or wafers. A comparatively high degree of usefulness is made possible by this kind of manufacture. These cells are expected to last for 25 to 30 years on average, and like other photovoltaic cells, their power naturally decreases with time [13,14,15].

I.5.2 Multi-crystalline silicon cells (Polycrystalline)

These cells have a $1m^2$ cell surface area and can convert $1.000W/m^2$ of solar light into 130 W of electricity. When compared to monocrystalline cells, these cells are more economically efficient to produce. After pouring liquid silicon into the blocks, the blocks are sliced into slabs. Crystal structures of different sizes are formed during the solidification process of materials. At the edges of these structures, flaws may appear, resulting in a somewhat decreased efficiency for the solar cell, which can vary from 10 % to 14 %. The anticipated lifetime is twenty to twenty-five years [15,16].

I.5.3 The thin-film method

Produces modules by depositing incredibly thin layers of photosensitive materials onto an inexpensive substrate, including plastic, glass, or stainless steel. Compared to relatively more intensive crystalline silicon technology, the technique of creating modules in thin-film technology has led in lower manufacturing costs. The current thin-film production's cost advantage is counterbalanced by crystalline silicon since thin-film efficiency is lower, ranging from 5 % to 13 %. Thin-film technology now holds a 15 % market share and is likely to grow over the coming years, reducing the unfavourable market ratio with respect to crystalline silicon photovoltaic modules. The average lifespan is 15-20 years [15,17,18] as shown in figure I.2.

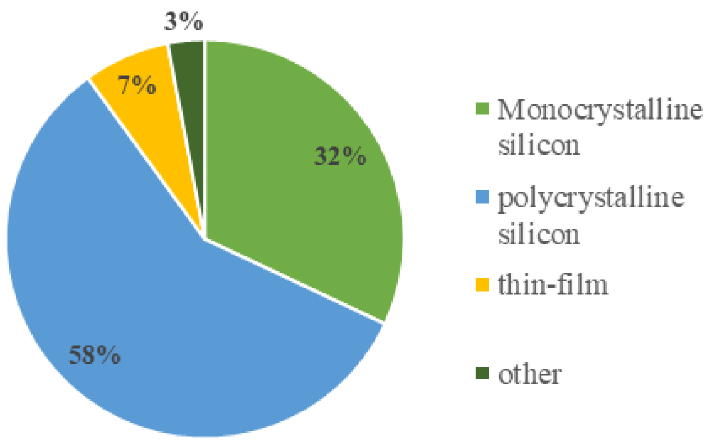


Figure I.2: Participation of different types of silicon in the global production of solar cells [12]

I.6 Faults in PV module

The most common problems in PV modules often impact a group of cells, modules, strings, and arrays. These flaws can arise as a result of weather-related events or manufacturing problems [19], In addition to physical and environmental failures, electrical faults are also a regular occurrence in photovoltaic systems. Poor soldering between joints or incorrect or loose conductor connections are the leading causes of the majority of electrical problems. The several types of defects that arise in the PV system lower efficiency, which in turn lowers output power. These mistakes must be found and fixed in order to prevent harmful situations and provide higher-quality output. Ignoring these faults might lead to power waste and reduced system performance. For the system to operate efficiently, proactive problem detection, rectification, and predictive maintenance are essential. The primary flaws that might emerge in a PVS are listed in this part [20], and Figure I.3 shows the classification of PV faults.

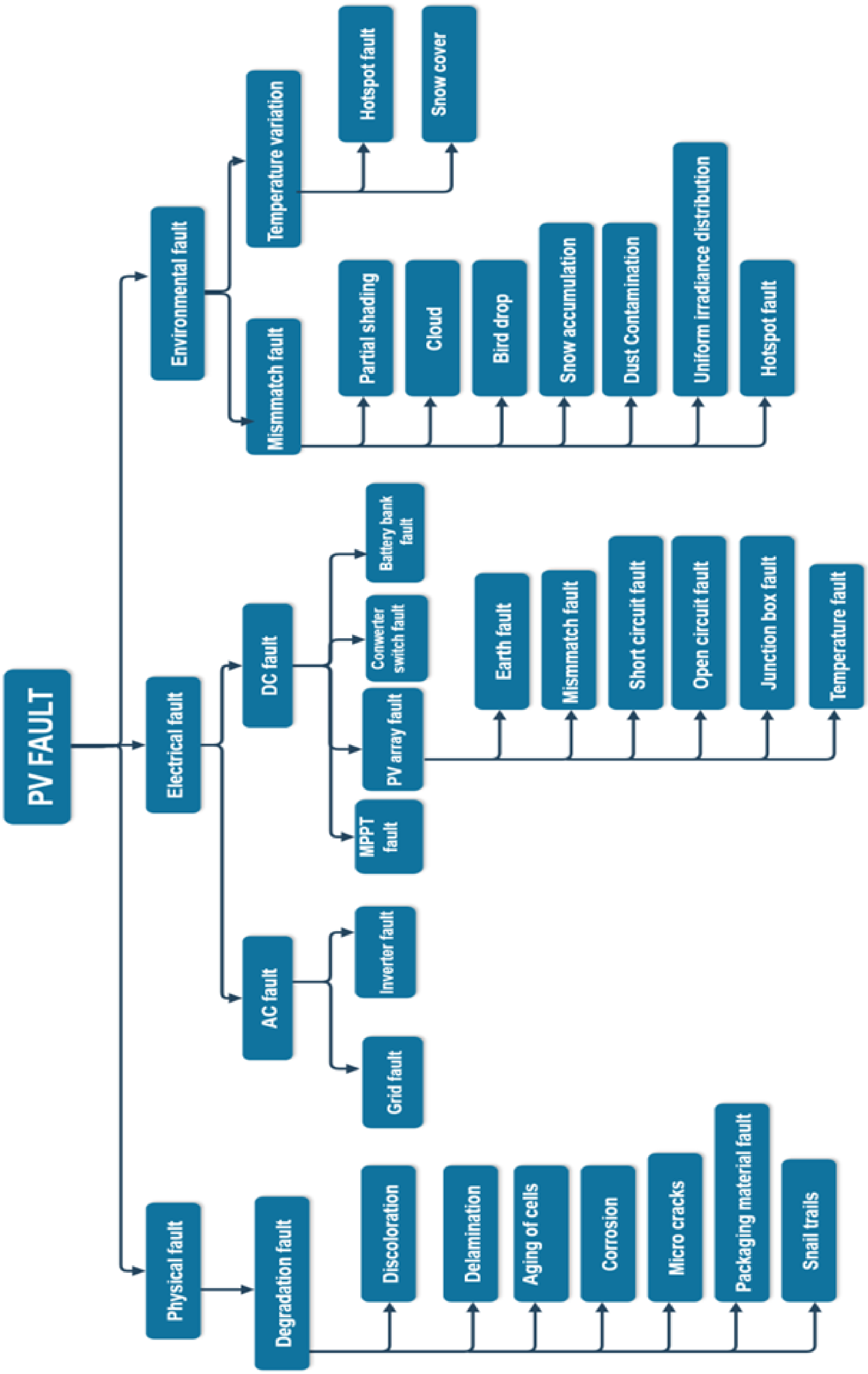


Figure I.3: Classification of solar PV faults

I.6.1 Physical faults

The majority of physical defects seen in photovoltaic arrays, such as encapsulation, corrosion, fractures, and deterioration, are either the result of mechanical stress or the nature of the material that was employed in the array's construction. By using materials that are durable and corrosion-resistant, PV array lifespans may be extended and the likelihood of mechanical failures can be decreased.

The photogenerated current may be affected and the colour of the cells may brighten as a consequence of the degradation of the solar cells, which may also cause a rise in series resistance, a fall in parallel resistance, and deterioration of the anti-reflection coating [21]. This degrading defect virtually reduces the generated power to half of the intended value.

I.6.1-a Discoloration

It is simple to see PV cell discolouration with the unaided eye. This problem causes the PV material's white tint to become yellow or brown [23, 24], lowering the amount of light that strikes the solar cells.

This might result in a temperature rise, seriously impairing the PV system's performance. Thermal stress, UV radiation exposure, the build-up of gases or acids between layers, the corrosion of metallic connections, and other factors are some of the primary reasons for discolouration.

I.6.1-b Delamination

This results from inadequate adhesion, which causes gaps or detachment between the module's successive layers (between the glass, encapsulant, encapsulant-cell, or encapsulant-back sheet). Increased light reflection (instead of absorption) and gas or moisture penetration are caused by the delamination of PV modules, and these conditions can result in a multitude of other faults. The PV module's delamination or discolouration is the root cause of encapsulation failure. The primary causes of this flaw are moisture intrusion, salt build-up, and other outside influences [22,23].

I.6.1-c Corrosion

Moisture intrusion into the module due to delamination or encapsulating fractures may result in PV material corrosion. Silver fingers on top of the cell and metal contacts connecting to the base of the cell are susceptible to corrosion when exposed to corrosive gases such as carbon dioxide, sulphur, oxygen, and other airborne substances [25]. Figure I.4 illustrates the damage to the PV panel produced by the corrosion defect. Corrosion of conducting wire can raise its resistance, which can ultimately result in exceptionally high-power loss, and corrosion of metallic connections can allow leakage current to pass through the system [22].

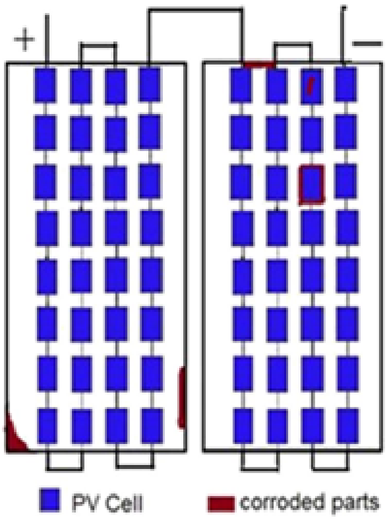


Figure I.4: Corrosion in the solar PV array [43]

I.6.1-d Cell cracks

As seen in Figure I.5, cell cracks are fractures that have formed in the silicon substrate of the PV module. In addition to the silicon substrate, fractures may also develop in the various lamination layers of the cell. When these cracks?also referred to as micro-cracks?become too tiny for the human eye to discern, electroluminescence imaging can be used to identify them. Several primary causes of cracks are mentioned in [22, 26] and include: mechanical stress during production, transportation, or installation; potential shocks during transportation; manufacturing flaws; improper handling during packaging; aging of cells; high temperatures and hailstorms; snow cover, wind, and rain.

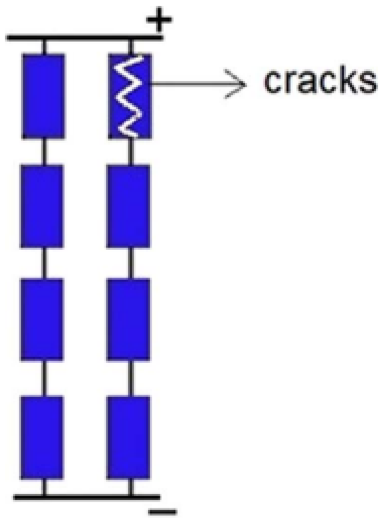


Figure I.5: Crack in solar PV panel [43]

I.6.1-e Snail trails

The staining of silver fingers caused by the creation of Ag2CO3 nanoparticles, silver carbonate, is known as snail trails [26, 27]. When silver reacts with moisture and carbon dioxide, it forms snail tracks. Snail trails are typically observed close to cell borders and fissures because these gases may readily enter through crevices [26].

I.6.1-f Packaging material fault

When PV cells are packaged, excessive pressure may be used, which might cause the cell to shatter. Any flaw in the packing or manufacturing process might lower the PV cells' output power.

I.6.1-g Cells aging

Photovoltaic systems typically have a 30 year lifespan. As cells age, they may develop several more flaws such as discoloration, delamination, fissures, etc. These might result in hotspots and lower cell performance.

I.6.2 Environmental faults

A PV array's performance is impacted by a variety of environmental variables, including temperature, sunlight intensity, shade, and weather. These elements have the potential to seriously harm cells in ways that may or may not be repairable. The many categories of environmental flaws are discussed in this section.

I.6.2-a Mismatch fault

PV modules differ when the electrical parameters are changed significantly, such as when the IV characteristics of the cell are different from one another.

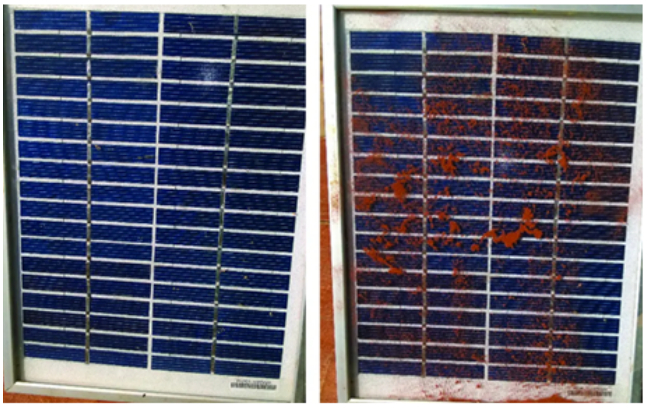
These defects have the potential to permanently harm the panels, which would result in an extremely high-power consumption. The researchers in [28] claim that there are two different types of mismatch faults:

- temporary mismatch faults, which result from temperature variations and partial shading and alter the open circuit voltage.
- permanent mismatch faults, which result from soldering errors, cracks, hotspots, or cell degradation. The total output power is significantly decreased. [28,29]

I.6.2-b Partial shading

Partial shading occurs when a portion of the module is partially shaded, lowering the system's output power. Partial shading causes the shaded cells to function as power dissipators rather than power providers, which might cause the cell's temperature to rise. Thus, cells that are darkened provide resistance. They produce hot spots, which have the potential to seriously damage the PV array. The following are the main causes of partial shading: bird droppings, shadowing from trees and buildings, leaves, clouds, dust pollution, and even dispersion of light all contribute to shading. Figures I.6 and I.7 show how solar PV systems are partially shaded.

