ESJ Natural/Life/Medical Sciences Peer-reviewed

Design and Implementation of a Detection and Diagnostic System for Anomalies in a Grid-Connected Photovoltaic System

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Doi:10.19044/esj.2026.v22n6p33

Submitted: 13 January 2026
Accepted: 24 February 2026
Published: 28 February 2026

Cite As:
Kani Mboyo, U.V., Mankiti Fati, A. & Samba, R.E.J. (2026). *Design and Implementation of a Detection and Diagnostic System for Anomalies in a Grid-Connected Photovoltaic System.* European Scientific Journal, ESJ, 22 (6), 33. https://doi.org/10.19044/esj.2026.v22n6p33

Abstract

This paper presents the design and implementation of a detection and diagnostic system for anomalies in a photovoltaic (PV) installation connected to the national EEC grid in Congo Brazzaville, under the framework of Denis SASSOU NGUESSO University. The main objective is to reduce maintenance costs and improve energy productivity, given that PV systems are inherently prone to operational failures. The study focuses on faults affecting the PV generator and proposes a method for detecting and precisely localizing anomalies that reduce energy output. The approach is based on analyzing the current–voltage (I–V) and power–voltage (P–V) characteristics of the PV generator under varying operating conditions. Results, summarized in tables for clarity, demonstrate that the Lambert W/numerical model accurately reproduces the module's electrical behavior, with a root mean square error (RMSE) of 0.1608 A for current (≈2 % of nominal current, 8 A) and 3.686 W for power (≈1.2 % of maximum power, 300 W). These low and unbiased errors validate the model for rapid performance drift detection, fault localization, and operating point optimization. The system provides a solid foundation for intelligent supervision and predictive maintenance, ensuring enhanced reliability, reduced downtime, and improved energy efficiency.

ISSN: 1857-7881 (Print)
e-ISSN 1857-7431 (Online)

Keywords: Photovoltaic generator, modeling, diagnostic, real-time simulation

Introduction

Background Review

In an effort to provide a scientific contribution to the challenges of photovoltaic (PV) systems in Africa in general, and in Congo Brazzaville in particular, this work focuses on the prevention of failures, malfunctions, and maintenance, whose costs remain particularly high. While several researchers are already engaged in this research area, our approach aims to provide a specific contribution anchored in the African context.

Over the past decade, the photovoltaic sector has experienced remarkable growth, driven by the progressive reduction in production costs and public policies promoting renewable energy (I.E. Al-Shetwi, 2025), (Photovoltaique.info). These developments have made PV installations increasingly attractive to both investors and end-users, due to a more favorable return on investment (Mikael, 2025).

However, like any industrial system, PV installations remain exposed to various faults and anomalies that can degrade performance or even cause complete system downtime (Benzagmout, 2021). Such malfunctions directly impact energy productivity, economic profitability, and associated maintenance costs (Djallel et al., 2020). In response to these challenges, the implementation of reliable and efficient diagnostic systems has become both an operational and strategic necessity (Bari, A. & Jarwar, 2025).

An effective diagnostic system must not only detect faults quickly but also locate them precisely, thereby reducing downtime and intervention costs (Achour, 2025). It is within this context that (Sepúlveda-Oviedo, 2023) was initiated, and the work presented in this thesis constitutes a direct contribution (Venkatakrishnan,2023). The primary objective is to design an integrated system capable of supervising, diagnosing, and optimizing the operation of PV installations, while remaining transparent to the end-user (Alosmani, 2023).

This research specifically focuses on the detection and localization of faults on the direct current (DC) side of the system, i.e., at the level of the PV generator. The adopted approach aims to minimize the number of required measurements, thereby respecting economic constraints while ensuring maximum efficiency (Benzagmout, 2021; Tahraoui, 2023). Currently, several monitoring systems measure power and energy output using voltage and current sensors (Guide Photovoltaïque, 2025). Some services go further by correlating production with meteorological data, such as satellite-measured solar irradiance (Tahraoui, M. et al, 2023). Although useful, these tools present

ISSN: 1857-7881 (Print)
e-ISSN 1857-7431 (Online)

notable limitations: they neither allow rapid detection nor precise localization of faults at their onset (Axiome energie, 2025).

In this context, we propose a methodology based on system modeling to characterize the current–voltage (I–V) and power–voltage (P–V) curves of the PV generator under different operating modes. Subsequently, a PV panel is simulated by integrating power failures, i.e., operational errors, and a corrective measure is proposed using the Lambert W model. This approach aims to strengthen diagnostic robustness and improve the overall reliability of the supervision system. In continuation of the research on photovoltaic systems, it was also essential to review the studies conducted by our predecessors in order to identify and refine the focus of our own investigation.

In the current context of energy transition, photovoltaic (PV) systems play a central role in renewable electricity generation. Their large-scale deployment is driven by undeniable advantages such as low operating cost, durability, modularity, and reduced environmental impact. However, despite their apparent reliability, PV installations remain vulnerable to various faults that can degrade performance. If not detected in time, these anomalies may lead to significant energy losses, service interruptions, or irreversible component damage. Consequently, research has intensified on advanced diagnostic methods aimed at improving the supervision, maintenance, and resilience of PV systems.

Several studies have proposed approaches based on electrical analysis of the PV generator, particularly through the current–voltage (I–V) characteristic. Benzagmout et al. (2021) developed a knowledge base linking each fault type to a specific I–V signature. Their discrete inference algorithm achieved more than 90% accuracy in anomaly detection and localization, which is highly relevant for grid-connected plants. However, the reliability of this method depends heavily on measurement quality, which can be difficult to obtain in real time without specialized instrumentation.

Djallel et al. (2020) adopted a comparative approach, evaluating different detection techniques through fault simulations. Neural network–based methods proved particularly effective for complex and nonlinear faults. Artificial intelligence enables automatic classification of symptoms and offers adaptability in dynamic environments, though it requires training on representative datasets, limiting applicability in poorly instrumented contexts.

Alosmani et al. (2023) proposed a hybrid approach combining thermal and electrical modeling with inference techniques. Their method improved energy yield by an average of 12% on tested sites, confirming the value of integrating physical data for refined diagnostics. Nevertheless, implementation remains complex and resource-intensive, which may hinder adoption in low-infrastructure settings.

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Spectral analysis of power curves was explored by Kouadri et al. (2022) to detect partial shading faults common in urban environments. This method achieved rapid detection with less than 5% error, useful for rooftop or dense-area installations. However, it is less effective for internal defects such as microcracks or cell degradation.

Achour et al (2024) developed low-cost monitoring systems using microcontrollers such as Arduino. These devices enable real-time data acquisition and local processing, reducing supervision costs. Pilot sites reported a 30% reduction in maintenance costs, demonstrating effectiveness for rural or domestic micro-installations. Yet, limited computational and storage capacity restricts their use in complex analyses or large-scale systems.

Tahraoui et al. (2022) analyzed transient responses of PV systems using MATLAB/Simulink simulations to localize faults with an error margin below two meters. This approach is relevant for large plants with extensive cabling but is sensitive to electromagnetic disturbances.

