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Implementation of an IEC 61215-oriented photovoltaic module test emulator with integrated predictive maintenance capabilities

Abstract

This paper presents a hybrid software-based framework for photovoltaic (PV) testing, monitoring, and predictive maintenance that combines a physically validated PV emulator with data-driven diagnostic models. The emulator reproduces selected IEC 61215-inspired test scenarios, including electrical characterisation, irradiance/temperature variations, simulated accelerated ageing, and electrical fault scenarios—without relying on real solar irradiation, enabling realistic I–V and P–V curve generation under controlled settings for performance assessment and algorithm validation. Note that the emulator is a complementary validation tool and does not substitute for formal IEC 61215 certification. Building on this emulator, a two-stage intelligent monitoring architecture is proposed. First, an unsupervised autoencoder learns normal PV behaviour and detects anomalies by analysing reconstruction errors. It shows strong discriminative capability, achieving a high ROC–AUC while remaining robust across varying environmental conditions, thereby enabling early detection of abrupt faults and progressive degradation. Second, a supervised bidirectional gated recurrent unit (BiGRU) model performs fault classification by explicitly exploiting temporal dependencies in electrical signals. The BiGRU classifier achieves an overall accuracy exceeding 99%, with high class-wise precision and recall across multiple fault categories, including resistive faults, degradation, soiling, and severe electrical failures. The framework is validated on emulator-based and analytically derived datasets (Sandia, Madison, Cenerg models), demonstrating strong generalisation and stability across operating conditions; field validation on real PV installations is identified as a key next step. Overall, integrating physical emulation, unsupervised anomaly detection, and supervised temporal classification provides a robust and scalable predictive maintenance solution for PV installations, particularly in environments with high climatic variability.

1. INTRODUCTION

The global energy transition places renewable energy at the core of decarbonization and energy-security strategies. Among renewables, solar photovoltaic (PV) energy stands out for its potential to provide clean and sustainable electricity, contributing to greenhouse gas emissions reduction (Peters, 2025; Wang et al., 2024). This momentum is particularly critical in Africa, where electricity access remains a structural challenge: in 2023, about 666 million people worldwide lacked access, including 565 million in Sub-Saharan Africa, and projections indicate that, under current trends, several hundred million people could remain without access by 2030. In this context, continental initiatives such as Mission 300 aim to accelerate electrification by connecting 300 million Africans by 2030.

In Cameroon, energy demand is rapidly increasing while electricity access remains limited, especially in rural areas where electrification is still below 30% (Fendzi Mbasso et al., 2025). The challenge is not only access: supply continuity and power quality are also major barriers. According to the ENACE-1 survey, 45%

of households reported outages “very often” over the last three months and 39% “often”. The most frequently cited issues include unpredictable interruptions (37.4%), insufficient hours of supply (24.1%), and voltage fluctuations (20.3%). Despite abundant solar resources (Fotsing Metegam, 2025) and significant hydropower potential, the country experiences frequent power cuts and load shedding (Iweh et al., 2023), which slow economic development and expose critical sectors (notably healthcare) to operational risks.

From this perspective, PV solar energy serves as a substitute for local electricity supply, notably through solar micro-plants in urban and rural areas. However, imported PV modules are often designed for temperate climates and can be poorly suited to tropical constraints (humidity, heat, UV exposure, dust/soiling). Manufacturer ratings rely on STC conditions (1000 W/m², 25°C, AM1.5), which do not reflect real operating conditions: climatic and environmental mismatches may affect field performance, ageing, and replacement cycles. These concerns are consistent with recent reviews on degradation mechanisms (thermal stress, moisture, UV, soiling) and their impact on module durability. Recent reviews on PV module durability in tropical and developing-country contexts report significantly elevated premature failure rates compared to temperate-climate deployments, with some studies indicating that a substantial fraction of imported modules exhibit performance degradation beyond acceptable thresholds within five years of operation under harsh environmental stresses (Mdallal et al., 2025; Sharma et al., 2025). While the exact magnitude varies with technology type, installation quality, and local climate, these findings underscore the urgency of developing adapted test protocols and predictive maintenance strategies in contexts such as Cameroon. PV modules, which directly convert solar irradiance into electricity, thus exhibit performance and durability that strongly depend on environmental conditions and manufacturing processes.