Figure I.6: Partial shading due to trees [43]



a b

Figure I.7: (a): Solar PV panel without dust. (b): Solar PV panel with dust. [43]

I.6.2-c Snow cover

During the winter, snow layers cover the solar cells, blocking the sunlight resulting in dramatic reduction in the amount of solar energy produced, also have an albedo effect which makes the reflected photons much more than in original conditions, furthermore, the weight of the snow on the PV panels may cause physical damage.

On the other hand, the snow causes coldness and already comes in a cold weather, and the temperature affects according to the used PV technology, some perform better, so the effect varies [30,31]. Figure I.8 illustrates how a solar PV panel is partially shaded by snow.

Figure I.8: (a): Solar PV panel covered due to snow [44]

I.6.2-d Hotspot faults

Since hotspot faults produce areas with comparatively greater temperatures than the panel as a whole, they are also classified as a sort of temperature fault. A few locations exhibit intense heat and distinct IV properties from the remaining panel sections. The partially darkened panels or the faulty cell architectures are the leading causes. A mismatch results when the parameters are not precisely translated from the feeding side to the output side, leading to localised heating on the panel's surface. Figure I.9 serves as an illustration of the hotspot fault. Hotspot heating happens when the value of the current during the operating period goes beyond the specified value of the current during a short circuit in the cells which are found to be faulty. The severity of the Hotspot fault depends on the mismatch level and duration. The occurrence of this fault can be mapped to various causes like ageing, accumulation of dust, soil, snow, and some other agents on the surface of the panel [32,33].

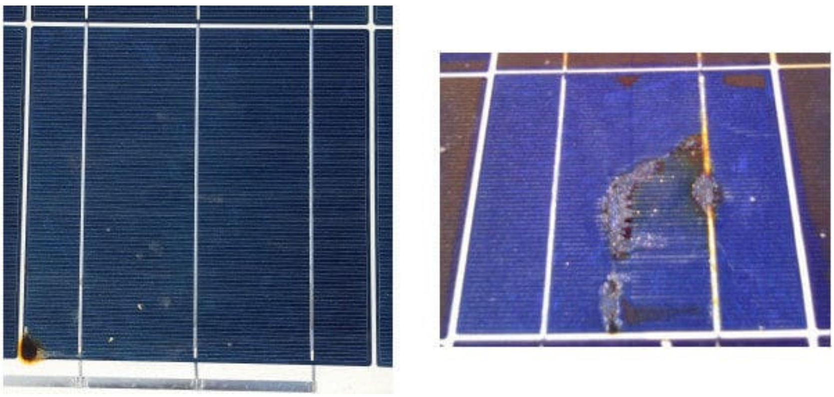


Figure I.9: Damaged cells due to hotspot fault [45]

I.6.3 Electrical fault

Include those that arise from connections between conductors, shorted circuits, circuits that open, and issues with electrical appliances and measurement instruments.

I.6.3-a AC faults

AC faults are those that occur on the side of the PV system where the alternating current circuit is present. This includes the inverter and the distribution set up's grid. The section that follows discusses grid and inverter problems, which fall within the AC fault category.

Grid fault : Through the use of an inverter, the PV array output of a grid-connected PV system is linked in parallel to the grid or power distribution system. In the event of a utility grid power outage, the PV system's output has to be disconnected in order to prevent any electricity from the PV system from entering the grid. Grid faults include PowerStation malfunctions, weak connections, transmission line damage, blackouts, overloading, and other issues [28].

Inverter fault : The photovoltaic array generates DC output current, the inverter receives this DC current from the PV output and transforms it into the necessary frequency-appropriate AC. Improper installation, unregulated voltage current, and high load power are the major causes of inverter failure [34]. When a grid breakdown occurs, grid-tied solar inverters are crucial in severing the PV system from the grid. The purpose of this is safety. Inverters' incapacity to carry out this function might endanger grid personnel.

I.6.3-b DC faults

The term "DC faults" refers to a variety of fault types, including PV array, battery bank, and maximum power point tracker (MPPT) failures.

MPPT fault : The PV array's maximum power delivered to the inverter is maximized using the Maximum PowerPoint Tracker (MPPT). In essence, it is an algorithm built into the charge regulator that, under specific circumstances, maximizes the power extracted from the PV module. The MPPT may not perform properly due to a malfunctioning charge regulator. The output voltage and power are reduced by any MPPT error [28].

Battery bank faults : If solar radiation is applied to them, solar cells have the ability to generate current. In the event that solar energy is unavailable, battery banks are employed to provide a steady supply to the load. Batteries that are charged throughout the day and power the load at night are linked to the PV array's output. Unusual charging circumstances are the major cause of these batteries' occasional malfunctions.

PV array faults : The seven types of PV array faults which are discussed in the following section are: Earth fault, Line-to-Line fault, Bridging fault, Open circuit fault, Arc fault, Bypass diode fault and Junction box fault.

Earth faults : Figure I.10 illustrates an example of a short circuit problem, often known as an earth fault or ground fault. When a circuit creates an unintentional path to the earth, it occurs [28]. Every nonconducting metal is grounded or linked to the earth in order to protect the user or consumer from potential electrical shock and other risks. Huge current flows through these non-conducting metals and into the earth when they come into contact with the current-carrying conductors [35]. The massive increase in current flowing via the non-current carrying conductors in the PV array is what causes the mismatch issue. The ground fault is the name given to this issue. There exist two types of earth faults: lower and higher.

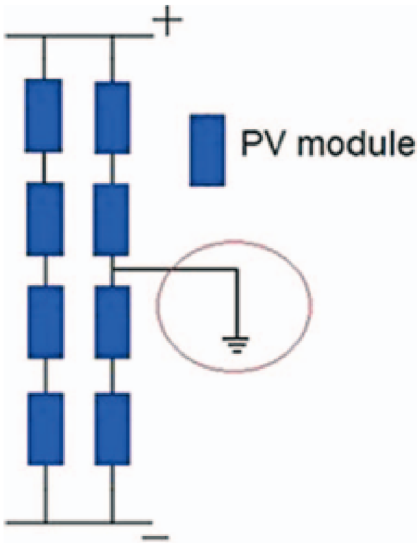


Figure I.10: Short circuit between the PV module and the ground [43]

Line to line faults : There is a change in the VI plot of a PV system due to voltage reduction [32]. The line-to-line fault in a PV array, as shown in Figure I.11, is caused by an accidental short circuit between two varying potentials or occasionally between array cables. This fault occurs in two ways with respect to its position: when it occurs within the same string, it is called an intra string fault, and when it occurs within neighbouring strings, it is called a cross string fault.

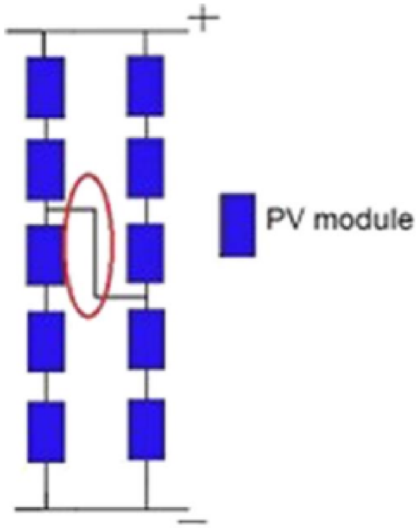


Figure I.11: Line to line fault [43]

Bridging faults : When a low resistance connection forms between PV modules, a bridging problem arises. These problems result in voltage drops and current swings and are brought on by physical damage, corrosion, or insulation failure of cables. When a line-to-line defect has zero fault impedance, it is frequently referred to as a bridging fault. [28, 36].

Open circuit fault : An open circuit defect arises when the current-carrying line that is linked in series with the load is cut off or removed from the circuit. The main source of this issue is incorrect or loose connections or plugs between the system's different components. Figure I.12 depicts the open circuit problem that is happening in the PV panel. As the number of detached strings increases, the open-circuit defect causes the short-circuit current and maximum power output to drop, but the voltage is kept almost exactly at normal levels [37, 38].

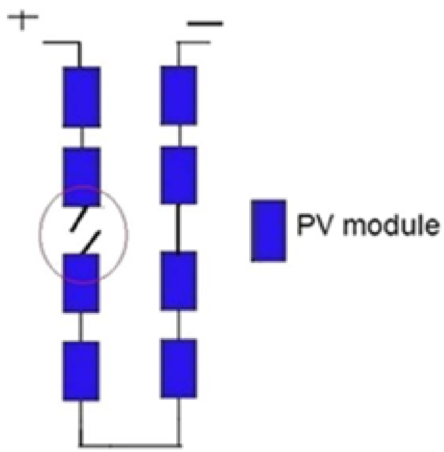


Figure I.12: Open circuit fault [43]

Arc fault : The intricate web of connecting structures that holds the circuitry's numerous series and parallel configurations of component connections together is the main cause of arc defects. Figure I.13 shows an example of the arc faults. Different types of arc defects might arise from solder joints with incorrect connections, lose or defective component connections, or failure of the insulators utilized in the circuitry. Extremely high temperature is reached because of the arc fault. As a result, the arc comes into contact with the components that are flammable. Arc faults can cause fire incidents if appropriate safety measures are not followed. This is because the arc ionizes the air, causing a plasma discharge that starts a fire [35, 39-40].

Series and parallel arc faults are further classifications for arc faults. A greater current is drawn in shunt arc faults than in series arc faults because of the presence of an exceptionally high potential difference in parallel arc faults [32, 41].

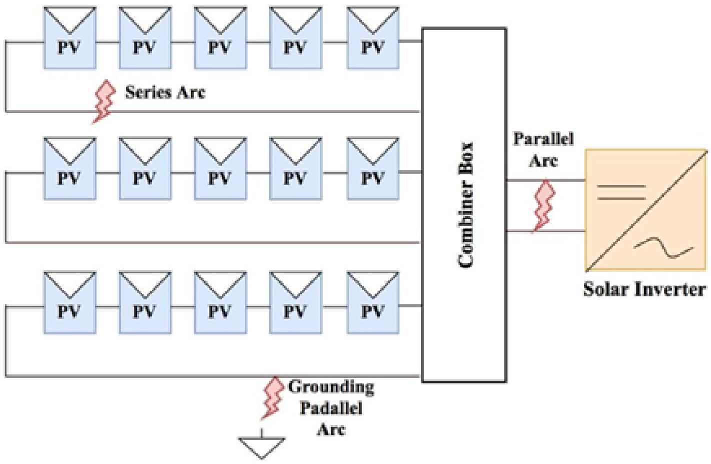


Figure I.13: Arc Fault [46]

Bypass diode faults : A few chosen cells in the PV panel have a shunt connection to the bypass diodes. There is no current flowing through the diode when the cells are not shaded, or under normal circumstances. Partial shading causes the shaded cells to function as power dissipators rather than power providers, which might cause the cell's temperature to rise. The components and bypass diodes must be connected in parallel to keep the darkened cells from acting as resistors. Bypass diodes are used to correct the shading problem's aftereffects [42]. These bypass diodes allow current to flow while the PV cell is shaded, which keeps the PV cells from heating up. When a defective bypass diode is employed, it might result in the production of hotspots because of the heat build-up from the defective part and the shading issue [38]. A bypass diode malfunction that results in a high temperature might catch fire and harm the photovoltaic array. As a result, when a faulty component is employed, an antiparallel connection of the diode becomes the solution to one problem and may even become the problem itself [38, 42].

Junction box failure : One of the main causes of junction box failure is energy loss from the system. Incorrect connections and burned bypass diodes can also cause a junction box malfunction [35].

I.7 Conclusion

After this study of the PV systems, the different construction of the cell and how they react to the environmental factors, the fault that may occur on the system temporal or permanent, also the electrical and physical faults depending on the cause or the effect, we can confirm that the PV system will face a lot of difficulties and thresholds, that will affect significantly on the overall performance of the production of energy, the lifespan of the photovoltaic cells or modules.

This gives us a good perspective of the functioning PV system in real life and helps to understand the problems and value it correctly.

Even so, every piece of knowledge gives us a step ahead to understand how to handle problems and deal with it in a more sophisticated way and find the right diagnosis to solve any problem, as we will see in the next chapter.

Chapter II

Diagnostic Methods

Contents

II.1 Introduction

Photovoltaic (PV) systems represent a cornerstone of renewable energy generation, offering a sustainable solution to the world's energy needs. However, to ensure the continuous and efficient operation of PV systems, effective fault diagnosis is paramount. This chapter delves into the intricate process of diagnosing faults in photovoltaic systems, offering insights into various methodologies and techniques employed for fault detection and classification.

Faults in photovoltaic systems can arise due to various factors, including environmental conditions, material degradation, and equipment malfunction. Left undetected, these faults can significantly impact system performance, efficiency, and reliability. Therefore, implementing robust fault diagnosis methodologies is essential for maximizing the lifespan and output of PV systems.

This chapter explores three primary methodologies for diagnosing faults in photovoltaic systems: Signal Processing Method, Artificial Intelligence Method and Inference Method.

II.2 Photovoltaic Fault Detection and Diagnosis Methods

Photovoltaic Fault Detection and Diagnosis (PV FDD) methods encompass a range of techniques and strategies aimed at identifying and addressing faults in photovoltaic systems. These methods are crucial for maintaining system reliability, maximizing energy yield, and ensuring the longevity of PV installations. In our study, we will discuss 3 methods of diagnosing faults.

II.2.1 Signal Processing Method

The ignal Processing Method involves the analysis and processing of electrical signals extracted from components within the photovoltaic (PV) system, with the aim of detecting and diagnosing faults and issues that may arise in this system. This method is used to detect any abnormal changes in the electrical signals, helping to identify the locations of faults and determine their causes.