Khan et al. (2023) applied convolutional neural networks to thermal images, achieving fault recognition rates above 95%. This method is well-suited for drone-based inspections, enabling fast and non-intrusive monitoring. However, its effectiveness depends on image quality and lighting conditions.

Mikael et al. (2025) studied correlations between PV production and satellite meteorological data. By analyzing monthly deviations between expected irradiation and actual production, they identified hidden anomalies. This approach supports remote supervision of isolated installations, though the limited temporal resolution of satellite data restricts real-time diagnostics.

Overall, the reviewed studies highlight the diversity of approaches developed to enhance PV system reliability, ranging from electrical analysis and image processing to thermal modeling and artificial intelligence. Most methods face limitations related to implementation complexity, data dependency, or environmental conditions. Current trends point toward hybrid systems that combine multiple information sources and integrate intelligent algorithms capable of adapting diagnostics to real-world conditions. These works provide a solid foundation for advanced supervision solutions such as the DLDPV system presented in this thesis, which aims to deliver rapid, localized, and economically viable fault detection on the DC side.

Methodology

Review of fundamental concepts

Structure of a photovoltaic system

A photovoltaic (PV) system is responsible for converting solar photon energy into usable electrical energy for various applications. The system consists of a **PV cell** that produces direct current (DC), converters for adapting

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and conditioning the power, batteries for energy storage, and charge controllers to regulate and protect the system.

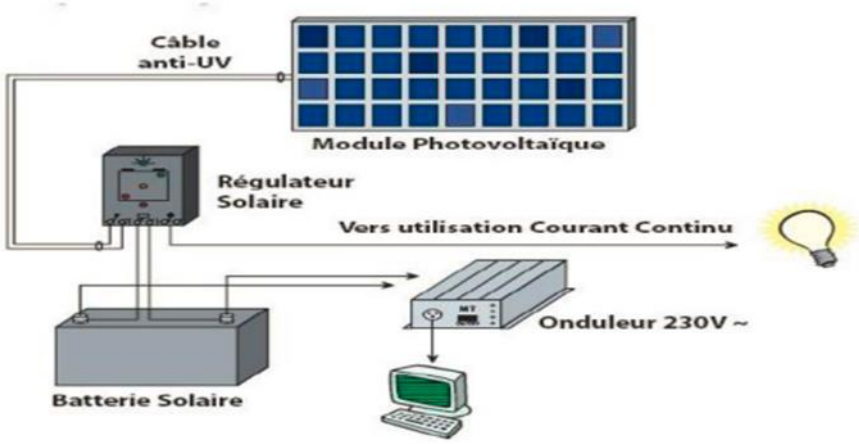

Figure 1: Structure of a Photovoltaic (PV) System

Photovoltaic generator

The photovoltaic (PV) **cell** is the unit responsible for producing electrical energy in the form of direct current (DC). The fundamental component that converts solar energy into electrical energy is the photovoltaic cell (A. Luque et al., 20211).

Photovoltaic cell

The photovoltaic cell is a semiconductor device, generally silicon-based, formed from two layers, one N-doped and the other P-doped, creating a PN junction (Bari, A. & Jarwar, 2025). It is the smallest constituent of a photovoltaic system, responsible for producing electricity from solar energy based on the principle of the photovoltaic effect.

Photovoltaic module

A single **PV cell produced** low power, insufficient for common applications. To produce usable power, multiple cells are interconnected either in series (to increase voltage at constant current) or in parallel (to increase current at constant voltage). A series grouping of these elementary components forms a PV module, which must be mechanically protected to withstand outdoor conditions. Since PV cells are fragile and sensitive to corrosion, the module ensures durability against humidity and temperature variations (Khaled Alosmani, 2023).

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Batteries

A solar battery stores electrical energy and releases it when demand exceeds PV production (e.g., at night or during insufficient sunlight). It ensures a quasi-continuous energy supply.

Charge controllers

The charge controller links the **PV cell** to the battery. It protects the battery against overcharging or deep discharging, making it essential for preserving battery lifetime (Bari, A. & Jarwar, 2025).

Conversion systems

An energy converter is installed either between the PV panel and the load (in systems without storage, using DC/DC converters) or between the battery and the load (using inverters or DC/AC converters) (Bari, A. & Jarwar, 2025).

DC/DC Converter

The DC/DC converter controls energy flow between the solar panel and the load. It adapts the apparent load impedance to the PV array impedance at the maximum power point. This adaptation system is commonly known as Maximum Power Point Tracking (MPPT) (Bari, A. & Jarwar, 2025).

DC/AC Converter (inverter)

The inverter is a key component of PV installations. It converts DC energy from PV modules into AC energy, either for local use or grid injection. In standalone systems (not connected to the public grid), inverters generate a 220 V, 50 Hz AC signal to create a local network. They can be combined with charge controllers and batteries to store energy for later use when PV production decreases (Bari, A. & Jarwar, 2025).

Grid-connected PV installation with surplus injection

This configuration allows users to produce their own electricity during sunny periods and feed surplus energy into the public grid, from which they can draw power when needed (Souaad Tahraoui, 2023).

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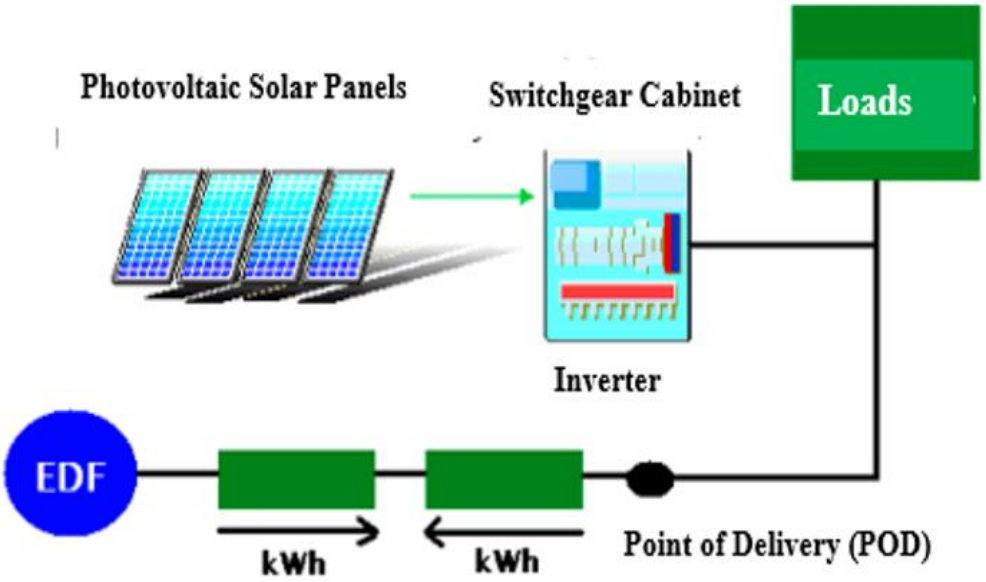
Figure 2: Grid-Connected Photovoltaic Installation with Surplus Energy Injection



(Souaad Tahraoui, 2023)

Figure 2 illustrates the schematic of a grid-connected photovoltaic installation integrating a surplus injection mechanism. The system includes two distinct meters: the first records the amount of electricity purchased by the photovoltaic panel (PV) owner from the energy supplier, while the second measures the energy reinjected into the grid when production exceeds local consumption (Souaad Tahraoui,2023).