To address these challenges, IEC 61215 defines qualification and durability tests for PV modules. Although widely adopted by industry, its implementation in Cameroon faces major barriers: high costs of characterisation equipment, technical complexity, and imperfect alignment with local constraints (Bamisile et al., 2025; Ali et al., 2025; Agoundedemba et al., 2023). Studies linking accelerated tests (IEC 61215/61730) to field performance highlight the value of reproducible experimental platforms for interpreting real durability and reducing the “test-to-field” gap. PV emulators have emerged as laboratory tools to simulate PV electrical behaviour without relying on direct sunlight (Korasiak et al., 2022; Ram et al., 2018). They have progressively evolved toward dynamic I–V curve generation, reproduction of extreme climatic conditions, and integration with control systems. Reviews of PV emulators describe these systems as “nonlinear sources” capable of accurately reproducing I–V/P–V characteristics under variations in irradiance, temperature, and shading, enabling testing of converters, MPPT algorithms, and architectures without relying on weather conditions.

Most PV emulators reported in the literature are designed around power-electronic circuits of varying complexity, which may make them inaccessible in practice, either because they are costly or because they are difficult to design and instrument (Ayop & Tan, 2017; Ram et al., 2018). Emulators are typically structured into three blocks: the PV model, the control strategy, and the power converter. However, many works focus primarily on control strategies and the power-conversion stage, while treating PV models either separately or as interchangeable components (Ayop & Tan, 2017; Ram et al., 2018). In a “software-first” paradigm, it may be more relevant to exploit three empirical model families simultaneously, Sandia, Madison, and CENERG, to better capture climatic and operational diversity. These models can reproduce most key characteristics of a PV module or array, thus providing a robust basis for emulation (Sandia National Laboratories, s.d.). Sandía PVPMP. With the rise of AI and digital-twin approaches, it has also become possible to improve emulator accuracy and virtualise the control strategy and selected conversion functions without systematically relying on dedicated electronic hardware, thanks to data-driven adaptation and calibration (Dimitrova-Angelova et al., 2025).

Recently, the integration of advanced software control, predictive maintenance, and AI has accelerated efforts to identify potential degradation before it affects the module (Gómez-Ruiz et al., 2024; Choi et al., 2023). These developments also enable the simulation of PV–battery–grid hybrid systems to optimise real-time operation (Gómez-Ruiz et al., 2024; Bai et al., 2022; Subramaniam et al., 2020; Patil et al., 2024).

In the Cameroonian context, where access to commercial emulators and standardised test benches remains limited, this work proposes a low-cost, low-tech approach to emulate PV behaviour and strengthen predictive maintenance. By leveraging multi-sensor data exploitation and predictive maintenance models, the proposed approach aims to detect critical anomalies early (e.g., hotspots, microcracks) and anticipate failures before they compromise system reliability (Al-Humairi et al., 2025). Recent review studies on PV fault diagnosis also confirm that AI-based approaches (IR thermography, electrical signatures, deep learning) improve sensitivity

and robustness, especially for defects such as microcracks and hotspots (Sepúlveda-Oviedo et al., 2023; Thakfan & Salaman, 2024; Yi et al., 2025).

Therefore, embedding a predictive module into an IEC 61215 test emulator constitutes a strategic lever to improve quality, reduce costs, and extend PV system lifetime in Cameroon (Porowski et al., 2025). In line with (Kull et al., 2025), our objectives are: (i) to develop a software emulator capable of simulating IEC 61215 tests (thermal cycling, humidity, UV exposure); and (ii) to integrate a predictive-maintenance module enabling early detection of critical anomalies. The expected impact is threefold: adapt PV systems to Cameroonian climatic realities; promote robust, cost-effective solutions; and strengthen local research, training, and innovation capacity in renewable energy.

How can we design a reproducible, cost-constrained PV emulator that replicates IEC 61215-type qualification scenarios and embeds climate-aware predictive maintenance for the Cameroonian tropics to reduce the gap between STC ratings and field performance and improve PV system durability?

- IEC 61215 software-first emulation: structured software emulation of qualification campaigns (temperature/humidity/UV) for resource-constrained contexts.
- Emulation + predictive maintenance coupling: native integration of AI/multi-sensor predictive monitoring for early fault detection (hotspots, microcracks, etc.).
- Cameroon climate adaptation: “tropical” scenarios (heat/humidity/soiling) to align tests with field conditions beyond STC-only decisions.