II.2.1-a Signal processing techniques utilized in PV FDD

Time-domain Analysis: Time-domain analysis involves examining signals directly in the time domain. This method focuses on parameters such as amplitude, frequency, and phase variations over time. Time-domain analysis is useful for detecting transient events, irregularities, and temporal patterns in signals generated by PV system components.

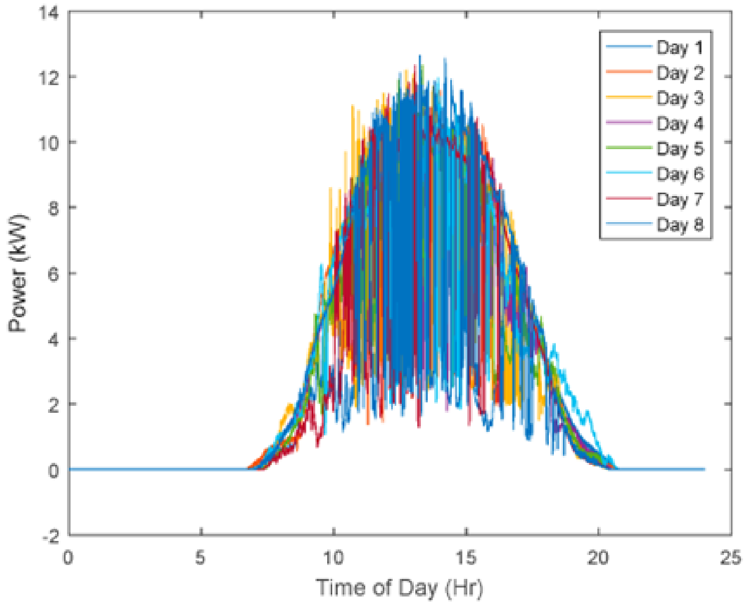


Figure II.1: Time-domain Analysis. [47]

Frequency-domain Analysis : Frequency-domain analysis involves transforming signals from the time domain to the frequency domain. Techniques such as Fourier Transform or Fast Fourier Transform (FFT) are commonly used for this purpose. Frequency-domain analysis reveals the frequency components present in signals, aiding in the detection of specific frequency signatures associated with faults or disturbances in PV systems. like in figure II.2.

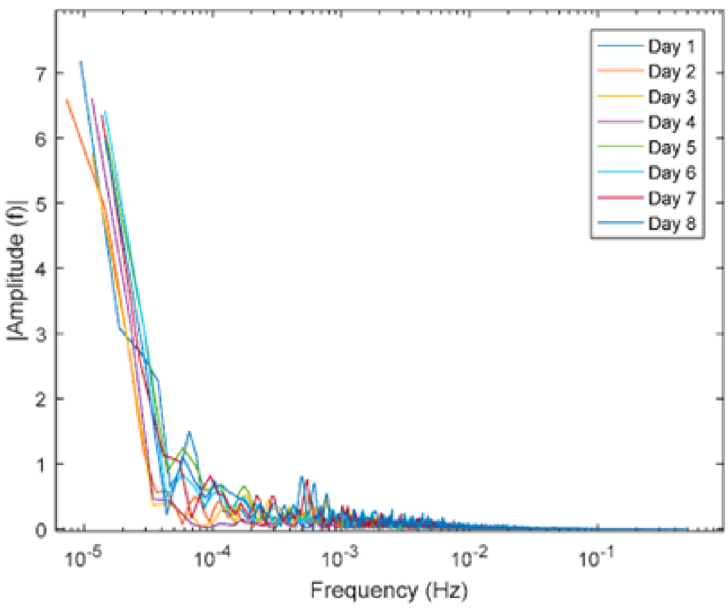


Figure II.2: Frequency-domain Analysis [47]

Wavelet Analysis : Wavelet analysis provides a localized frequency representation of signals, making it suitable for analysing signals with time-varying and frequency-varying characteristics. Unlike Fourier analysis, which provides a global frequency representation, wavelet analysis allows for the detection of transient events and localized anomalies in signals.

Statistical Analysis : Statistical methods play a crucial role in analysing signal data and identifying patterns or anomalies indicative of faults. Techniques such as hypothesis testing, regression analysis, or probability distributions can be applied to assess the significance of observed deviations from expected behaviours.

I–V curve analysis : I-V curve analysis is a traditional FDD strategy used in photovoltaic (PV) systems. It involves analysing the electrical characteristics of a module, including short-circuit current and open-circuit voltage, to detect system failures. The current-voltage curve is monitored and measured as the voltage or current across the module changes with the application of an external load or power source. Typically, identical response characteristics of cells or modules are used as a reference for comparison with the module under test. Under normal operation, the I-V characteristics follow a specific curve, like in Figure II.3, which changes during a fault. The degree of change in the curve depends on the type and severity of the fault [48].

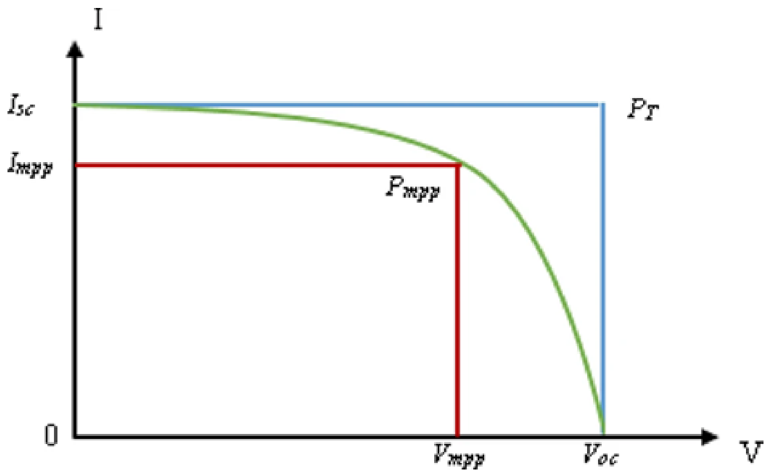


Figure II.3: I-V curve parameters. Isc short circuit, Voc open-circuit, Pmpp maximum power point, and PT for virtual power point [61]

The I-V curve of a module can be valuable for detecting various faults in photovoltaic (PV) systems. However, it typically doesn't provide precise information about the exact location of these failures. Therefore, additional techniques are often required to pinpoint the locations of faults. This can complicate the fault detection process, requiring significant time and resources to implement [49, 50].

Signal Filtering and Denoising : Signal filtering techniques are used to remove noise and interference from signal data, enhancing the quality of signals for fault diagnosis. Filters such as low-pass, high-pass, band-pass, or adaptive filters can be applied to suppress unwanted noise components

Feature Extraction : Feature extraction involves identifying relevant features or characteristics from signal data that are indicative of system behaviour or fault conditions. This process often involves extracting time-domain or frequency-domain features from signals for further analysis.

By applying these signal processing techniques, practitioners can effectively analyse, process, and extract meaningful information from signals generated by PV system components, enabling accurate fault detection and diagnosis.

II.2.1-b Advantages of Signal Processing Method

1. **Early Detection:** Signal processing allows for early detection of faults by analysing electrical signals, enabling timely intervention and minimizing system downtime.
2. **Accuracy :** It offers precise and quantitative analysis, facilitating accurate identification and classification of faults within the PV system.
3. **Comprehensive Analysis :** Signal processing methods consider multiple parameters, providing a holistic view of system performance and enabling comprehensive fault diagnosis.
4. **Real-time Monitoring :** It enables real-time monitoring of system operations, allowing immediate detection and response to faults as they occur.
5. **Automation :** Signal processing techniques can be automated, reducing the need for manual intervention and ensuring continuous monitoring of system performance.
6. **Cost-effective :**Early fault detection helps reduce maintenance costs by addressing issues before they escalate into major problems, thereby maximising system lifespan.

II.2.1-c Disadvantages of Signal Processing Method

1. **Complexity:** Implementation requires specialised knowledge and expertise, posing challenges for inexperienced users.
2. **Data Quality:** Effectiveness depends on the quality of data collected, with poor-quality data compromising the accuracy of fault diagnosis results.
3. **Resource Intensive:** Some techniques may require significant computational resources, limiting scalability and implementation.Some techniques may require significant computational resources, limiting scalability and implementation.
4. **Dependency on Models:** Accuracy may be affected by deviations between mathematical models and real-world conditions.
5. **Limited Scope:** Some methods may not detect certain types of faults, necessitating additional diagnostic techniques for comprehensive fault detection.
6. **Maintenance Overhead:** Continuous monitoring and analysis require ongoing maintenance and calibration of equipment, adding to operational overhead.

Understanding these advantages and disadvantages is crucial for selecting the most appropriate fault diagnosis method for a given PV system, ensuring effective maintenance and optimal performance.

Finally, signal processing methods play a crucial role in ensuring the efficiency and reliability of PV systems, offering a powerful means of detecting and addressing faults to optimize system performance and minimize downtime. Continued research and development in this area are essential for advancing fault diagnosis capabilities and further enhancing the effectiveness of signal processing techniques in the field of photovoltaics.

II.2.2 Artificiels intelligence (AI) techniques for FDD system

AI techniques have had many applications in different fields in recent decades, like medicine, astronomy, engineering, robotics, speech recognition, natural language processing, behavioural sciences, etc. It is a powerful and important tool that is used in many areas of research in PV systems, including forecasting or prediction [51, 52]. Different techniques can be used in data-driven fault detection for PV systems, like statistical methods or machine learning (ML) which can handle complex and nonlinear problems. AI system examples that are used in PV systems include artificial neural networks [53, 54], fuzzy logic [55], support vector machine [56], decision tree, and k-nearest neighbour algorithm [57].

Machine Learning (ML) methods are a subset of AI techniques that empower computers to learn from past experiences, such as databases, without explicit programming by humans. Deep Learning (DL) is a specialized form of ML, where both ML and DL are integral components of AI tools. Additionally, Computer Vision (CV) applications play a crucial role, enabling computers to process, analyse, and interpret the visual world using AI techniques, like in Figure II.4. Recent advancements in DL have revolutionized traditional CV problems, solving them more effectively than before [58].

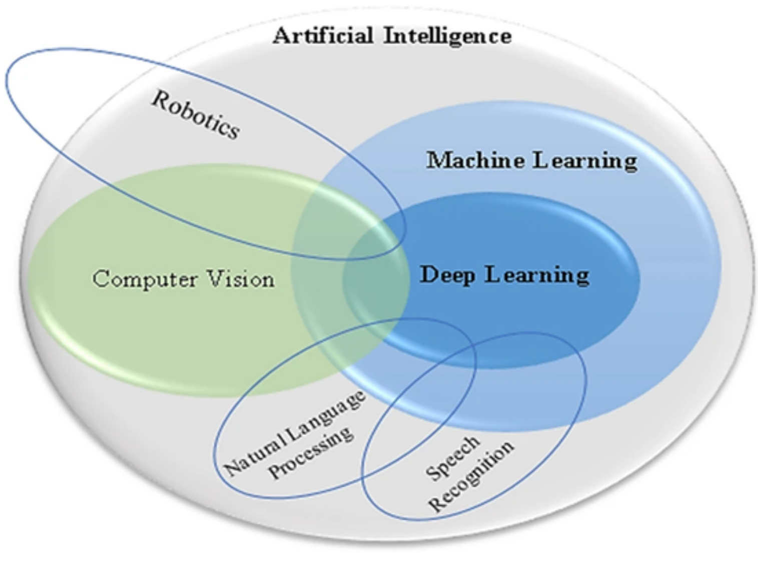


Figure II.4: An analysis of how AI, ML, DL, and CV relate [61]

When traditional techniques can't find a solution to complex problems, machine learning techniques are used. It can handle unstable environments due to its ability to adapt to new data. Machine learning is useful for solving lengthy and difficult problems since the links between inputs and outputs are straightforward.

In [55], the authors propose a fuzzy classification algorithm where failure is classified using thermal images. The pixel counting technique is employed to detect discoloration of Ethylene Vinyl Acetate (EVA) and delamination failures based on three index values. However, this method primarily focuses on locating hot spots and does not diagnose other types of faults.

On the other hand, [56] introduces a machine learning methodology using a hybrid features-based support vector machine (SVM) model for hot spot detection and classification of PV panels. A data fusion approach is utilized to combine colour histograms, a second-order co-occurrence matrix, and features of a local binary pattern, enhancing efficiency in fault detection and classification.

DL is more powerful than ML. It is considered a multi-computational neural network with many hidden layers that accepts and learns a large amount of data.

II.2.2-a Machine Learning (ML)

Machine learning techniques, such as neural networks, support vector machines, and decision trees, can be employed for inference in PV systems. These methods learn patterns and relationships from historical data to make predictions or classifications based on new data. In the context of fault diagnosis, machine learning models can analyze sensor data to identify patterns indicative of system faults. Machine learning approaches offer scalability and adaptability, as they can handle large datasets and learn from diverse sources of information.

II.2.2-b Fuzzy Logic

Fuzzy logic inference methods use linguistic variables and fuzzy sets to represent imprecise or uncertain information in PV systems. These methods allow for flexible reasoning and decision-making in situations where precise rules or models may be difficult to define. Fuzzy logic inference can capture the inherent uncertainty and complexity of PV system behavior, enabling more nuanced fault diagnosis and decision-making.

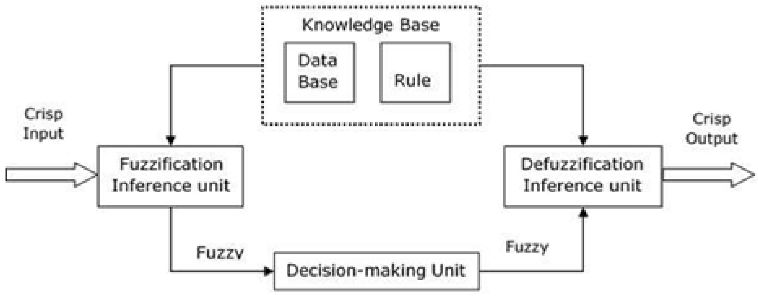


Figure II.5: Fuzzy Logic - Inference System [61]

II.2.2-c Deep learning (DL) frameworks

The convolutional neural network (CNN), long short-term memory (LSTM) network, recurrent neural network (RNN), generative adversarial network (GAN), Boltzmann machine, and autoencoder/decoder are widely recognized as the most popular deep learning frameworks for photovoltaic fault detection and classification [59, 51].