Defects in photovoltaic panels

During operation, a photovoltaic installation may be subject to various faults or abnormal operating conditions (A. Luque et al,20211). These anomalies can affect the overall performance of the system and compromise its energy reliability.

The most common and significant defects are classified according to the affected PV system component(A. Luque et al,20211):

- ✓ **PV array:** defects related to **PV cells**, such as microcracks, hot spots, or surface degradation;
- ✓ **junction Box:** anomalies affecting protection devices, particularly when multiple strings are connected in parallel;
- ✓ **cabling and Connectors:** insulation, connection, or continuity faults that may disrupt the series association of modules;
- ✓ **protection Diodes:** failures of bypass or blocking diodes, leading to power losses or overheating risks.

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Table 1: Origin of Faults and Anomalies in a Photovoltaic System

PV System Element	Origin of Faults and Anomalies
PV Generator	- Tree leaves, bird droppings, pollution, sand, snow, etc. - Cell deterioration, cracks, cell overheating - Moisture penetration, interconnection degradation, corrosion of cell links - Modules with different performance levels - Torn or broken module - Short-circuited or reversed modules
Junction Box	- Electrical circuit break - Electrical short circuit - Connection destruction - Corrosion of connections
Cabling and Connectors	- Open circuit - Short circuit - Incorrect wiring (reversed module) - Contact corrosion - Electrical circuit break
Protection Diodes (Bypass and Blocking Diodes)	- Diode destruction - Absence or malfunction of diodes - Incorrect polarity during installation, poorly connected diode

(Photovoltaique.info, 2025)

Table 2: Defects of PV Field Components

PV Field Component	Nature of Defects	Defect Classification
Cell	- Torn or broken module - Shading from pylons, chimneys, sand, snow, etc. - Cell overheating - Interconnection degradation - Cracks - Corrosion of cell links - Modules with different performance levels - Cell deterioration - Moisture penetration	Mismatch and shading defect
Cell Groups	- Diode destruction - Absence of diodes	Bypass diode defect

(J. Cubas et al, 2014)

This table highlights the main defects observed in photovoltaic modules, particularly at the cell and cell-group levels. Most anomalies originate from environmental factors (sand, snow, humidity, shading) or physical degradation (cracks, corrosion, overheating). These defects lead to performance losses, mismatches between cells, and failures in protection diodes, which can significantly affect the overall energy production of the PV system.

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Table 3: Classification of Defects in a Photovoltaic Field

PV System Component	Identified Defects	Defect Category
Diodes	- Polarity inversion - Incorrect connection - Short-circuited diode	Diode defect
Modules	- Short-circuited modules - Module polarity inversion - Shunted modules	Module defect
Strings	- Electrical circuit break - Connection destruction - Connection corrosion - Contact corrosion - Circuit short circuit - Disconnected module	Connectivity defect
PV Field	- Diode destruction - Absence of diodes - Diode inversion - Incorrect connection - Short-circuited diode	Anti-return diode defect

(J. Cubas et al, 2014)

This table presents the main defects observed in a photovoltaic field according to system components: diodes, modules, strings, and the PV field. The identified failures mainly involve polarity inversions, short circuits, poor connections, and corrosion. These defects can lead to performance degradation, loss of electrical continuity, or material damage. Such classification facilitates detection, diagnosis, and preventive maintenance of PV installations.

Diagnostic methods

In the analysis of photovoltaic (PV) installations, two essential diagnostic functions must be distinguished: **fault detection** and **fault localization**. Some methods are limited to identifying the presence of anomalies, while others allow precise localization of their origin. This distinction is fundamental for guiding maintenance interventions and optimizing system reliability. This section presents the main diagnostic methods used in the PV industry, as well as those proposed in scientific literature (A. Luque et al, 2021).

Infrared imaging method

Among diagnostic techniques applied to PV cells, several approaches identify defects such as cracks or internal degradation. Mechanical bending tests, photoluminescence imaging, and electroluminescence provide fine visualization of structural alterations. For PV modules, infrared imaging (thermal camera) is widely used. This method relies on the principle that all

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e-ISSN 1857-7431 (Online)

materials emit infrared radiation proportional to their temperature. By analyzing the thermal distribution on the module surface, localized anomalies can be detected. Defects identified through this technique include(Mikael,,2025):

- ✓ Leakage currents in cells;
- ✓ Increased resistance of cell interconnections;
- ✓ Abnormal heating due to internal defects;
- ✓ Unintended conduction of bypass diodes.

These results confirm the effectiveness of thermal imaging for rapid and non-intrusive localization of PV module defects.

Reflectometry

Reflectometry is a non-intrusive diagnostic method that injects a signal into a circuit and analyzes reflections caused by discontinuities or impedance variations. Applied to PV strings, it detects faults such as open circuits, short circuits, or impedance anomalies. Its experimental efficiency makes it a precise and rapid tool for fault localization, particularly useful in large-scale PV systems(Mikael, 2025).

Power and energy analysis

Analyzing the power and energy produced by a PV field enables fault detection and localization. The principle is to compare measured values with expected ones: significant deviations indicate anomalies. To refine localization, attributes of power or energy drops, such as duration, amplitude, frequency, and occurrence time, are studied. The defect whose calculated attributes best match observed ones is identified as the probable cause of failure(Mikael,2025).

Operating point analysis

Comparing measured maximum power points (current and voltage) with expected values provides additional information on PV system status. This binary analysis of currents and voltages identifies problems classified into four categories: defective modules within a string, defective strings, non-discriminable faults (shading, MPPT error, aging), and false alarms.

Static characteristic analysis

A PV field is characterized by its static current–voltage (I–V) curve under normal operation. Any modification of this characteristic may indicate a change in system state, either due to operating conditions (irradiance, temperature) or the appearance of one or more faults in the PV system (Mikael, 2025):

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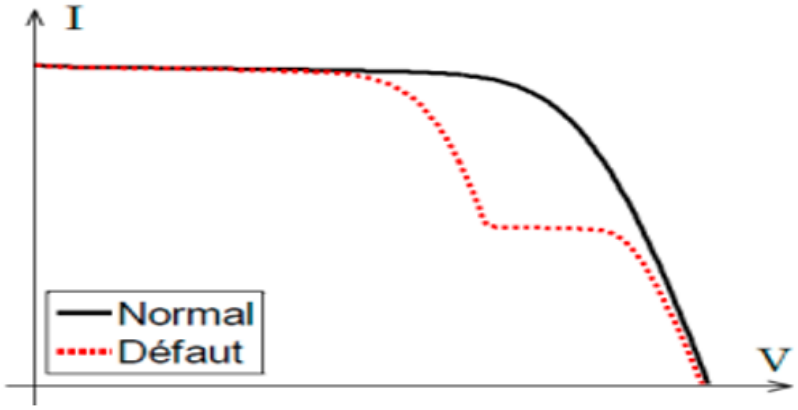
Figure 3: Characteristic current–voltage (I–V)