2. MATERIALS AND METHODS

PV emulation is widely considered an effective and flexible tool for the functional and electrical evaluation of PV modules, complementing IEC 61215 normative testing for design qualification and type approval of terrestrial PV modules (Commission, Terrestrial photovoltaic (PV) modules – Design qualification and type approval: Part 1: Test requirements, IEC 61215-1, 2021 (IEC, InternTerrestrial photovoltaic (PV) modules – Design qualification and type approval; Part 2: Test procedures, IEC 61215-2, 2021). IEC 61215 provides a rigorous experimental framework to ensure long-term reliability, safety, and durability under environmental and operational stresses.

In this setting, PV emulator platforms can reproduce PV electrical behaviour with high fidelity through I–V and P–V characteristics, while incorporating irradiance and temperature effects, mismatch phenomena, reverse currents, and bypass-diode activation (Choi et al., 2023; Krismadinata et al., 2025). This makes emulation particularly relevant for: validating initial and final electrical performance (before/after scenarios), analysing electrically induced hot-spot phenomena caused by partial shading and assessing MPPT algorithms under controlled and reproducible conditions (Abad et al., 2025). IEC 61215 relies on a consistent set of qualification tests (e.g., visual inspection, initial performance measurements, insulation and grounding tests, hot-spot test, UV exposure, thermal cycling, humidity–freeze, damp heat, mechanical load, hail, LID, reverse-current overload, wet leakage current, post-ageing performance, and outdoor exposure) (IEC, 2021a; 2021b). These tests are crucial for characterising physicochemical and mechanical failure mechanisms that govern lifetime under real operating conditions.

However, only a subset of these tests can be directly reproduced through emulation—primarily those linked to the module’s electrical behaviour and to degradations that can be represented parametrically. PV emulators can notably simulate: initial and final electrical performance, parametric ageing effects (including LID), electrical fault scenarios and reverse-current overload and bypass-diode behaviour. Thus providing an efficient framework for electrical robustness analysis and for optimising control and grid-integration strategies (Hwang et al., 2025; Zulhani et al., 2018; Krismadinata et al., 2025).

Recent work further indicates that advanced emulation, combined with thermo-electric modelling and HIL (Hardware-in-the-Loop) approaches, is a major lever for accelerating design, reducing experimental costs, and improving the reliability of PV systems integrated into microgrids and smart grids (Paspatis, Kontou, et al., 2024). Accordingly, in this work, emulation is positioned as a complementary tool: it does not replace IEC 61215 certification, but enhances the ability to: analyse the gap between manufacturer STC ratings and harsh-condition behaviour, test controlled fault scenarios, and validate predictive maintenance and diagnostic algorithms using reproducible data.

2.1. Knowledge extraction models for assessing PV technical characteristics

To clarify the architecture of the proposed framework, the three models play distinct and complementary roles: (i) the Sandia model acts as a meteorologically-driven operational benchmark, leveraging field irradiance, temperature, and incidence-angle data to compute expected electrical output and provide a baseline for anomaly and soiling-loss detection; (ii) the Madison model serves as a datasheet-driven performance baseline, initializing emulator parameters from manufacturer STC specifications and enabling comparison between rated and in-field performance; and (iii) the Cenerg model provides empirical calibration under tropical operating conditions, capturing realistic performance variability driven by high irradiance variability and elevated temperatures. Together, these three models form a multi-model supervision scheme that improves the robustness of both emulator calibration and anomaly detection. The following subsections detail each model in turn.

Several knowledge extraction models are used to assess PV module technical characteristics and explain the gap between manufacturer ratings (STC) and real-world field performance. In this work, we distinguish two complementary families of approaches. The first family relies on experimental identification of PV electrical parameters under real operating conditions, using well-established empirical models such as the Sandia model and the Cenerg model, which is employed for experimental identification of PV parameters across diverse climatic environments. These models are particularly suitable when the goal is to accurately capture the influence of environmental drivers (irradiance, temperature, incidence angle, spectral effects) on energy yield and efficiency.