1. **Convolutional neural network (CNN):**

   A Convolutional Neural Network (CNN) is a deep learning architecture primarily designed for processing structured grid data, such as images. CNNs are composed of multiple layers, including convolutional layers, pooling layers, and fully connected layers.

   Convolutional layers are the key components of CNNs, where the network learns to extract spatial hierarchies of features from the input data through convolution operations. These layers consist of learnable filters (also called kernels) that slide across the input data and perform element-wise multiplications, generating feature maps that capture local patterns.

   Pooling layers are typically used after convolutional layers to reduce the spatial dimensions of the feature maps while retaining important information. Common pooling operations include max pooling and average pooling, which down sample the feature maps by taking the maximum or average value within a local region.

   Fully connected layers, also known as dense layers, are used at the end of the network to perform classification or regression tasks. These layers connect every neuron in one layer to every neuron in the next layer, allowing the network to learn complex relationships between features extracted by the convolutional layers.

   CNNs have demonstrated remarkable performance in various computer vision tasks, including image classification, object detection, and semantic segmentation. Their ability to automatically learn hierarchical representations of features from raw data makes them well-suited for photovoltaic fault detection and classification tasks, where analysing visual data such as thermal images or photographs of PV panels is essential as shown in Figure II.6.

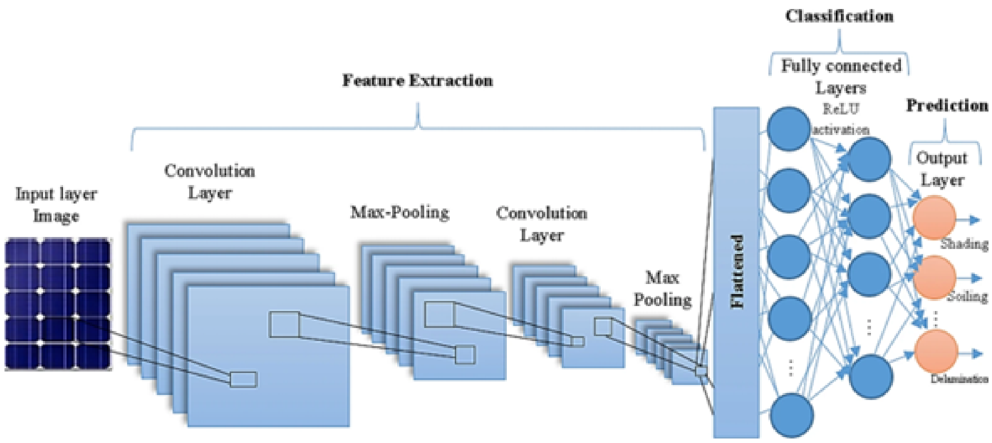


Figure II.6: CNN Structure for PV FDD system [61]

2. **Long short-term memory networks (LSTM):**

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) architecture designed to overcome the vanishing gradient problem and capture long-range dependencies in sequential data.

Unlike traditional RNNs, which suffer from the vanishing gradient problem due to the repeated application of a single activation function, LSTMs utilize a more sophisticated gating mechanism to regulate the flow of information over time. This gating mechanism consists of three main components: the input gate, the forget gate, and the output gate as shown in Figure II.7.

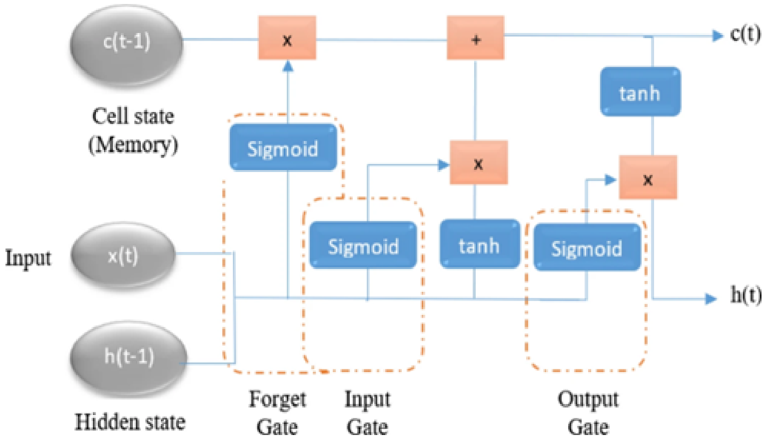


Figure II.7: LSTM Structure [61]

Input Gate : The input gate determines which information from the current input should be stored in the cell state. It computes a candidate value using the current input and decides how much of this information should be added to the cell state.

Forget Gate : The forget gate decides which information from the previous cell state should be discarded. It computes a forget factor based on the current input and the previous hidden state, indicating how much of each component of the cell state should be forgotten.

Output Gate : The output gate determines the output of the LSTM unit. It controls which information from the current cell state should be output to the next time step based on the current input and the previous hidden state.

3. **Generative adversarial network networks (GAN) :**
Generative Adversarial Networks (GANs) are a type of deep learning architecture consisting of two neural networks: a generator and a discriminator, as shown in Figure II.8.

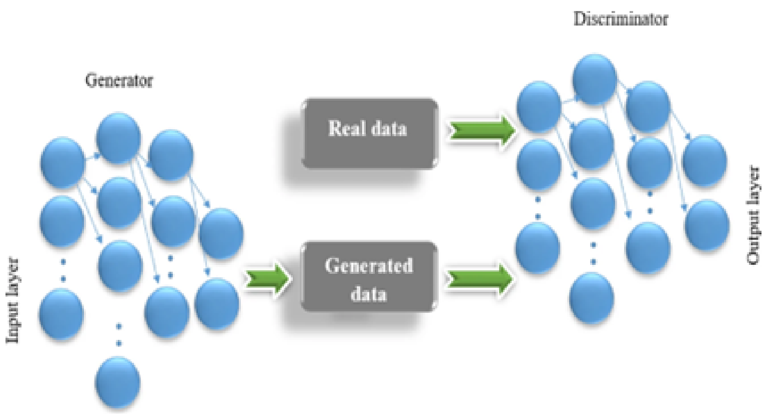


Figure II.8: GAN architecture [61]

The generator creates synthetic data samples, while the discriminator distinguishes between real and synthetic samples. Through adversarial training, GANs learn to generate realistic data samples that closely resemble the training data. GANs have been successfully applied in various domains, including image generation, style transfer, and data augmentation. In photovoltaic fault detection and classification, GANs can be used to generate synthetic fault data for training models or to augment existing datasets, improving model performance and robustness.

In [60], the use of GAN is to detect DC series arc faults, which has been used in domain adaptation with a convolutional GAN.

4. **Auto-encoder/decoder networks :**

Autoencoder networks are a type of neural network architecture used for unsupervised learning and dimensionality reduction. They consist of an encoder and a decoder, which compress input data into a lower-dimensional representation and then reconstruct the original data from this representation. Autoencoders have applications in data denoising, anomaly detection, and feature learning, making them useful for photovoltaic fault detection and classification tasks.

5. **Boltzmann machine networks (BM):**

Boltzmann Machines (BM) are a type of stochastic neural network that uses a form of unsupervised learning called energy-based learning. They consist of symmetrically connected units organized into visible and hidden layers. Boltzmann Machines are trained to model the probability distribution of the input data by learning the dependencies between visible and hidden units. They have applications in various tasks such as feature learning, dimensionality reduction, and collaborative filtering. In the context of photovoltaic fault detection and classification, Boltzmann Machines can be used for unsupervised feature learning or to model complex relationships within the data. as shown in Figure II.9.

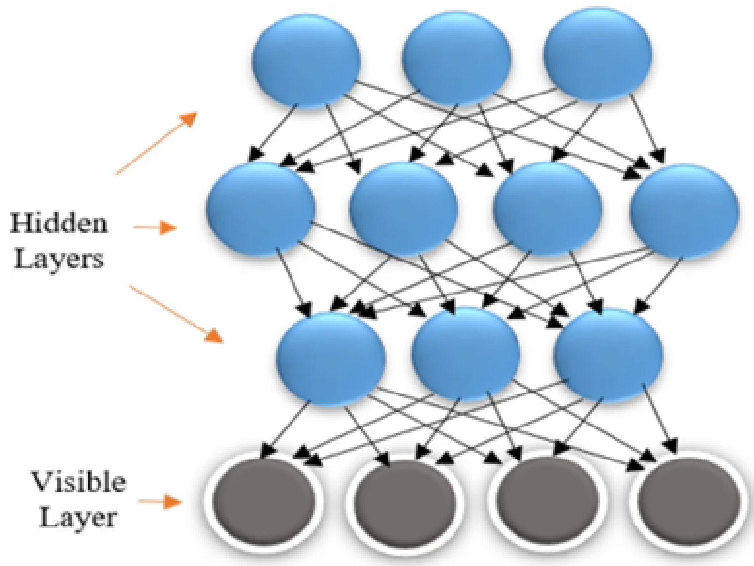


Figure II.9: DBN architecture [61]

The DBN is used to train the initial values of the NN in order to solve the crack problem of the PV module in [60]. The reconstructed and training images are used as the supervised data.

Artificial intelligence (AI) techniques for FDD system, comes with its own set of advantages and disadvantages. Here's a brief overview:

- **Advantages:**
  (a) **Accurate Fault Detection:** Artificial intelligence techniques can analyze large and complex datasets from photovoltaic systems effectively, enabling accurate fault detection and diagnosis even in cases that may be challenging for humans.
  (b) **Improved Efficiency and Accuracy:** AI-based models can enhance the accuracy of fault diagnosis and reduce false positives, increasing the ef-

ficiency of maintenance operations and minimizing costs associated with system downtime.

(c) **In-depth Information Analysis:** AI-based models can utilize advanced techniques to analyze various aspects of data such as spectral frequencies and temporal patterns, aiding in the precise identification of fault origins.

(d) **Prediction of Future Faults:** AI-based models can analyze system behavior and predict potential future faults based on historical data, enabling proactive maintenance before faults occur.

- **Disadvantages:**

  (a) **Data Reliance:** The performance of AI-based models relies on the quality and quantity of available data, and obtaining sufficient and representative data for all potential conditions and faults may be challenging.

  (b) **Model Complexity:** AI-based models for fault diagnosis can be highly complex, making them difficult to understand, analyze, and implement, requiring technical expertise in mathematical analysis and programming.

  (c) **Continuous Updating Requirement:** Using AI-based models for fault diagnosis requires continuous maintenance and updating to adapt to new conditions and changes, necessitating significant time and effort resources.

  (d) **Technical Challenges:** AI-based models may face technical challenges such as accurate parameter estimation, optimizing model performance in different operating environments, and ensuring model compatibility with photovoltaic system requirements.

Using artificial intelligence for fault diagnosis in photovoltaic systems can lead to significant improvements in maintenance efficiency and cost reduction. However, it is essential to address challenges related to data collection, analysis, and model implementation carefully, considering technical and operational factors.

II.2.3 Inference methods

The inference method employs statistical and probabilistic techniques to interpret data and infer the condition of the PV system. It relies on predefined rules or models to assess the likelihood of different fault scenarios. Various techniques are employed within the inference method, including:

1. **Visual Inspection:** Visual inspection involves visually examining PV modules for physical abnormalities such as cracks, discoloration, corrosion, or other visible signs of damage or degradation. It is a straightforward and cost-effective method for identifying surface-level faults.

2. **Ultraviolet (UV) Fluorescence Imaging:** UV fluorescence imaging utilizes ultraviolet light to induce fluorescence in certain materials. This technique can reveal hidden defects or contamination on PV modules that may not be visible to the naked eye. By detecting fluorescence patterns, UV imaging can identify areas of potential concern, as shown in Figure II.10.

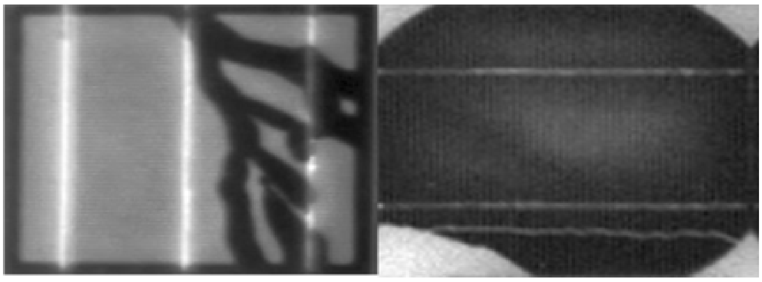


Figure II.10: UV FL Failure images [61]

3. **Electroluminescence Imaging:** Electroluminescence imaging captures images of PV modules while they are under electrical stress, such as during operation or under applied voltage. This technique can highlight defects or irregularities within the internal structure of the module, including cell cracks, inactive areas, or soldering issues. as shown in Figure II.11.

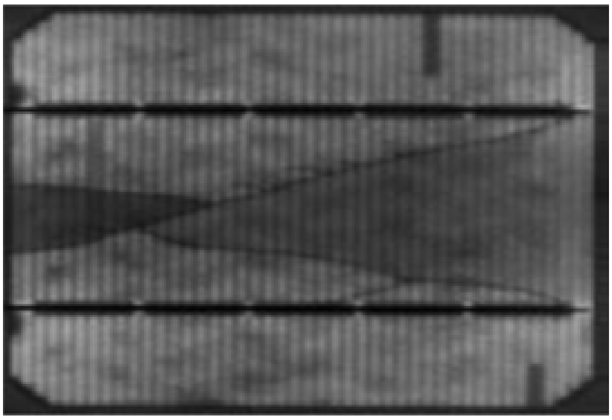


Figure II.11: EL Failure image Example [61]

4. **Thermography:** Thermography utilizes infrared imaging to measure surface temperatures of PV modules. Temperature variations across the module surface can indicate potential faults such as hot spots, cell defects, or shading effects. By identifying temperature anomalies, thermography provides insights into the thermal behavior of PV modules and helps pinpoint areas requiring further investigation or maintenance. like in Figure II.12.