(Mikael, 2025)

Modeling of photovoltaic array

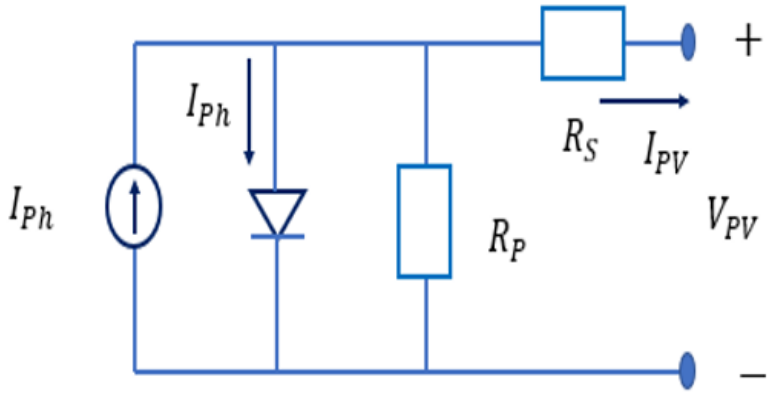
The modeling of photovoltaic (PV) cells involves two principal approaches:

- ✓ Single-diode model (simple exponential);
- ✓ Two-diode model (double exponential).

Modeling of the single-diode photovoltaic cell

The single-diode model provides a simplified representation of the electrical behavior of a photovoltaic cell. It is an empirical model that employs an ideal diode, parasitic resistances, and a current source to reproduce the current–voltage (I–V) characteristics of the cell. This approach captures the essential performance of PV devices while maintaining computational efficiency, making it widely adopted in both academic research and practical applications(A. Benzagmout, 2021).

Figure 4: Single-diode model schematic



(A. Benzagmout, 2021)

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Single-diode model circuit representation

The schematic of the single-diode model (Figure 4) consists of the following elements (A. Benzagmout, 2021).:

Photocurrent Source (I_{Ph}): Represents the current generated by the photovoltaic effect within the cell. Its magnitude depends on the incident irradiance and the intrinsic characteristics of the cell.

Series Resistance (R_S): Accounts for internal Ohmic losses in the cell due to the resistivity of semiconductor materials and metallic contacts.

Shunt Resistance (R_{Sh}): Models parasitic leakage currents within the cell.

Ideal Diode (D): Represents the p–n junction of the cell. The current flowing through the diode (I_d) is expressed by the Shockley equation(A. Benzagmout,2021).:

$$\boldsymbol{I_d = I_0\left[exp\left(\frac{q(V_{PV}+R_S.I_{PV})}{nKT}\right)\right]} \quad \textbf{(1)}$$

$$\boldsymbol{I_d = I_{SC}\left[exp\left(\frac{V_{PV}}{V_t}\right) - 1\right]} \quad \textbf{(2)}$$

The single-diode photovoltaic model incorporates the following parameters:

- ✓ **Short-Circuit Current (I_{SC})**: Represents the current delivered by the cell when the output terminals are short-circuited.
- ✓ **Photovoltaic Voltage (V_{PV})**: Denotes the voltage across the terminals of the cell.
- ✓ **Thermal Voltage (V_t)**: Defined as the thermal potential of the cell, approximately 26 mV under ambient temperature conditions.
- ✓ **Parasitic Series Resistance (R_P)**: Models the internal resistive losses due to semiconductor material properties and contact resistances.
- ✓ **Parasitic Shunt Resistance (R_{Sh})**: Represents leakage paths within the cell that contribute to parasitic current losses.

I–V Velation of the single-diode model

The total current (I) flowing through the photovoltaic cell is given by the sum of the photocurrent source (I_{Ph}) and the diode current (I_d)(Z. Djallel et al, 2020):

$$I = I_{Ph} - I_d \quad (3)$$

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By substituting I_dWith its expression from the Shockley equation, the I–V relation of the single-diode model becomes:

$$I = I_{Ph} - I_{SC}\left[\exp\left(\frac{V_{PV}}{V_t}\right) - 1\right] + \frac{V}{R_P} - \frac{V_{PV}}{R_{Sh}} \tag{4}$$

This equation enables the simulation of the I–V curve of the photovoltaic cell under varying irradiance and temperature conditions.
The diode current (I_d) is expressed by the Shockley equation as:

$$I_d = I_0\left[\exp\left(\frac{q(V_{PV} + R_S I_{PV})}{nkT}\right) - 1\right] \tag{5}$$

where:

- ✓ $k = 1.380662 \times 10^{-23}$ J/(K)is Boltzmann's constant,
- ✓ $n$is the diode ideality factor (typically between 1 and 2),
- ✓ $q = 1.602 \times 10^{-19}$ Cis the electron charge.

The current through the parallel shunt resistance (R_{Sh}) is given by:

$$I_{sh} = \frac{V_{PV} + R_S I_{PV}}{R_{Sh}} \tag{6}$$

where:

- ✓ $R_S$is the series resistance of the cell,
- ✓ $R_{Sh}$is the shunt resistance of the cell,
- ✓ $V_{PV}$is the output voltage of the cell.

Finally, the four-parameter model of the photovoltaic cell is expressed as:

$$I_{PV} = I_{Ph} - I_0\left[\exp\left(\frac{q(V_{PV} + R_S I_{PV})}{nkT}\right) - 1\right] - \frac{V_{PV} + R_S I_{PV}}{R_{Sh}} \tag{7}$$

Four-parameter model

Figure 5 represents a four-parameter model.

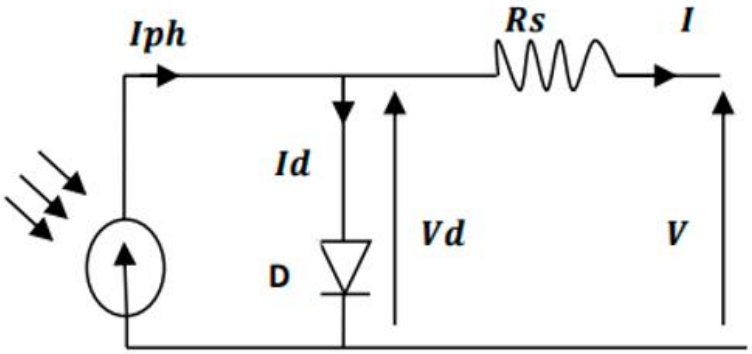

Figure 5: Four-Parameter Model [14]

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The series resistance $R_S$is added as the fourth parameter [14].