The second family primarily uses datasheet information and extrapolates module performance from STC using single-diode-derived formulations, such as the Madison model (Gonzalez-Longatt, 2006; Villalva, 2009). This approach is widely adopted when field measurements are limited or when a rapid initialisation of emulator parameters is needed. Combining Sandia, Cenerg, and Madison enables: (i) real-time tracking of deviations between expected and observed performance, (ii) indicators for degradation detection, (iii) emulator calibration under tropical operating conditions, and (iv) improved reliability of PV system supervision. Next, we first detail the Sandia model, and then describe how the three models are jointly exploited for supervision and emulator calibration.

2.1.1. The “Sandia” model for PV module performance characterisation in operation

The Sandia model is one of the most widely used empirical models due to its versatility and accuracy. It integrates electrical, thermal, and optical components to map measured weather and solar inputs (hourly data, ambient temperature, wind speed, irradiance, etc.) to the PV module's expected electrical outputs. It was designed to operate directly from field data, making it well-suited for performance assessment under real operating conditions. A key advantage of this model is its ability to account for solar spectrum variation (spectral effects on module response), incidence-angle effects of direct irradiance (orientation-dependent optical losses), and the combined impact of climate conditions on power output.

In practice, the Sandia model enables real-time comparison between expected production (given environmental conditions) and measured production, providing a robust basis for anomaly detection, loss quantification (e.g., soiling-related losses or thermal drifts), and performance optimisation. To analyse and model the performance of our PV modules, we employ the system of equations (1)–(4) to compute the expected power and energy under operating conditions. These equations form the reference baseline that will later be compared against electrical signatures generated within the emulator and multi-sensor measurements. Transition to the next part (keep this): In the next section, equations (1)–(4) are detailed, and Sandia-estimated parameters are aligned with Madison and Cenerg estimates to build a multi-model supervision scheme tailored to the tropical Cameroonian climate.

$$I_{sc} = \frac{\phi}{\phi_{ref}} * f_1(AM) \times f_2(\beta) * (I_{sc_r} + \mu_{I_{sc}}(T_c - T_{ref})) \quad (1)$$

$$I_{MP} = C_0 + \frac{I_{sc}}{I_{sc_r}} * (I_{MP_r} + \mu_{I_{MP}} * (T_c - T_{ref})) \quad (2)$$

$$V_{oc} = V_{ocr} + C_1 * \ln\left(\frac{I_{sc}}{I_{sc_r}}\right) + \mu_{I_{sc}} * (T_c - T_{ref}) \quad (3)$$

$$V_{MP} = V_{MP_r} + C_2 * \ln\left(\frac{I_{sc}}{I_{sc_r}}\right) + C_3 * \left[\ln\left(\frac{I_{sc}}{I_{sc_r}}\right)\right]^2 + \mu_{V_{MP}} * (T_c - T_{ref}) \quad (4)$$

Where:

C_0 , C_1 , C_2 , and C_3 – experimentally identified parameters accounting for non-idealities (curve asymmetries, technology dispersion, connection/mismatch effects not captured by a simple scaling law).

I_{sc} , I_{scr} – measured and reference short-circuit currents (A).

I_{MP} , I_{PMr} – measured and reference current at maximum power point (A).

V_{oc} , V_{ocr} – measured and reference open-circuit voltages (V).

V_{MP} , V_{MP_r} – measured and reference voltage at maximum power point (V).

$\emptyset$, $\emptyset_{ref}$ – incident irradiance and reference irradiance (W/m^2).

$\mu_{I_{sc}}$, $\mu_{I_{MP}}$ – temperature coefficients for I_{sc} and I_{MP} .

μ_{voc} , μ_{VMP} – temperature coefficients for V_{oc} and V_{MP} .

T_c , T_{ref} – cell temperature and reference temperature.

AM : air mass and β : incidence-angle/optical-loss related variable.