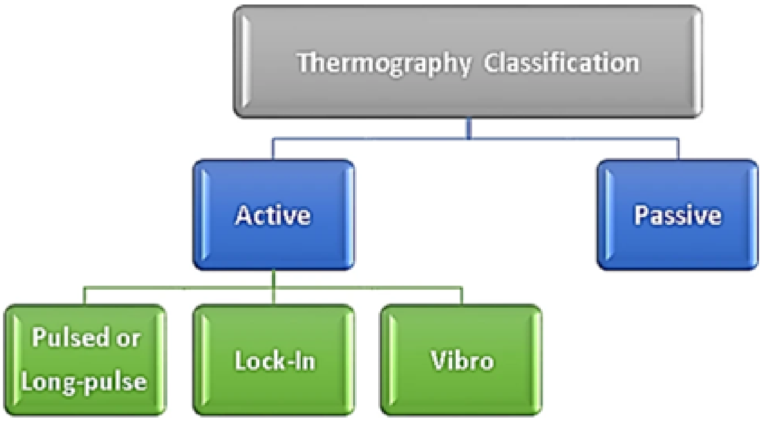


Figure II.12: Thermography techniques [61]

II.2.3-a Types of inference methods

Active model inference and passive model inference are two approaches used in fault diagnosis and system monitoring, each with distinct characteristics and applications.

- **Active Model Inference:**

  Active model inference involves actively interacting with the system under observation to gather data and make diagnostic decisions. In this approach, diagnostic tests or interventions are performed on the system to elicit specific responses or behaviours that help identify faults or anomalies. This proactive approach typically requires the system to be temporarily taken offline or subjected to controlled conditions for testing purposes.

  Key characteristics of active model inference include:

  1. **Intervention:** Active model inference involves active intervention or manipulation of the system to provoke responses that aid in fault diagnosis. This may include applying stimuli, changing operating parameters, or executing diagnostic procedures.
  2. **Real-time Testing:** Diagnostic tests are often conducted in real-time or near real-time to assess the system's performance and identify potential faults promptly.
  3. **Controlled Environment:** Active model inference may require the system to be operated under controlled conditions or subjected to specific test scenarios to isolate and replicate fault conditions accurately.
  4. **Higher Resource Requirements:** This approach may involve higher resource requirements, including specialized testing equipment, skilled personnel, and downtime for system testing or maintenance.

- **Passive model inference:**

  on the other hand, relies on observing the system's behaviour under normal operating conditions without actively intervening or perturbing the system. Instead of inducing specific responses, passive model inference analyses data collected from sensors or monitoring devices to detect patterns, anomalies, or deviations from expected behaviour indicative of faults.

Key characteristics of passive model inference include:

1. **Observation:** Passive model inference focuses on observing the system's behaviour passively without directly influencing its operation. Data is collected continuously or periodically from sensors embedded within the system or its environment.
2. **Anomaly Detection:** Passive model inference often involves anomaly detection techniques, where deviations from normal behaviour are identified based on statistical analysis, machine learning algorithms, or predefined thresholds.
3. **Continuous Monitoring:** Monitoring and data collection occur continuously or intermittently over time, allowing for the detection of transient faults, gradual degradation, or unexpected changes in system behaviour.
4. **Reduced Resource Requirements:** Passive model inference typically requires fewer resources compared to active model inference since it does not involve active intervention or specialized testing procedures. However, it still necessitates robust sensor infrastructure and data processing capabilities.

II.2.3-b Applications

- **Active Model Inference:** Common applications include diagnostic testing in laboratory settings, troubleshooting during system commissioning or maintenance, and validation of system models through controlled experiments.

- **Passive Model Inference:** Passive model inference is widely used in condition monitoring, predictive maintenance, and fault detection in various systems, including industrial machinery, power plants, and renewable energy systems like photovoltaic arrays.

In summary, active model inference and passive model inference represent two complementary approaches to fault diagnosis and system monitoring, each offering unique advantages and considerations depending on the specific application requirements and operational context.

The inference method in fault diagnosis has a set of advantages and disadvantages that should be considered when using it:

- **Advantages:**

  1. **Utilization of Expert Knowledge:** The inference method relies on expert knowledge and human expertise in analysing data and diagnosing faults. This allows for the inclusion of non-numeric information and leveraging practical experience in decision-making processes.
  2. **Priority Focus:** The inference method can prioritize attention towards high-priority faults by identifying critical faults that should be addressed first to improve system performance.

3. **Availability of Sufficient Data:** The inference method can be valuable when sufficient data about the system's condition and performance are available. This data can be used to analyse faults and guide maintenance actions effectively.
4. **Ease of Interpretation:** The inference method is easily interpretable and understandable, allowing supervisors and technicians to comprehend the reasoning behind the decisions made and the recommended actions.

- **Disadvantages:**

  1. **Expert Knowledge Constraints:** Results may be influenced by the expert knowledge constraints of the experts or technicians who have defined the rules and conclusions. Knowledge-based systems may lack the ability to deal with previously unknown cases.
  2. **Maintenance Complexity:** Updating and maintaining inference systems may be complex and require significant time and effort resources. Changes in rules or system updates may be necessary to keep up with changes in the system environment.
  3. **Noise and Error Impact:** Inference results may be susceptible to the impact of noise in the data or errors in the conclusions. This can lead to inaccurate decisions or ineffective actions for fault repair.
  4. **Parameterization and Maintenance:** The use of inference methods may require the correct parameterization and regular maintenance to ensure proper system performance and result accuracy. This can be a time-consuming and costly endeavor.

II.3 Conclusion

This chapter provides a comprehensive examination of various aspects of photovoltaic (PV) fault diagnosis, encompassing classification, detection, and identification through an extensive review of contemporary literature. The findings underscore the critical role of such diagnostic methods in safeguarding PV systems against potential losses in power, efficiency, and reliability. Notably, thermal imaging emerges as a pivotal tool within the PV Fault Detection and Diagnosis (FDD) methodology, offering a non-destructive and straightforward approach for effectively pinpointing and locating failures.

Furthermore, the investigation delves into a spectrum of computational methods employed in the analysis of PV system failures, encompassing both statistical techniques and artificial intelligence (AI) methodologies. This review elucidates a significant research avenue with potential for further advancement. Prospective research directions could concentrate on enhancing fault categorisation and refining the process of fault identification by leveraging hybrid configurations of deep learning models.

Chapter III

Simulation

Contents

III.1 Introduction

Photovoltaic (PV) systems, despite their increasing efficiency and reliability, are prone to various types of failures that can significantly impact their performance and longevity. These failures necessitate robust methods for diagnosing and detecting faults. In the previous chapter, we explored numerous diagnostic techniques, each with its own set of advantages and applications. Among these methods, the analysis of current-voltage (IV) and power-voltage (PV) characteristics stands out as one of the most prevalent and effective approaches for identifying electrical faults within PV systems. The IV and PV characteristics provide critical insights into the operational status of a PV system. By examining the relationship between current and voltage, and subsequently power and voltage, it becomes possible to pinpoint discrepancies that may indicate underlying issues. These diagnostic techniques are particularly valuable because they offer a non-invasive means of monitoring the health of a PV system, allowing for early detection and rectification of faults, thereby minimizing downtime and maintenance costs.

In this chapter, we will simulate a PV farm arranged in a 4x4 configuration under Standard Test Conditions (STC) using MATLAB SIMULINK. This simulation will serve as a practical demonstration of the impact of various faults on the system's performance. Through the simulation, we will examine how different fault conditions affect the IV and PV characteristics of the PV system.

By plotting the IV and PV characteristics under these conditions, we aim to illustrate the variations from normal operation, making it easier to understand the system's behaviour under fault conditions. This study will underscore the importance of continuous monitoring and timely fault detection in maintaining the optimal performance and safety of photovoltaic systems.

III.2 Photovoltaic cell parameters

the main construction unit of the PV system is the cell, here are the definitions of the PV cell parameters.

III.2.1 Open-Circuit Voltage (U_{oc})

Open circuit voltage is the voltage at the output of the PV panel (cell) without a connected load. It is the maximum voltage at the output, given the radiation intensity and temperature.

III.2.2 Short Circuit Current (I_{sc})

The short-circuit current is the maximum current that the cell can supply at the given radiation intensity to the temperature of the photovoltaic cell. It is thus equal to the current generated by the light $I_{sc} = I_L$, assuming that the resistance R_s is zero.

The open-circuit voltage, as well as the short-circuit current, changes with the temperature of the panel. Temperature affects the position of the operating point of the PV cell. With limited cooling of the PV cell or with prolonged exposure to solar radiation on the cell, the surface temperature of the PV cell can reach up to 80 °C at an air temperature of 40 °C. Such an increase in temperature significantly affects the electrical properties of the PV cell and there is a drop in the terminal voltage of the cell on its load characteristic. A drop in this voltage means a drop in the power supplied to the load. We can express the change in power by the relation.

$$\eta_{ef} = \frac{dP}{d\vartheta} \cong \frac{\Delta P}{\Delta \vartheta} = \frac{\Delta U \cdot \Delta I}{\Delta \vartheta} \tag{III.1}$$

Where ΔU is the change in PV cell voltage (V) and ΔI is the change in PV cell current (A). From the relations above, it follows that the change in the PV cell power depending on the temperature is most influenced by the change in its voltage, since the change in the current value is almost zero Figure III.1 and Figure III.2.

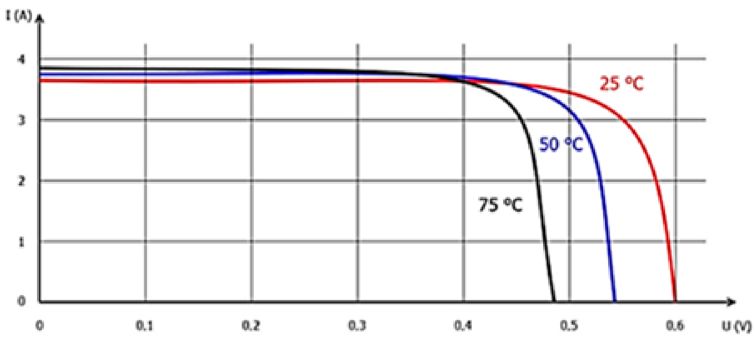


Figure III.1: Change in I-V characteristics due to temperature change

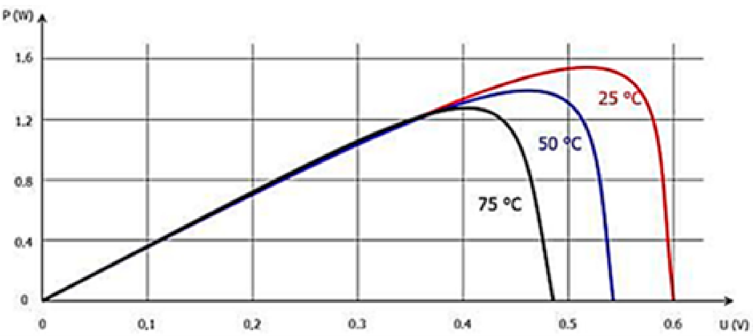


Figure III.2: Change in power characteristics due to temperature change

III.2.3 Maximum Power P_{MPP}

The main unit is W_p (Watt Peak). This is the maximum power that the panel is able to deliver under STC conditions. The value of the maximum power is given by the relation:

$$P_{MPP} = U_{MPP} \cdot I_{MPP} \tag{III.2}$$

The voltage at the Maximum Power Point (U_{MPP}) is where the panel operates at its highest power output, and similarly, the current at the Maximum Power Point (I_{MPP}) is where the panel achieves its peak power.

III.2.4 Effectiveness η

The maximum theoretically possible efficiency of direct conversion of light-solar radiation into electrical energy through solar cells with a P-N junction is about 30 %. The efficiency is given by the formula:

$$\eta_{ef} = \frac{P_{MPP}}{P_{rad}} = \frac{P_{MPP}}{E \cdot A_c} \tag{III.3}$$

where P_{rad} is the power of the incident radiation, E is the light intensity under standardized test conditions; A_c is the area of the photovoltaic cell.

III.2.5 Series Resistance R_s

It is an indicator of the quality of a PV cell. It is a parasitic resistance that is derived from the total resistance of the semiconductor material, the resistance of contacts and connections. A good cell should have the lowest R_s value, because its high value causes a voltage drop at the panel terminals.

III.2.6 Parallel Resistance R_p

In most cases, it is caused by extensive defects. Too low a R_p value indicates a poor PV cell that behaves almost in the manner of a short circuit. The resistance value should be as high as possible [62].

III.3 Photovoltaic module modelling

in order to accurately comprehend how a photovoltaic cell functions, a comparable model (Figure III.3) should be made from of components whose behavior is previously understood. An alternate design for a photovoltaic cell includes a current source with a diode and a resistor linked in parallel. The transient resistance is modeled by a resistor connected in series.