- ✓ R_S: Represents the resistance of the connections.
- ✓ The diode voltage is expressed as:

$$V_d - V + R_S I_{rs} = 0 \tag{8}$$

Thus, the current is given by:

$$I = I_{ph} - I_{sat}\left[\exp\left(\frac{V + IR_S}{nkT}\right) - 1\right] \tag{9}$$

Under standard test conditions (irradiance of 1000 W/m² and temperature of 25 °C):

$$\frac{kT}{q} \approx 26\,\text{mV}$$

with:

- ✓ $k = 1.38 \times 10^{-23}$ J\pK^{-1}(Boltzmann constant),
- ✓ $T = 25 + 273 = 298$ K,
- ✓ $q = 1.16 \times 10^{-19}$ C(electron charge).

Therefore, the relation becomes:

$$I = I_{ph} - I_{sat}\left[\exp\left(\frac{V + IR_S}{n \cdot 0.026}\right) - 1\right] \tag{10}$$

Two-diode model

We present the two-diode model to study the effect of partial shading on the energy production of photovoltaic (PV) panels. For this purpose, a comprehensive analysis of all available PV module configurations is carried out. The two-diode model is introduced as follows (A. Benzagmout et al. 2021):

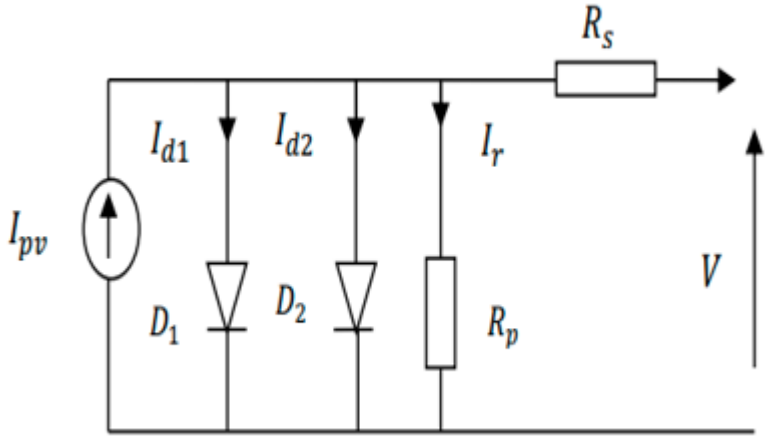

Figure 6: Equivalent Electrical Circuit of a Crystalline Silicon Cell – Two-Diode Model (2-D Rs)

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The following equation describes the output current of the photovoltaic cell for the two-diode model:

$$I_{PV} = I_{Ph} - I_{01}\left[-1 + \exp\left(\frac{V_{PV} + R_S.I_{PV}}{A_1.V_{t1}}\right)\right] - I_{02}\left[-1 + \exp\left(\frac{V_{PV} + R_S.I_{PV}}{A_1.V_{t2}}\right)\right] - \frac{V_{PV} + R_S.I_{PV}}{R_P} \quad (11)$$

where:

- ✓ I_{d1}: Reverse saturation current of diode D1.
- ✓ I_{d2}: Reverse saturation current of diode D2.
- ✓ V_{r1}: Thermodynamic potential of diode D1.
- ✓ V_{r2}: Thermodynamic potential of diode D2.
- ✓ A_1: Ideality factor of the junction of diode D1.
- ✓ A_2: Ideality factor of the junction of diode D2.

Modeling and simulation of PV cells using single- and two-diode models
Parameter estimation methods for PV modules

Several techniques have been developed to extract the characteristic parameters of photovoltaic modules. These can be grouped into three main categories(A. Benzagmout et al 2021),(K. Alosmani et al, 2023):

- ✓ Analytical methods ;
- ✓ Iterative methods ;
- ✓ Intelligent methods.

These approaches provide varying levels of accuracy depending on the models and application conditions. One example is the simple conductance method.
The optimization of solar panel model parameters is a complex problem, involving determining the optimal combination of parameters to achieve the best possible performance. Different optimization approaches, such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Artificial Neural Networks (ANN), can be employed to solve this type of problem.
In this study, we analyze the effectiveness of these three approaches by comparing them according to several criteria: their ability to converge to an optimal solution, their convergence speed, and their robustness under different experimental conditions. The results of this comparative analysis provide valuable insights for researchers and engineers seeking to optimize solar panel model parameters (Z. Djallel, 2020).
In the continuation of this work, each of these methods will be presented in detail, applied to the determination of the predicted current obtained from solving the nonlinear equation of the photovoltaic (PV) cell current.

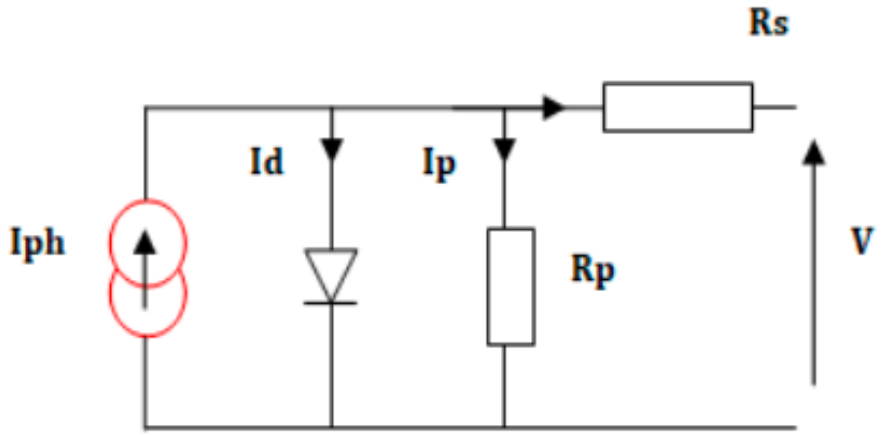
ISSN: 1857-7881 (Print)
e-ISSN 1857-7431 (Online)

Since the I–V characteristic equation is inherently nonlinear, its resolution requires the application of numerical methods capable of providing either an exact solution vector or an approximate solution vector.
Several methods have been developed in recent years to solve this nonlinear equation, including (A. Luque et al,20211):

- ✓ Lambert-W function method ;
- ✓ Newton–Raphson method ;
- ✓ Simple conductance method.

In this study, we restrict ourselves to the application of the analytical method based on the Lambert-W function, which is used to determine the predictive current by explicitly solving the nonlinear equation characterizing the current delivered by the photovoltaic (PV) cell (A. Luque et al, 2011).

Figure 7. Real Photovoltaic Cell Model



(Guide Photovoltaïque, 2025)

Analytical Method – Lambert-W Function

The Lambert-W function is defined as the function that satisfies the following relation:

$$Z = W(X) \cdot e^{W(X)} \tag{12}$$

where:

- ✓ Zrepresents the argument of the function W;
- ✓ $e$denotes the exponential function;
- ✓ $X$is a real or complex vector.