The empirical functions $f_1(AM)$ and $f_2(\beta)$ account for: (i) spectral effects on the photogenerated current and (ii) optical losses associated with the incidence angle (reflection/transmittance and geometric effects). Their coefficients are determined experimentally and depend on local solar resources, temperature, and calibration reference conditions. In this model, $f_1(AM)$ (Eq. (5)) depends on atmospheric properties (water vapour content, aerosol type and concentration) and the effective path length of sunlight through the atmosphere. It captures the short-circuit current variation driven by the non-linear relationship between ISC and irradiance, daily changes in optical efficiency, potential misalignment, and solar spectral influence. Complementarily, $f_2(\beta)$ represents incidence-angle optical losses and helps bring model-based expectations closer to observed operating performance. The function $f_1(AM)$ is modelled through a 4th-order polynomial fit:

$$f_1(AM) = a_0 + a_1 * AM + a_2 * (AM)^2 + a_3 * (AM)^3 + a_4 * (AM)^4 \quad (5)$$

To account for the relative position of the sun, meteorology and climatology studies on solar irradiance attenuation through the atmosphere and clouds (atmospheric turbidity) introduce the notion of air mass AM . This quantity allows the coefficients a_i to be identified through a 4th-order polynomial fit. Hence, $f_1(AM)$ mainly depends on the solar zenith angle z , notably through $\cos(z)$, since AM is directly linked to the sun-atmosphere geometry.

$$f_1(AM) = 6,5567 + 1,7513 * AM - 0,1202 * (AM)^2 + 0,0065 * (AM)^3 - 0,00013 * (AM)^4 \quad (6)$$

The zenith angle z is related to site latitude ϕ , solar declination δ , and hour angle ω by:

$$AM = \frac{1}{\cos(z)} \quad (7)$$

$$\cos(z) = \cos\phi * \cos\delta * \cos\omega + \sin\phi * \sin\delta \quad (8)$$

The declination δ , as a function of day number N , is:

$$\delta = 23,45 * \sin\left[\frac{360}{365} * (N + 284)\right] \quad (9)$$

$$\omega = 15 * (12 - H + (\frac{\lambda}{15})) + E_t \quad (10)$$

The hour angle ω depends on longitude λ , GMT time H , and the equation of time E_t , Eq. (11) :

$$E_t = (9,87 * \sin(2B) - 7,5 * \cos B - 1,5 * \sin B) * 1 / 60 \quad (11)$$

$$B = \left[\frac{2\pi * (N - 81)}{364} \right] \quad (12)$$

Minor updates of constants lead to the expression of $f_1(AM)$ given in Eq. (13):

$$f_1(AM) = 5,7429 + 3,0312 * AM - 0,06329 * (AM)^2 + 0,091 * (AM)^3 - 0,00512 * (AM)^4 \quad (13)$$

A parameter identification approach related to spectral mismatch, described as a function of time of day, provides a practical formulation for f_1 :

$$M \approx f_1(AM_a) = \frac{I_{sc_t}}{E^*} * \frac{I_0^*}{I_{sc_{t_0}}} \quad (14)$$

The same works propose a measurement procedure to obtain the second empirical function $f_2(\beta)$, which links the module short-circuit current to the angle of incidence (AOI):

$$f_2(\beta) = \frac{I_{sc}(AM_a = 1,5; T = T_a) - C_2 * \frac{E_{diff}}{1000}}{C_1 * \frac{E_{dni}}{1000} * \cos(AOI)} \quad (15)$$

with

$$AOI = \cos^{-1} [\cos(T_m) \cos(Z_s) + \sin(T_m) \sin(Z_s) \cos(AZ_s - AZ_m)] \quad (16)$$

Where: AOI – the solar incidence angle (degrees);

T_m – the module tilt angle (degrees), with 0° being horizontal;

Z_s – the solar zenith angle (degrees);

AZ_m – the module azimuth angle (0° =North, 90° =East) ;

AZ_s – the solar azimuth angle;

$I_{sc_{t_0}}$ – the module short-circuit current at reference temperature and $AM_a=1.5$;

I_{sc_t} – the measured short-circuit current at ambient conditions;

E_o^* – the reference irradiance and E^* is the total irradiance measured by the pyranometer during the test.

Finally, the first three Sandia model equations (Eqs. (1)–(3)) enable generating the standard current–voltage (I – V) and power–voltage (P – V) curves and estimating the module output power under operating conditions.