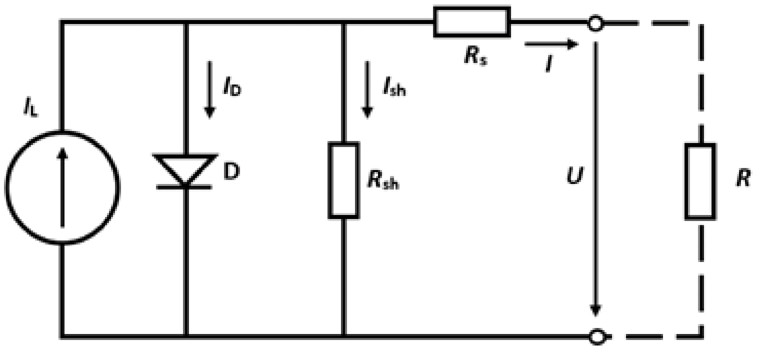


Figure III.3: PV cell module modelling

The current supplied by the photovoltaic cell to the load follows Kirchhoff's current law:

$$I = I_L - I_D - I_{sh} \tag{III.4}$$

This equation represents the full formulation of the photovoltaic cell current [30,31]:

$$I = I_L - I_s \left[\exp\left(\frac{U + IR_s}{nU_T} \right) - 1 \right] - \frac{U + IR_s}{R_{sh}} \tag{III.5}$$

The current flowing through the diode is denoted by I_D in the equation, the current created by radiation in the solar cell by current I_L, and the loss current traveling through the parallel resistance R_{sh} is denoted by current I_{sh}.

Local PN junction faults along the borders of the solar cells are the source of the parallel resistance, which has an endlessly high ideal value. Higher-grade cells have $R_{sh} = 300 - 400k\Omega$. Resistance R_s is a series resistance and the value of this resistance should be as low as possible; this resistance is caused by imperfections in the connections between individual cells. For high-quality cells, the R_s resistance is up to 0.10Ω.

The quantity indicates the ideality factor of the diode, and the value ranges from 1 to 2, The ideality factor n is assumed to have a constant value in the single-diode equation. The ideality factor actually depends on the voltage across the device. The ideality factor approaches unity at high voltage, when the bulk and surface regions dominate the recombination within the device.

At reduced voltages, on the other hand, the ideality factor becomes close to two and recombination in the junction takes over. By placing a second diode in parallel with the first and usually setting the ideality factor to two, the junction recombination is mimicked. Nevertheless, there will be two unknown diode quality factors if we choose a two-diode model to explain the behavior of diodes, bringing the total number of equations and unknown parameters to two (4).

The computations get more intricate as a result. In spite of this, at lower temperatures and irradiance, the two-diode model yields far more accurate curve features than the single diode model. Therefore, considering all aspects, the single diode model is faster and has less computational errors due to its less complex equation and fewer iterations. On the other hand, the two-diode model provides more precise and accurate characteristics under varying weather conditions with longer iterations and parameter calculations [62].

$$I = I_L - I_{s1} \cdot \left[\exp\left(\frac{U + IR_s}{n_1 \cdot U_T}\right) - 1\right] - I_{s2} \cdot \left[\exp\left(\frac{U + IR_s}{n_2 \cdot U_T}\right) - 1\right] - \frac{U + IR_s}{R_{sh}} \qquad \text{(III.6)}$$

III.4 The simulation of a 4×4 PV farm and the parameters

After the validation of the farm, we used a standard 4×4 PV farm and tested it under STC (standard test conditions), and down is the used configuration for a single PV module containing 60 PV cell as presented in MATLAB SIMULINK shown in (Table III.1):

Table III.1: PV user-defined parameters that have been used to build our PV module

Open circuit voltage V_{oc} (V)	36.3
Short circuit current I_{sc} (A)	7.84
Voltage at maximum power point V_{MPP} (V)	29
Current at maximum power point I_{MPP} (A)	7.35
Temperature coefficient of V_{oc} (% /deg.C)	0.036099
Temperature coefficient of I_{sc} (% /deg.C)	0.102
Light-generated current I_L (A)	7.8654
Diode saturation current L_0	$2.9273e^{-10}$
Diode ideality factor	0.98119
Shunt resistance R_{sh} (ohms)	313.0553
Series resistance R_s (ohms)	0.39381
Maximum power (W)	213.15
Cells per module (N_{cell})	60

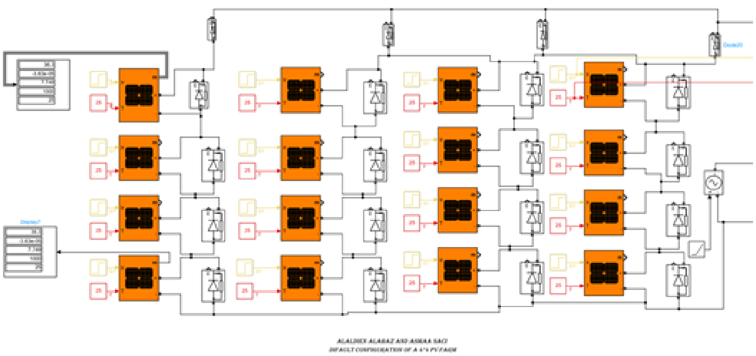


Figure III.4: (4×4) Built PV farm in SIMULINK in (STC)

A picture explains how the farm constructed with 4 modules in series between each module and another is a basic diode, there are 4 strings of 4 module connected with each other also with a diode in every upper node. the farm is off-grid in 25 C temperature and 1000 sun irradiance as in standard test conditions.

III.5 The validation of the user-defined PV cell

To validate the PV cell, the first choice is to build it and test it in a lab, however, due to unfortunate event we couldn't. the second choice is to make a cell in MATLAB Simulink by function blocks (Annexes) and applying equation and see the deference, below you'll see build PV cell IV and PV characteristics compared to the plotting from the PV build-in user-defined PV cell.

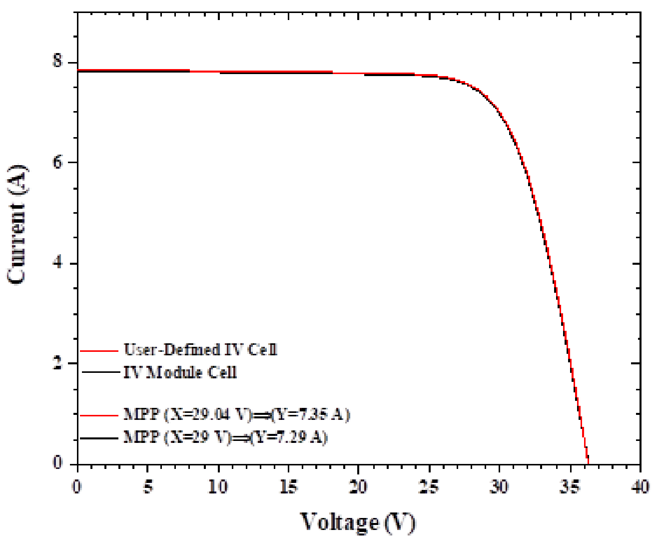


Figure III.5: I-V characteristics comparison between user-defined array and built PV array in (STC)

The red curves in both IV and PV plotting referred to build-in plots, the black is the PV is the valid cell which is our reference. By calculating the IV(corr):

$$IV(corr) = \left[1 - \frac{y_1 - y_2}{y_1}\right] \times 100\% = 1 - 0.00519 = 99.48\%$$

For PV(corr):

$$PV(corr) = \left[1 - \frac{y_1 - y_2}{y_1}\right] \times 100\% = (1 - 0.00823) \times 100\% = 99.177\%$$

For general corr :

$$ARV - PIV_{total} = \sum \left(\frac{CORR_{ixy}}{ixy}\right) = 99.328\%$$

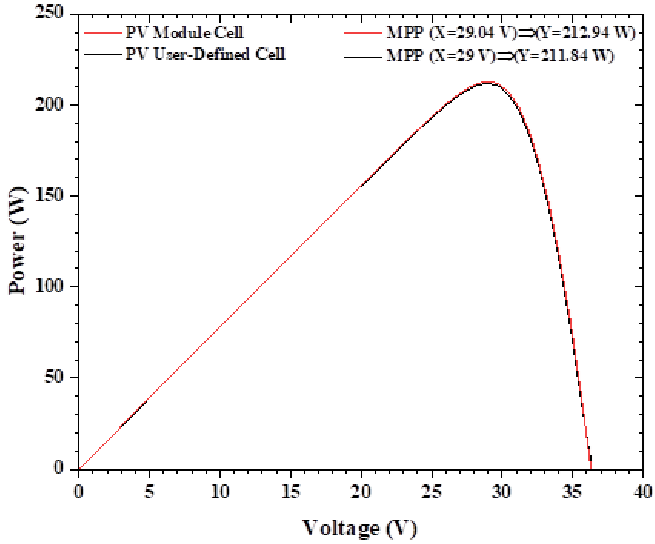


Figure III.6: P-V characteristics comparison between user-defined array and built PV array in (STC)

All calculation done by MATLAB for MPP comparison.

Validating an individual PV cell is enough because of the excellent results of similarity between that we've accomplished.

Table III.2: MPPs in the user-defined array V_s. MPPs in the validation built-in PV array

PV array Stats	Current MPP	Voltage MPP	Power MPP
user-defined PV array	7.29 A	29.00 V	211.84 W
Validation Built-in PV array	7.35 A	29.04 V	212.94 W

III.6 Faults effect simulation

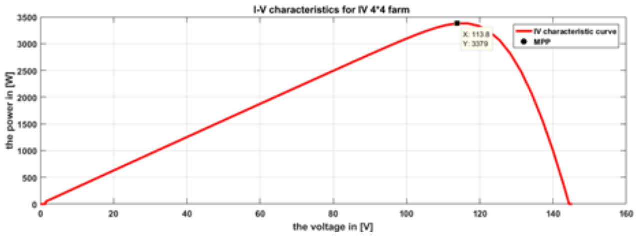


Figure III.7: I-V for PV 4×4 farm in normal conditions

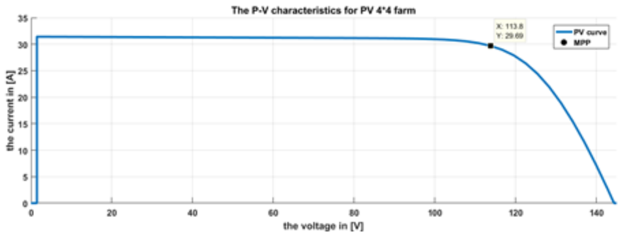


Figure III.8: P-V characteristics PV 4×4 farm in normal conditions

Table III.3: Max power, open circuit voltage and short circuit current for the PV farm in normal state

PMPP in (w)	U_{oc} in (v)	I_{sc} in (A)
3379.29	113.83	29.68

To see the effect on our output effectively we use the VI and PV characteristic plotting using workspace data that we extracted from the simulations off each case.

III.6.1 Partial shading

A PV array may experience partial shade when it is subjected to unequal radiation due to passing clouds, nearby structures, tall trees, and other factors.

When there is a partial shading defect (shown in the figure), the output power is reduced because one section of the PV array is shaded while the other is completely irradiated based on the current irradiation value.

III.6.1-a Case one

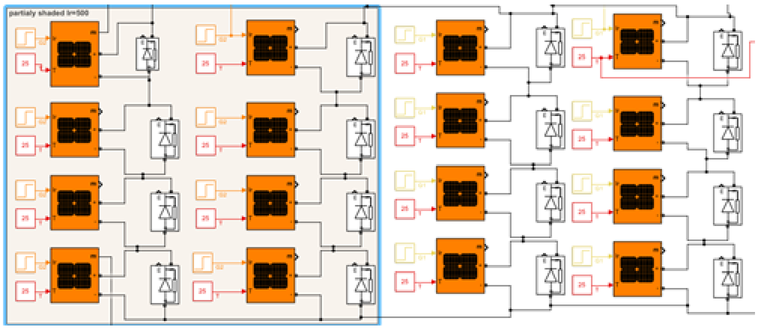


Figure III.9: First 2 columns partially shaded (500 Ir)

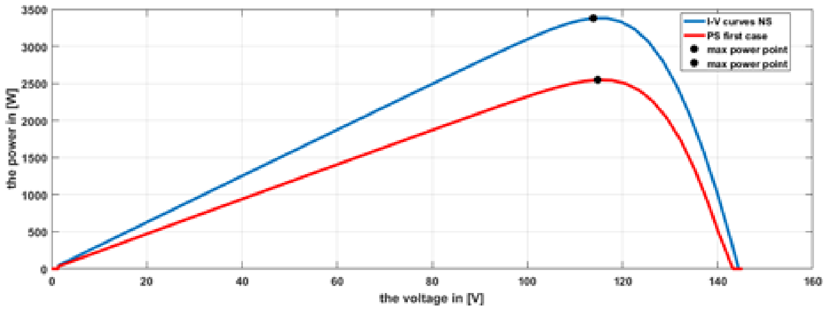


Figure III.10: I-V curves comparison between partial shading first case and normal state

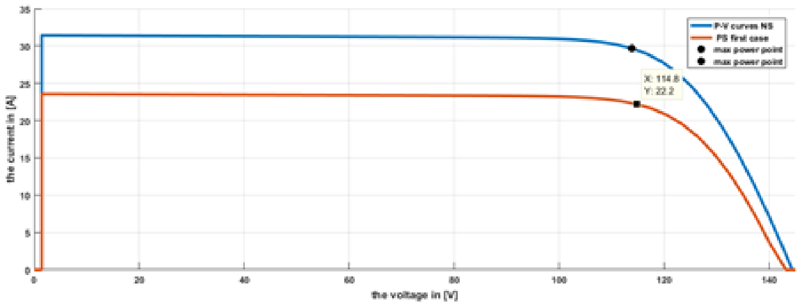


Figure III.11: P-V curves comparison between partial shading first case and normal state

The MPP current of the PV array clearly decreases when it is partially shaded, while the open-circuit voltage and short-circuit current of the PV array almost remain constant.

When analyzing defects, it is also necessary to consider the real irradiation value because it is always changing. So, the second time we changed the radiation value from 500 to 300 on the lower section of the effected as shown in the picture below.