Consequently, the vector $X$is obtained in the following form:

$$X = W(Z)$$

The application of the Lambert-W function to the equation used to calculate the predicted current I_{PV}can be simplified as follows (Guide Photovoltaïque, 2025):

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$$(R_P + R_S)I_{PV} = R_P I_k - R_P I_0 \exp\left(\frac{V_{PV} + R_S I_{PV}}{AV_t}\right) - V_{PV} \tag{13}$$

where I_k is defined as:

$$I_k = I_{PV} + I_0$$

By multiplying both sides of (13) by the term $\frac{R_S}{R_P+R_S}$, we obtain:

$$R_S I_{PV} = \frac{R_S}{R_P + R_S}\left(R_P I_k - R_P I_0 \exp\left(\frac{V_{PV} + R_S I_{PV}}{AV_t}\right) - V_{PV}\right) \tag{14}$$

Equation (14) is further simplified, yielding:

$$\frac{V_{PV} + R_S I_{PV}}{AV_t} + \frac{R_S R_P I_0}{AV_t(R_P + R_S)} \exp\left(\frac{V_{PV} + R_S I_{PV}}{AV_t}\right) = \frac{R_S}{AV_t(R_P + R_S)}\left(R_P I_k + \frac{R_P V_{PV}}{R_S}\right) \tag{15}$$

$$\frac{R_S R_P I_0}{AV_t(R_P + R_S)} \exp\left[\frac{V_{PV} + R_S I_{PV}}{AV_t}\right] \exp\left[\frac{R_S R_P I_0}{AV_t(R_P + R_S)} exp\left(\frac{V_{PV} + R_S I_{PV}}{AV_t}\right)\right] = \frac{R_S R_P I_0}{AV_t(R_P + R_S)} \exp\left[\frac{R_S}{AV_t(R_P + R_S)}\right]\left(R_P I_k + \frac{R_p V_{PV}}{R_S}\right) \tag{16}$$

Equation (17) is further simplified, yielding:

$$\frac{R_S R_P I_0}{AV_t(R_P + R_S)} \exp\left[\frac{V_{PV} + R_S I_{PV}}{AV_t}\right] = LambertW\left(\frac{R_S R_P I_0}{AV_t(R_P + R_S)} \exp\left(\frac{R_S}{AV_t(R_P + R_S)}\left(R_P I_k + \frac{R_p V_{PV}}{R_S}\right)\right)\right) \tag{17}$$

Equation (17) is further simplified, yielding:

$$R_P I_0 \exp\left(\frac{V_{PV} + R_S I_{PV}}{AV_t}\right) = \frac{AV_t(R_P + R_S)}{R_S} ambertW\left(\frac{R_S R_P I_0}{AV_t(R_P + R_S)} \exp\left(\frac{R_S}{AV_t(R_P + R_S)}\left(R_P I_k + \frac{R_p V_{PV}}{R_S}\right)\right)\right) \tag{18}$$

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According to Equation (18), the term

$$R_P I_0 \exp\left(\frac{V_{PV} + R_S I_{PV}}{AV_t}\right)$$

is rewritten as:

$$R_P I_0 \exp\left(\frac{V_{PV} + R_S I_{PV}}{AV_t}\right) = R_P I_k - (R_P + R_S) - V_{PV} \quad (19)$$

Thus, the exact predicted output current is obtained by comparing Eq. (III.11) with Eq. (III.9), giving:

$$I_{PV} = \frac{R_P(I_{Ph} + I_0) - V_{PV}}{R_P + R_S} - \left(\frac{AV_t}{R_S} LambertW\left(\frac{R_S R_P I_0}{AV_t(R_P+R_S)} \exp\left(\frac{R_S}{AV_t(R_P+R_S)}\left(R_P I_k + \frac{R_p V_{PV}}{R_S}\right)\right)\right)\right) \quad (20)$$

Equation (20) therefore represents the exact solution of the nonlinear current equation of the photovoltaic cell.

Results and Discussion

The experimental study focused on analyzing the behavior of a photovoltaic module of type ISOFOTON I-50 PV. This module, composed of monocrystalline silicon cells, has a nominal power rating of 50 W and is commonly used in residential and commercial applications due to its reliability and stable performance.

The typical electrical characteristics of the ISOFOTON I-50 PV module are summarized in Table 4.

Table 4: Typical Electrical Characteristics of the ISOFOTON I-50 PV Module

Parameter	Value
Maximum Power P_{max}	39.10 W
Optimal Voltage V_m	14.9 V
Optimal Current I_m	2.62 A
Number of Cells	36

Influence of Different Parameters on Current and Power Characteristics

The I–V and P–V curves of solar panels provide valuable information about their electrical behavior and allow analysis of the influence of irradiance and temperature on performance. These insights are essential for the design, modeling, and optimization of photovoltaic systems.

Influence of Irradiance

Figures 8 and 9 present the I–V and P–V curves of a photovoltaic module under different irradiance conditions. The analysis of these curves shows that :

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- ✓ The current generated by the solar panel increases proportionally with irradiance. In other words, the higher the incident light, the greater the current produced.

The output voltage of the panel is less sensitive to irradiance variation compared to the current.

- ✓ However, a slight increase in voltage can be observed as irradiance rises.
- ✓ The delivered power, corresponding to the product $P = V \times I$, increases significantly with irradiance. This indicates an improvement in module efficiency under higher sunlight intensity.