2.1.2. The “Madison” model for PV module performance characterisation

PV module ratings are typically provided under Standard Test Conditions (STC), which often differ from real operating conditions. STC-based assessment relies on datasheet parameters, enabling extrapolation of performance to other reference or operating conditions. Accordingly, the Madison model (Eq. (17)) estimates PV module performance from manufacturer datasheet data by linking irradiance and temperature to electrical quantities (I – V / P – V behavior). In our approach, this model is used as a datasheet-driven baseline to initialise parameters, compare expected performance, and support emulator calibration.

$$I = I_{ph} - I_s \left[\exp\left(\frac{q(V + R_s * I)}{A * k * T_c}\right) - 1 \right] - \frac{V + R_s * I}{R_{sh}} \quad (17)$$

The main parameters governing the photocurrent and the diode reverse saturation current in this model are:

$$I_{ph} = I_{ph}(T_1) + k_0(T - T_1) \quad (18)$$

$$I_{ph}(T_1) = I_{sc}(T_{1,nom}) * \frac{G}{G_{ref}} \quad (19)$$

And finally

$$I_s(T_1) = \frac{I_{sc}(T_1)}{\frac{qV_{oc}(T_1)}{e^{nkT_1} - 1}} \quad (20)$$

Where: V – the voltage across the sensor (V);

I_{ph} – the photo-generated current (A);

I_s – the reverse saturation current of the diode (A);

A – an adjustment parameter;

T_c – the junction temperature;

R_s – the series resistance;

R_{sh} – the shunt resistor and n the adjustment parameter, equal to the number of cells in series.

n denotes the number of series-connected cells in the module, introduced to account for the electrical scaling of the PV generator.

2.1.3. The “Cenerg” model for PV module performance characterisation in operation

Under specific assumptions, the “Cenerg” model, similar to the Sandia approach, relies on experimental data to characterise a PV module under operating conditions. It establishes a relationship between the terminal current I and voltage V , from which the delivered power is obtained as $P=VI$. Such an empirical formulation is useful for capturing realistic performance variability driven by climatic conditions (variable irradiance and elevated temperatures) and technology dispersion, making it suitable for emulator calibration and “datasheet vs field” comparison. The Cenerg model can be expressed as:

$$I = P_1 * \Phi [1 + P_2(\Phi - \Phi_{ref}) + P_3(T_c - T_{ref})] - \left[P_4 * T_c^3 \exp\left(-\frac{E_g}{k * T_c}\right) * \left[\exp\left(\frac{q(V + R_s * I)}{A * n * k * T_c}\right) - 1 \right] - \frac{V + R_s * I}{R_{sh}} \right] \quad (21)$$

Where Φ is the incident irradiance (W/m²) and Φ_{ref} is the reference irradiance; T_c is the cell temperature (K) and T_{ref} is the reference temperature. P_1 - P_4 are identification coefficients fitted from experimental measurements. E_g denotes the bandgap energy, q is the elementary charge, and k is Boltzmann’s constant. R_s and R_{sh} are the series and shunt resistances, A is the diode ideality factor, and n is the number of series-connected cells.

This formulation explicitly accounts for the combined influence of irradiance and temperature on both the photogenerated component and the diode term (via the thermal factor involving E_g), making it well-suited for tropical operating conditions. In our work, Cenerg is used as a complementary experimental block alongside Sandia (resource- and meteorology-driven) and Madison (datasheet-driven) to strengthen emulator calibration and monitor performance deviations.

By identifying the terms of the Cenerg formulation with those of the Madison single-diode model, the correspondence between model components can be clarified and the differences in parameterisation highlighted. In the Cenerg model, the first term is equivalent to the photocurrent of the Madison model:

$$I = P_1 * \phi \left[1 + P_2(\phi - \phi_{ref}) + P_3(T_c - T_{ref}) \right] \quad (22)$$

The cell temperature T_c can be approximated from the ambient temperature T_a using a NOCT-based relation:

$$T_c = T_a + \phi * \left(\frac{N_{oct} - 20}{800} \right) \quad (23)$$

where NOCT denotes the Nominal Operating Cell Temperature (here 45°C). The diode reverse saturation current is modelled as a temperature-dependent quantity:

$$I_s = \left[P_4 * T_c^3 \exp\left(-\frac{E_g}{k * T_c}\right) \right] \quad (24)$$

The third term corresponds to the shunt-branch (leakage) current:

$$I_{sh} = \frac{V + R_s * I}{R_{sh}} \quad (25)$$

Accordingly, the complete Cenerg current–voltage relationship can be written as:

$$I = I_{ph} - I_s \left[\exp\left(\frac{q(V + R_s * I)}{A * n * k * T_c}\right) - 1 \right] - I_{sh} \quad (26)$$

2.2. Integrating a machine learning-based predictive maintenance system into the PV emulator — Cameroonian context

In Cameroon, where photovoltaic deployments are expanding rapidly to mitigate electrification gaps in rural and peri-urban areas, integrating a Machine Learning (ML)-based predictive maintenance module into a PV emulation platform provides an innovative yet pragmatic pathway to improve system reliability, availability, and lifetime. This approach is particularly relevant because local environmental stressors, such as dust accumulation, high humidity in equatorial zones, marked thermal variations, and UV exposure, significantly contribute to energy yield losses and premature PV module degradation.