III.6.1-b Case two

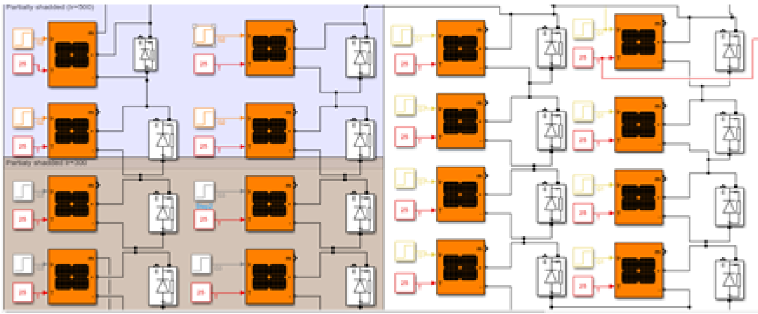


Figure III.12: first half of the first 2 columns partially shaded (500 I_r) and the second half (300 I_r)

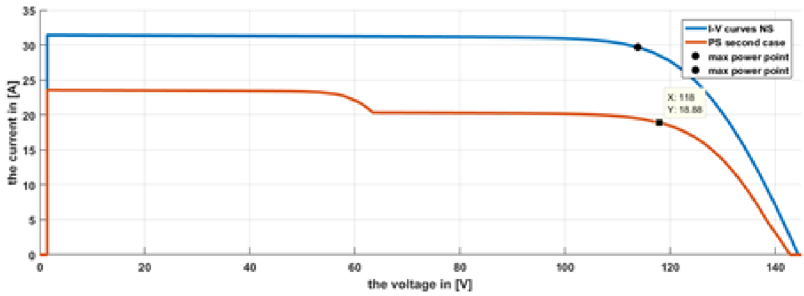


Figure III.13: I-V curves comparison between partial shading second case and normal state

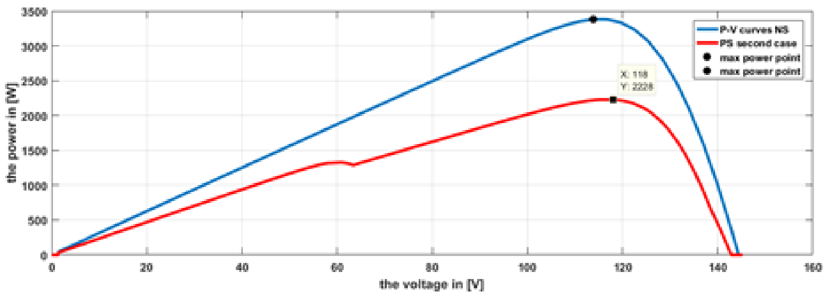


Figure III.14: P-V curves comparison between partial shading second case and normal state

III.6.1-c Discussion

When there is partial shading, the open-circuit voltage gradually drops as the number of shaded modules increases. Every shaded group's I-V curve has more than one step, equal to the number of solar insolation levels the string receives. The findings show that the position of the greatest PowerPoint is not independent of the number of solar modules in shadow and that the bigger the number of shaded solar modules, the lower the power output value.

The findings demonstrate that shade has an impact that cannot be disregarded and that it must be considered when installing solar systems. As a remedy, it is essential to choose the PV plants' locations, so suitable It should be highly beneficial to take the installation location's topography and geological conditions into account.

III.6.2 Bypass diode fault

Typically, a bypass diode is linked in parallel across several cells to enhance the solar system's performance under nonuniform conditions. Frequent usage or lightning strikes might cause a bypass diode to fail owing to thermal runaway. According to this study, simulation findings revealed bypass diode degradation.

Lightning strikes produce a reverse current from the working string to the failing string, producing heat and burning away the string. Furthermore, by quickly switching from the forward bias state to the reverse bias state, bypass diodes can degrade due to thermal runaway's high temperature. A study was published that details how a failure of the PV module might alter its electrical properties [12].

The diode is used for bypass. When solar cells are linked to a fault bypass diode, the failure bypass diodes lose their forward and reverse bias characteristics and turn into micro-resistance, placing them in a short circuit condition. In addition, new studies have shown that a junction box's temperature rises when a bypass diode shorts out while the photovoltaic system is turned off.

III.6.2-a Case One

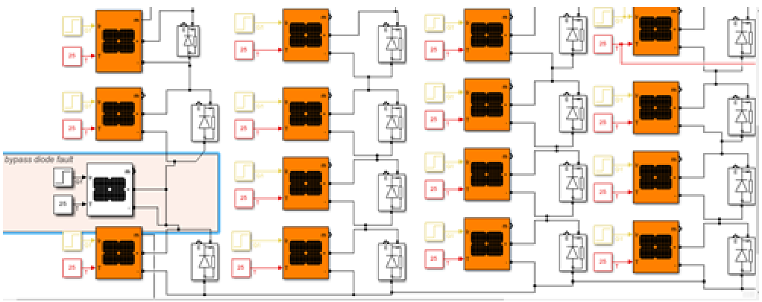


Figure III.15: One diode is eliminate

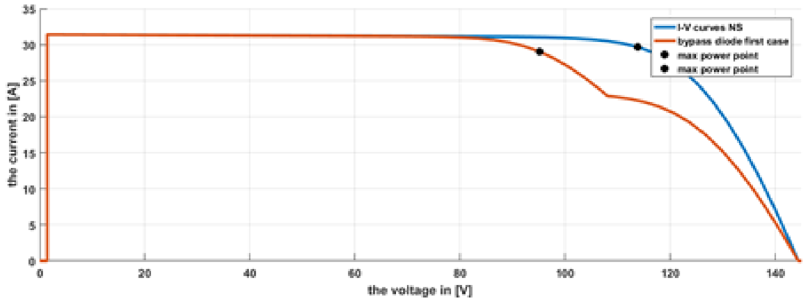


Figure III.16: I-V curves comparison between bypass diode first case and normal state

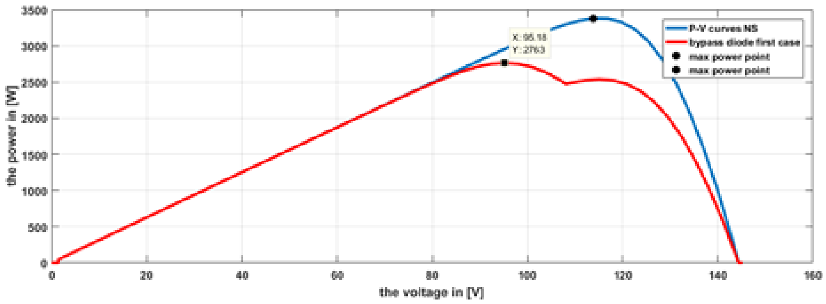


Figure III.17: P-V curves comparison between bypass diode first case and normal state

The maximum power and (U_{oc}) and (I_{sc}) of the PV array decrease even if only one complete module is shorted by a bypass diode.

III.6.2-b Case two

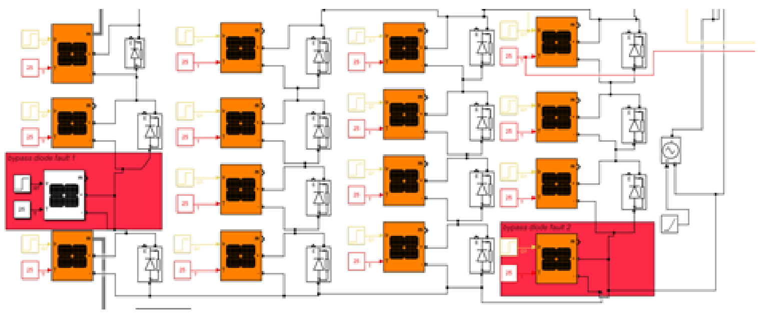


Figure III.18: two diodes from different columns are eliminated

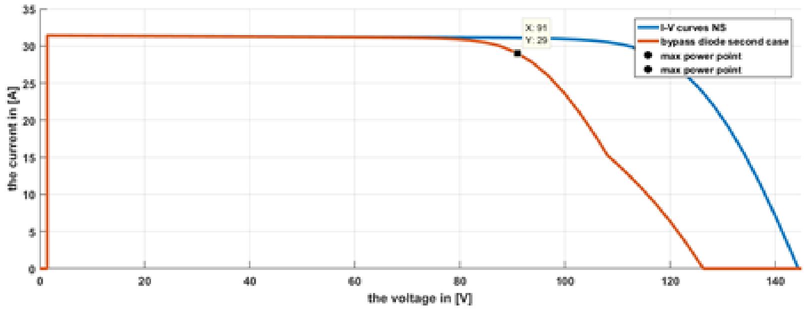


Figure III.19: I-V curves comparison between bypass diode second case and normal state

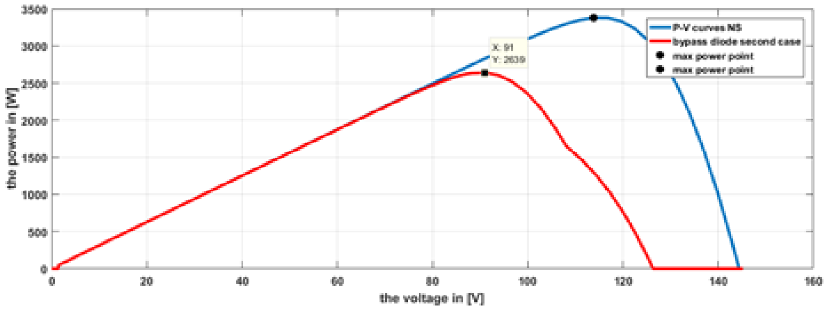


Figure III.20: P-V curves comparison between bypass diode second case and normal state

In the second case, the maximum power and U_{oc}, I_{sc} and P_{MPP} of the PV array drop dramatically.

III.6.2-c Discussion

These mismatch variables alter the PV modules' or strings' Maximum Power Point (MPP), which results in system output loss for the PV system. The PV array's maximum power and U_{oc} decrease dramatically even if only one complete module is shorted by a bypass diode, while the short-circuit current stays the same as in other regular strings.

III.6.3 Line-to-line fault

In PV array systems, line-to-line faults are symmetrical across strings. Low impedance between two distinct strings in the PV array is the result of several kinds of defects. It could occur inside photovoltaic arrays and entail dc arcs or a significant fault current.

An unintentional short circuit between two sites in the array with differing potentials is known as a line-to-line fault. The current flowing through the problematic string can be reversed by a line-to-line fault. The voltage differential between the locations of the strings that are creating the fault determines the amplitude of the fault current.

III.6.3-a Case one

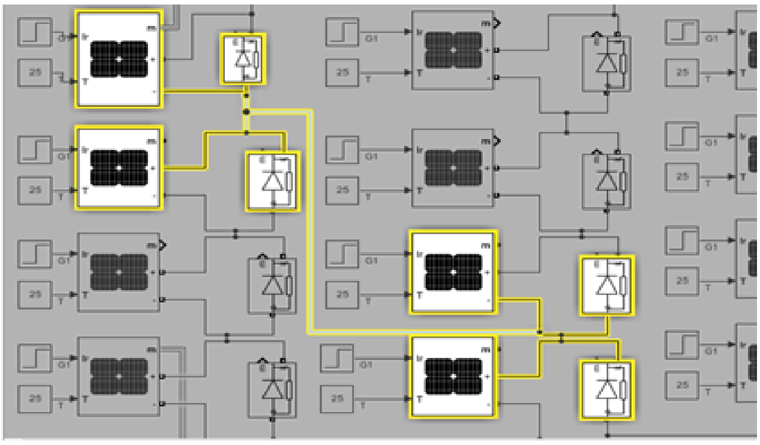


Figure III.21: Line-to-line between the first two columns

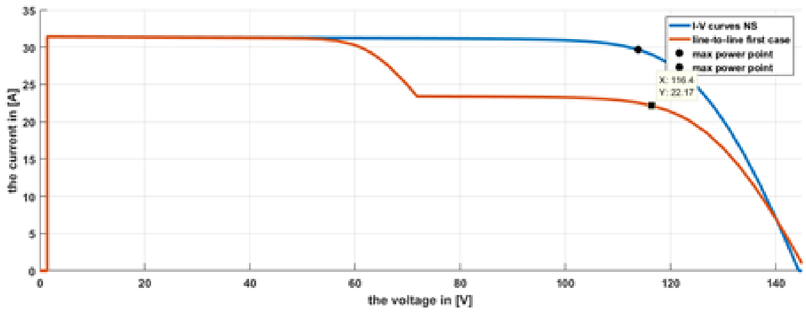


Figure III.22: I-V curves comparison between the line-to-line first case and normal state

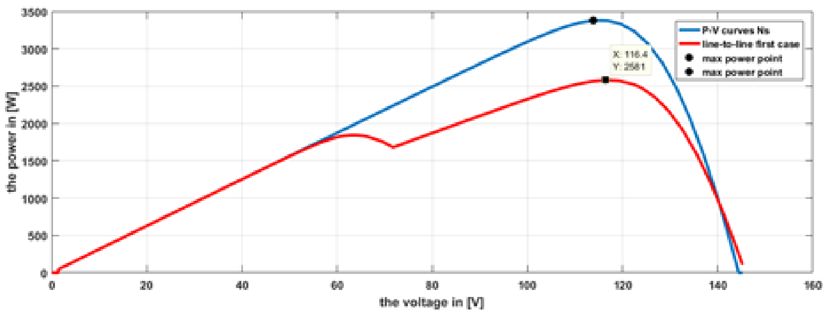


Figure III.23: P-V curves comparison between the line-to-line first case and normal state

Note that there is a drop in all of V, I and P in MPPs, almost after 55 Volts the curves varies from their normal state.