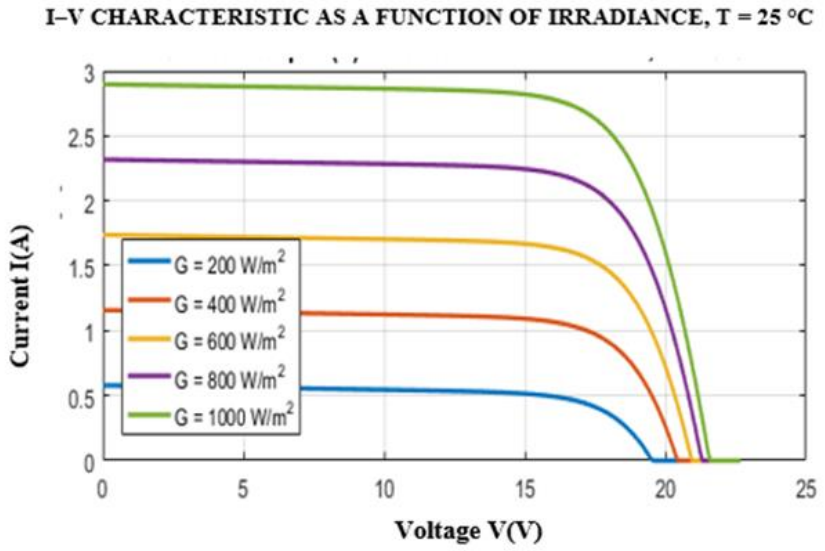

Figure 8: I–V Characteristic as a function of irradiance

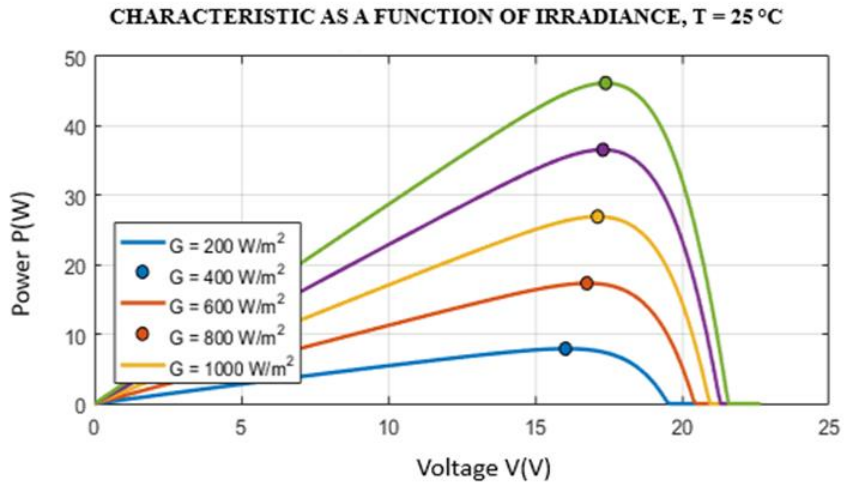

Figure 9: Characteristic $P = f(V)$as a Function of Irradiance

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Figures 10 and 11 present the I–V and P–V curves of a solar panel under different temperature conditions. It is observed that the short-circuit current increases slightly with temperature, while the open-circuit voltage decreases significantly. This voltage drop is associated with the increase in the saturation current of the panel's internal diode, a phenomenon that is accentuated by heat. Consequently, the shape of the I–V curves shifts toward lower voltages as temperature rises.

As a result, the maximum power produced by the solar panel decreases with increasing temperature. The optimal operating point (MPP) shifts toward lower voltages, indicating a loss of energy efficiency. In other words, even though the current increases slightly, the voltage drop dominates and leads to a reduction in the available power. Therefore, the solar panel exhibits reduced performance under high-temperature conditions.

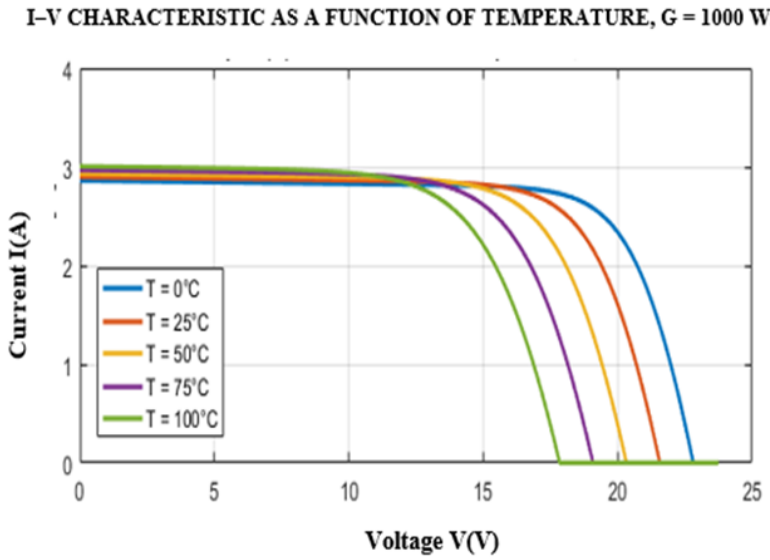

Figure 10: Characteristic $P = f(V)$as a Function of Temperature

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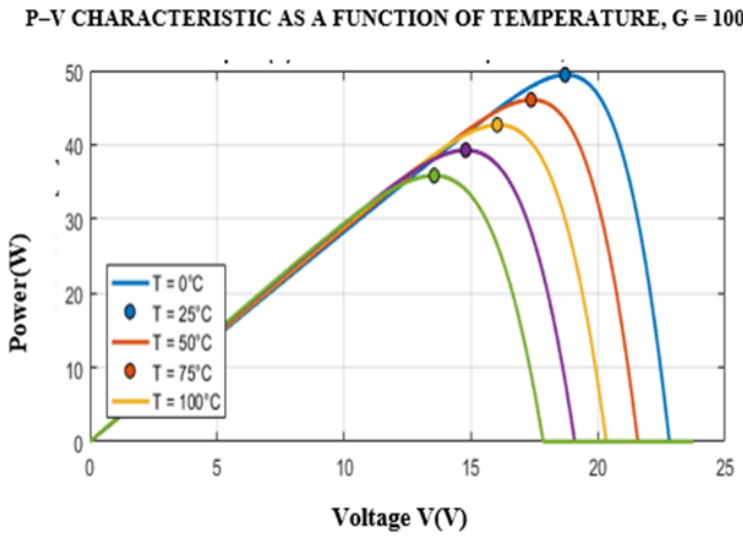

Figure 11: Characteristic $I = f(V)$as a Function of Temperature

Simulation of current–voltage (I–V) and power–voltage (P–V) characteristics

Figures 12 and 13 illustrate the current–voltage (I–V) and power–voltage (P–V) characteristic curves obtained from the numerical model of the photovoltaic module, compared with noisy simulated measurements. These results validate the consistency of the model and allow assessment of its accuracy in the context of photovoltaic system monitoring.

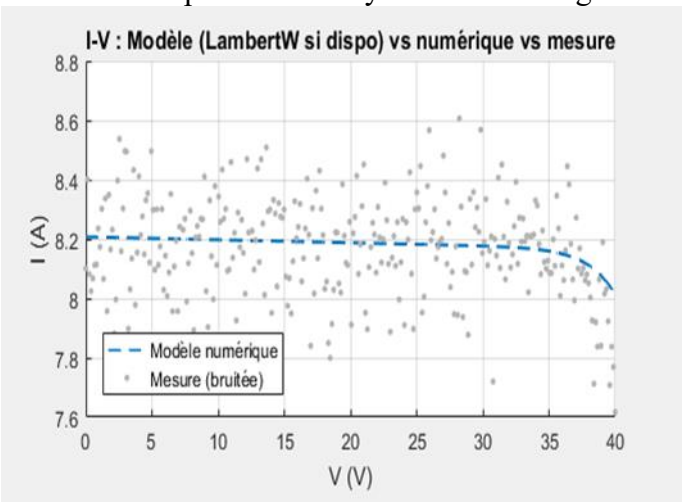

Figure 12: Current–Voltage (I–V) Characteristics

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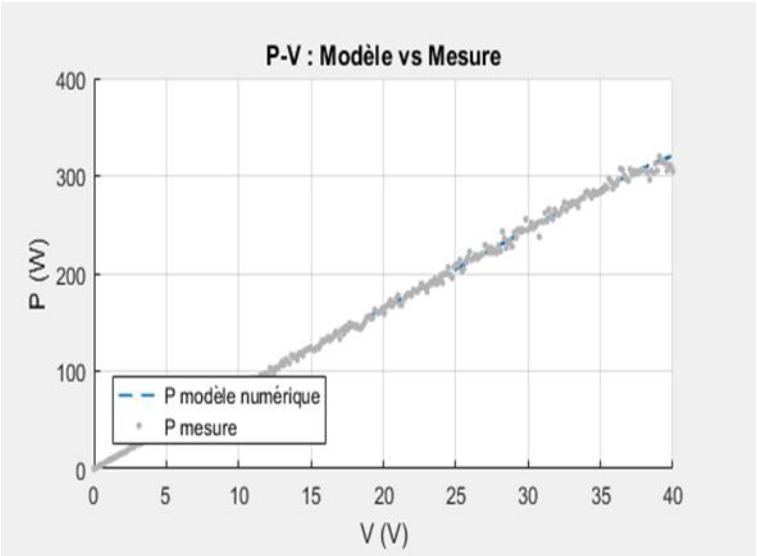

Figure 13: Characteristic P-V

Figure 12 shows that the numerical model curve (blue line) closely follows the general trend of the noisy measurement points (gray). The current remains nearly constant up to a voltage of approximately 35 V, after which it drops, a typical behavior of a photovoltaic generator. The slight fluctuations around the modeled curve originate from the added measurement noise, which simulates the inaccuracy of real sensors (thermal noise, temperature variation, electronic tolerances, etc.).