A predictive maintenance strategy relies on real-time measurements (electrical variables, irradiance, temperature, humidity, wind speed) to anticipate faults and optimise interventions, thereby reducing operational costs and downtime. Recent studies further indicate that ML approaches covering anomaly detection (often unsupervised) and supervised fault classification can effectively identify fault and degradation scenarios in PV systems, strengthening the operational reliability of solar plants (Sepúlveda-Oviedo et al., 2023), while deep-learning pipelines (CNN/RNN/AE) are increasingly adopted for feature learning and decision-making in PV diagnostics.

Beyond monitoring, the emulator itself becomes a data-generation engine: it can produce synthetic datasets representing both healthy and degraded conditions (e.g., soiling, resistive faults, ageing, severe electrical failures), which are valuable for training and validating ML-based diagnostic models. This is especially advantageous in Cameroon, where access to labelled field data is often limited, as it provides a controlled virtual laboratory for generating complex fault scenarios without relying solely on historical maintenance logs. Figure 1 summarises the proposed functional architecture: multi-sensor acquisition; feature extraction and database generation using Sandia/Madison/Cenerg models; and a two-stage ML chain (autoencoder-based anomaly detection followed by GRU-based diagnosis), ultimately feeding a decision-support module (alerts, severity, recommended actions).

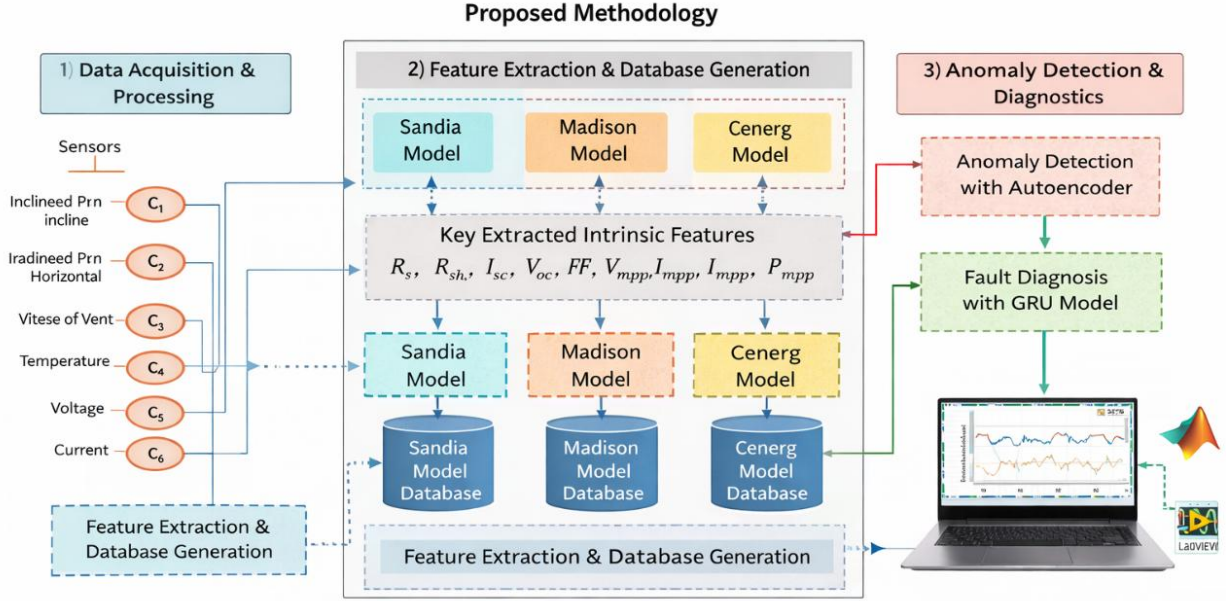


Fig. 1. Architecture of the emulator and decision estimation

The proposed architecture relies on a laboratory-grade photovoltaic emulator capable of generating electrical signals and reproducible fault scenarios (shading, mismatch, reverse currents), thereby enabling the creation of rich and balanced datasets for training and validating machine-learning models. Upstream, the Madison, Sandia, and Cenerg photovoltaic models are simulated beforehand to realistically reproduce PV module electrical behaviour under a wide range of operating and environmental stress conditions, serving as a reference for emulation and for generating IEC 61215-oriented test scenarios. Data are collected through an embedded acquisition system built around Arduino-based sensors, which communicate with a Raspberry Pi that serves as both a gateway and a central data-collection unit. This setup measures key PV electrical quantities (I–V and P–V curves, V_{oc} , I_{sc}) as well as contextual and environmental variables such as irradiance, temperature, and humidity. A rigorous preprocessing stage is then applied, including time synchronisation of measurements, outlier filtering, and extraction of relevant features, particularly derived parameters and performance-drift indicators.