III.6.3-b Case two

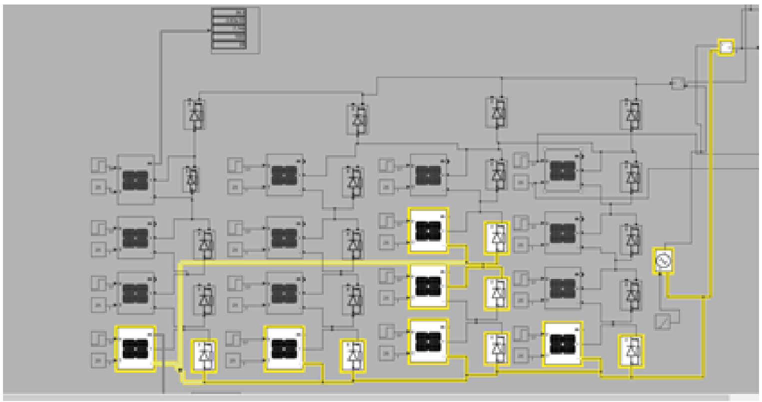


Figure III.24: Line-to-line between the last row and the third column

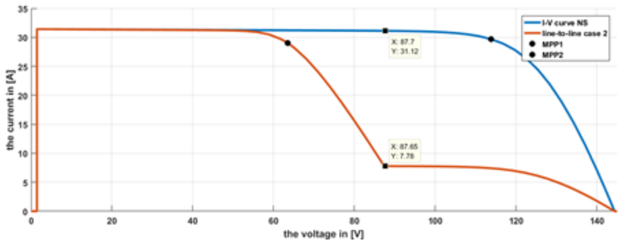


Figure III.25: I-V curves comparison between line-to-line case Two and normal state

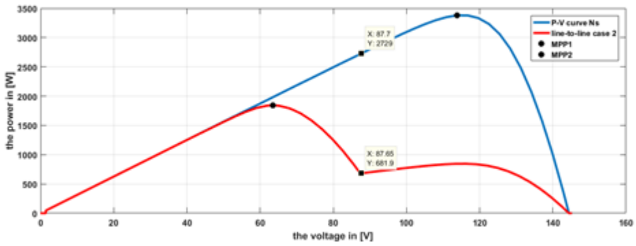


Figure III.26: P-V curves comparison between line-to-line case Two and normal state

In this case, there is a contact between the first and third columns, but also the affected area, as shown in (Figure III.24) above, includes the lower row of the PV farm, causing a significant drop in all the XY parameters.

III.6.3-c Discussion

Two cases: a line-to-line fault with two to two modules (mass between 3rd and 4th in 2nd column and 1st and 2nd in 1st column) (First case). A line-to-line fault with six modules

(The second case) is examined in the simulations. The I-V curve of the faulty PV string changes according to the line-to-line fault. $4 \times U_{oc}$ reduced the open circuit voltage of the faulty string. However, the short circuit current at (I_{sc}) remained the same as for the other strings.

III.7 Conclusion

In partial shading, we have two cases:

Case 1: the first two columns have a 500 I_r, which is 50 % of the typical conditions (NC), making a drop of power from 3379.29 W to 2547.91 W, which is about 75.39 % of the (PMPP) and 75.56 % of the original (I_{sc}) and a slight peak in voltage (+0.81 %).

Case 2: affecting the first two columns, but this time with different irradiances: 500 I_r for the upper part and 300 I_r for the lower part. It produces 65.93 % of power, 63.61 % of current and an increase in voltage by (+3.66 %); there is also a notable drop in curves after 54 V.

In the bypass diode:

Case 1: The elimination of the diode bypasses it, causing a sudden drop and a decrease in power and voltage, represented respectively by 81.76 %(W) and 83.61 %(V). The current is almost unaffected.

Case 2: Two diodes were eliminated, each one from a different column, power = 78.09 % and voltage (78.93 %), and the end voltage decreased from 144 to 126 V.

In line to line:

Case 1: a mass between two lines causes a big drop in both I-V and P-V curves starting with 54 V, the power, current, and voltage: 76.37 % W, 74.68 % A, and (+2.27 %) volts.

Case 2: A huge drop completely changes the curve with a 54.52 % MPP, 55.78 % voltage, and 97.74 % current.

Conclusion general and perspectives

This memoir provides a comprehensive examination of photovoltaic (PV) systems through the creation, validation, and simulation of a PV array and farm. The research began with developing a PV array consisting of 60 cells connected in series, which was meticulously validated to ensure accuracy and reliability. Following the successful validation of the array, a 4x4 PV farm was constructed to enable broader analysis and provide a real-world context for studying fault scenarios. The simulations conducted in this study focused on three common faults: partial shading, bypass diode failure, and line-to-line faults. These faults were analysed regarding their impact on the farm's performance, comparing its operation under fault conditions with its performance under standard test conditions (STC). This approach allowed for a detailed understanding of how these faults affect both the short-term and long-term functioning of PV systems.

The effects of each fault on the system's performance were systematically assessed and quantified by applying signal processing methods, particularly through I-V and P-V curve analysis. These methods provided clear insights into how each fault impacts critical performance indicators such as energy output, efficiency, and overall system health. The results of the simulations demonstrated the critical impact these faults can have on the PV system's efficiency and operational lifespan. This emphasises the essential role of effective fault detection and diagnosis (FDD) in maintaining the long-term functionality of solar energy systems. Common faults like partial shading or bypass diode failure without proper and timely FDD can lead to significant efficiency losses, equipment degradation, and increased maintenance costs. Proactive FDD approaches are thus crucial for minimising downtime, preventing further damage, and ensuring that PV systems operate at their optimal capacity.

Looking toward future improvements, the integration of advanced technologies offers significant opportunities to further enhance the efficiency, reliability, and overall performance of PV systems. One promising advancement is the adoption of moving tracking systems. These systems allow the PV panels to adjust their alignment with the sun's position continuously, optimising the angle of incidence and thereby significantly improving energy capture throughout the day. In addition, optimising the tilt and orientation of panels based on geographic location is another key strategy for maximising energy yield. This is particularly important in fixed installations, where factors such as latitude and seasonal sunlight changes must be carefully considered to ensure year-round efficiency. When selecting installation sites, prioritising areas with high sunlight exposure, such as deserts or open fields, would maximize energy production. However, urban rooftop installations can also be a cost-effective solution, utilising underused space for clean energy generation.

Panel selection and maintenance are also vital to optimising performance. Regular cleaning is essential to prevent dust or pollution from reducing energy output. Monocrystalline panels are ideal for installations where space is limited due to their higher efficiency, while bifacial panels can increase energy generation in reflective environments like snowy or sandy areas. Hybrid systems, which combine PV with other renewable energy sources, and the integration of energy storage solutions, such as batteries, can enhance reliability and ensure a stable energy supply even during low sunlight periods.

Looking ahead, future research could focus on the integration of the Internet of Things (IoT) and edge computing for remote monitoring and fault diagnosis in PV systems. These technologies would allow for real-time data collection and analysis, reducing response times to issues and preventing failures. Additionally, saving and uploading monitoring data could support the development of machine learning (ML) or neural network (NN) models, which could analyse the data to predict faults before they occur, paving the way for more efficient predictive maintenance strategies.

In conclusion, this memoir underscores the critical importance of effective fault detection and management in photovoltaic systems. Through the use of advanced technologies and proactive maintenance strategies, the efficiency, reliability, and cost-effectiveness of PV systems can be significantly improved. As the field continues to evolve, embracing innovations such as IoT, predictive maintenance, and optimised panel technologies will be essential in meeting the growing global demand for clean and sustainable energy. By advancing both the technical and operational aspects of PV systems, the future of solar energy is poised for continued growth and innovation, contributing to a more sustainable energy landscape for generations to come.

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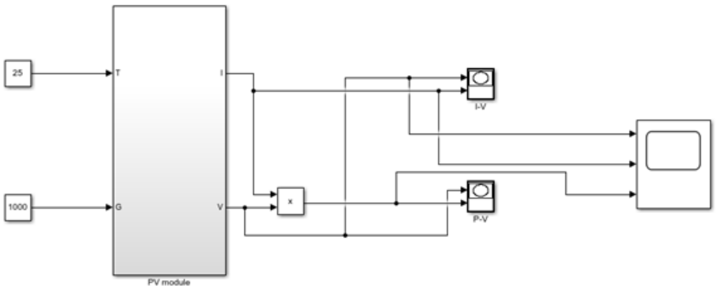

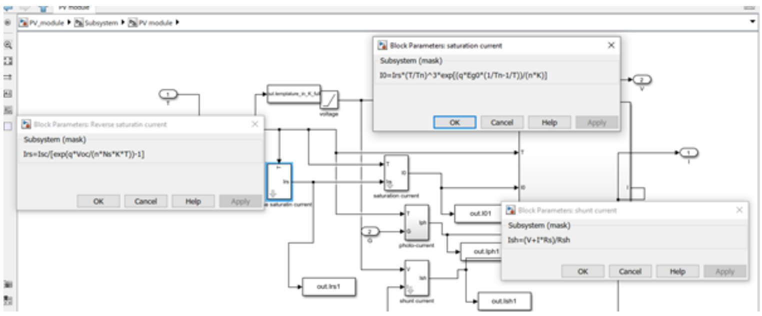

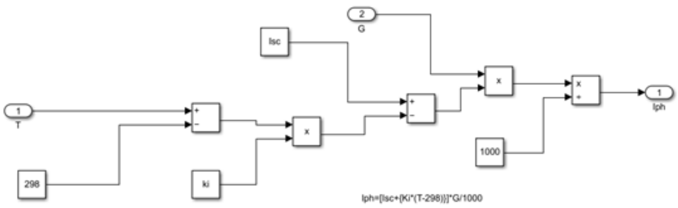

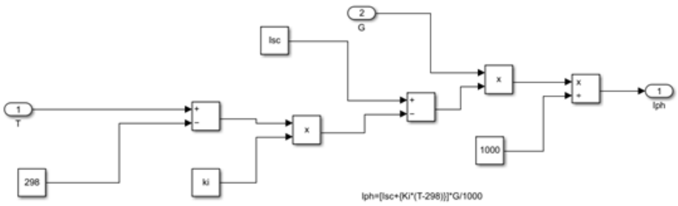
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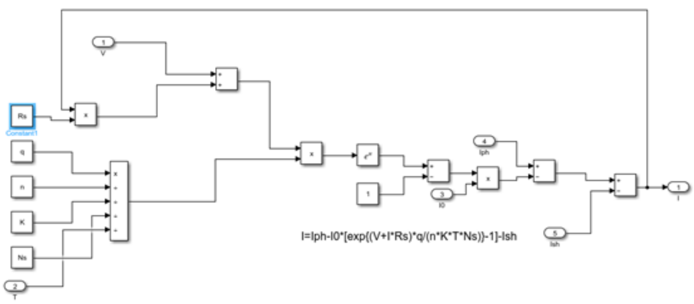
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Abstract:

This memoir explores the simulation and analysis of photovoltaic (PV) systems, focusing on fault detection and diagnosis (FDD). Chapter 1 provides an overview of PV systems, including their history, types of PV cells, and operational principles. Chapter 2 categorises FDD methods into signal processing, AI techniques, and inference methods, discussing their applications, benefits, and limitations. Chapter 3 details the creation and validation of a custom PV array (60 cells) and the development of a 4x4 PV farm. It includes simulations of three fault scenarios (partial shading, bypass diode failure, and line-to-line faults), each evaluated under two cases. Signal processing methods (I-V and P-V curve analysis) assess performance differences between normal and faulty states. The findings highlight the impact of faults on PV system efficiency and provide recommendations for improved fault detection.

Keywords: Photovoltaic, FDD, partial shading.

Résumé:

Ce mémoire explore la simulation et l'analyse des systèmes photovoltaïques (PV), avec un accent sur la détection et le diagnostic des défauts (FDD). Le Chapitre 1 présente un aperçu des systèmes PV, y compris leur histoire, les types de cellules PV, et les principes de fonctionnement. Le Chapitre 2 catégorise les méthodes de FDD en traitement du signal, techniques d'IA et méthodes d'inférence, en discutant de leurs applications, avantages et limitations. Le Chapitre 3 détaille la création et la validation d'un réseau PV personnalisé (60 cellules) et le développement d'une ferme PV 4x4. Il comprend des simulations de trois scénarios de défauts—ombrage partiel, défaillance de la diode de contournement, et défaut ligne-à-ligne—chacun évalué sous deux conditions. Des méthodes de traitement du signal (analyse des courbes I-V et P-V) sont utilisées pour évaluer les différences de performance entre les états normal et défectueux. Les résultats soulignent l'impact des défauts sur l'efficacité des systèmes PV et fournissent des recommandations pour une meilleure détection des défauts.

Mots clés : Photovoltaïque, DDP, ombrage partiel.

الملخص:

تستكشف هذه الأطروحة محاكاة وتحليل الأنظمة الكهروضوئية، مع التركيز على اكتشاف الأخطاء وتشخيصها (FDD). يقدم الفصل الأول نظرة عامة على الأنظمة الكهروضوئية، بما في ذلك تاريخها وأنواع الخلايا الكهروضوئية ومبادئ التشغيل. يصنف الفصل الثاني أساليب FDD إلى معالجة الإشارات، وتقنيات الذكاء الاصطناعي، وطرق الاستدلال، ويناقش تطبيقاتها ومزاياها وقيودها. يعرض الفصل الثالث تفاصيل إنشاء مجموعة كهروضوئية مخصصة (60 خلية) والتحقق من صحتها وتطوير مزرعة كهروضوئية (4*4) ويتضمن محاكاة لثلاثة سيناريوهات للخطأ - التظليل الجزئي، وفشل الصمام الثنائي الالتفافي، والخطأ من خط إلى خط - يتم تقييم كل منها في ظل حالتين مختلفتان. تُستخدم طرق معالجة الإشارة (تحليل المنحنى I-V وP-V) لتقييم اختلافات الأداء بين الحالات الطبيعية و حالة كل خطأ. تسلط النتائج الضوء على تأثير الأخطاء على كفاءة الأنظمة الكهروضوئية وتقدم توصيات لاكتشاف الأخطاء بشكل أفضل.

الكلمات المفتاحية: الخلايا الكهروضوئية، كشف وتشخيص الأخطاء، التظليل الجزئي.