The obtained RMSE of the current (≈ 0.1608 A) corresponds to a relative error of less than 2% of the nominal current (≈ 8 A), indicating excellent agreement between the theoretical model and the measurements.

Figure 13 demonstrates an evolution consistent with theory: the power increases with voltage until reaching a maximum power point (MPP) around 33–35 V, then decreases beyond this value. The near-perfect overlap between the modeled curve and the noisy measurements confirms the validity of the numerical model for predicting the energy behavior of the module.

The obtained RMSE of the power (≈ 3.6860 W) is also very small compared to the maximum power (≈ 300 W), corresponding to a relative error of about 1.2%. This level of accuracy is more than sufficient for intelligent supervision applications, particularly for detecting efficiency drifts or operational faults.

Model errors and evaluation

Figures 14 and 15, respectively, present the deviations between the model and the measurements for current and power. The current error

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oscillates randomly around zero without systematic drift, indicating an unbiased and statistically reliable model.

The power deviations remain generally small but increase slightly in the high-voltage region, where the operating point sensitivity is maximal.

These observations confirm the robustness of the model against disturbances and parametric uncertainties (variations in R_s, R_p, I_0, etc.).

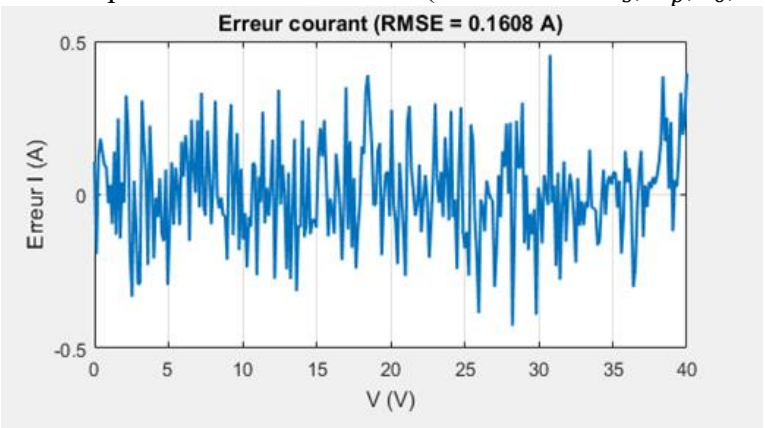

Figure 14: Current Error (RMSE = 0.1608 A)

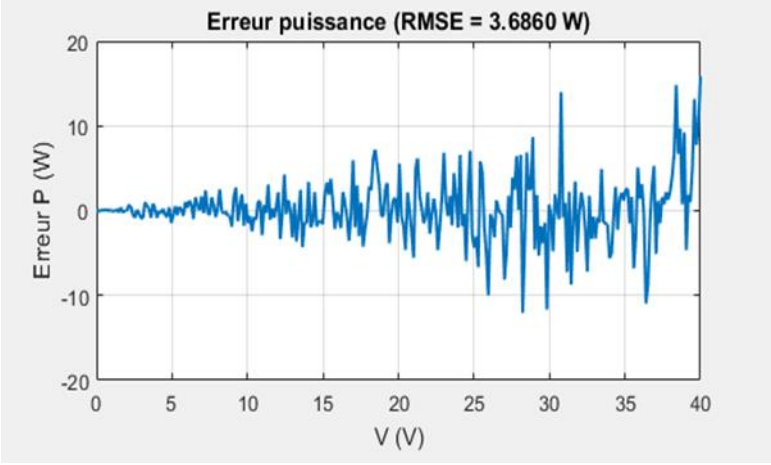

Figure 15: Power Error (RMSE = 3.6860 W)

The overall results demonstrate that the implemented PV model faithfully reproduces the electrical behavior of the photovoltaic module. The low RMSE values confirm the excellent accuracy of the Lambert-W/numerical model, enabling its use as a reliable reference for supervision.

In a real supervision architecture (e.g., via Zabbix or MQTT), this model can serve as a basis for:

- ✓ automatically detecting performance drifts,
- ✓ identifying losses due to soiling or interconnection faults, and

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- ✓ optimizing the operating point of the PV system.

This validation step, therefore, constitutes proof of the proper functioning of the supervision model and ensures its reliability for monitoring and predictive maintenance of the photovoltaic field.

Table 5 below presents a summary of the results related to the current–voltage and power–voltage characteristics, as well as the types of detected anomalies and the proposed solutions.

Table 5: Module Characteristics and Detection Performance

Parameter / Indicator	Value / Result	Remarks / Interpretation
PV Module	ISOFOTON I 50	Monocrystalline, 36 cells
Nominal Power (P_nom)	50 W	Standard residential capacity
Optimal Voltage (V_m)	14.9 V	Voltage at maximum power point (MPP)
Optimal Current (I_m)	2.62 A	Current at maximum power point (MPP)
Number of Cells	36	—
Current RMSE (I)	0.1608 A	Relative error < 2 %
Power RMSE (P)	3.686 W	Relative error ≈ 1.2 %
Anomaly Detection	Yes	Based on the Lambert W model / I–V measurements
Types of Errors Detected	Performance drift, losses due to soiling, and interconnection faults	Rapid detection and localization possible
Model Validity	Excellent	Agreement between simulated measurements and noisy data

Conclusion

This study provides a scientific contribution to improving the reliability and maintenance of photovoltaic (PV) systems, with a focus on the African and Congolese context. The analysis confirms that PV installations, despite their economic and energy advantages, remain susceptible to faults that can reduce performance and availability. The proposed methodology, based on modeling the I–V and P–V characteristics of the **PV cell** and applying the Lambert W model, enables precise simulation and analysis of operational failures. Results, summarized in Tables 1 and 3, show a root mean square error (RMSE) of 0.1608 A for current (≈2 % of nominal 8 A) and 3.686 W for power (≈1.2 % of maximum 300 W), validating the model's accuracy. These findings demonstrate the system's effectiveness for rapid fault detection, precise localization, and operating point optimization, providing a solid foundation for intelligent supervision and predictive maintenance, ultimately enhancing PV system reliability, efficiency, and energy productivity.

Conflict of Interest: The authors reported no conflict of interest.

Data Availability: All data are included in the content of the paper.

ISSN: 1857-7881 (Print)
e-ISSN 1857-7431 (Online)

Funding Statement: The authors did not obtain any funding for this research.

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