On this basis, the machine-learning module performs anomaly detection, fault diagnosis, and classification of abnormal behaviours using models such as deep neural networks, while also incorporating predictive models dedicated to health-state estimation and early anticipation of performance losses, tailored to local environmental variability. The outputs feed a decision-support component and an operational interface that generates intelligent alerts and supports optimised maintenance planning (cleaning, inspection, replacement), with prioritisation driven by fault criticality and energy impact. Real-time monitoring and performance visualisation are provided via a dedicated LabVIEW-based interface, enabling intuitive tracking of electrical and environmental parameters, as well as health indicators, even with limited connectivity. Finally, a continuous learning loop is supported through field feedback: real operational data and label corrections are reinjected into the pipeline to progressively enhance the robustness and accuracy of the predictive models.

2.3. Sensor and data acquisition system

The data acquisition system is built around an Arduino-based sensor array, interfaced with a Raspberry Pi 4 that serves as a central gateway and data-collection unit. Time synchronisation across all sensor streams is ensured via NTP (Network Time Protocol), with a maximum inter-channel latency of less than 50 ms. Raw signals undergo a median-filter preprocessing stage (window = 5 samples) to suppress spike noise before feature extraction. Table 1 summarises the sensors used, their measured quantities, measurement accuracy, and sampling rates.

Tab. 1. Sensor specifications and data acquisition parameters.

Measured quantity	Sensor model	Measurement accuracy	Sampling rate
Current (I)	ACS712 Hall-effect sensor	$\pm 1.5\%$ FS	10 Hz
Voltage (V)	Resistive voltage divider	$\pm 0.5\%$ FS	10 Hz
Solar irradiance	Silicon pyranometer	± 3 W/m ²	1 Hz
Module temperature	DS18B20 digital thermometer	$\pm 0.5^\circ\text{C}$	1 Hz
Relative humidity	DHT22	$\pm 2\%$ RH	0.5 Hz
Ambient temperature	DHT22	$\pm 0.5^\circ\text{C}$	0.5 Hz

2.4. Dataset description and experimental protocol

Three independent datasets were generated from the Sandia, Madison, and Cenerg models, respectively, each covering six fault classes: decreased shunt resistance, degradation, increased series resistance, open circuit, short circuit, and soiling. For each dataset, a total of $N = 12,000$ labelled sequences were generated (2,000 per fault class), ensuring balanced class distribution without over-representation of any single fault type. Each sequence covers a sliding window of 30 consecutive time steps, sampled at 10 Hz, capturing both transient and steady-state fault signatures. The datasets were partitioned at the scenario level (i.e., all time steps from a given simulation run were assigned exclusively to a single partition) into training (70%), validation (15%), and test (15%) sets, thereby preventing temporal data leakage between splits. Class balance in the training split was verified; no synthetic oversampling was required, given the balanced generation procedure.

Hyperparameters for all models (BiGRU units: 64/128, learning rate: {0.001, 0.0005}, dropout rate: {0.2, 0.3}, sequence length: {20, 30}) were optimised via a grid search and evaluated exclusively on the validation set. The test set was held out and used only for final performance evaluation. To assess result stability, all experiments were repeated 5 times with different random seeds; performance metrics are reported as the mean $\pm$ standard deviation across these 5 runs. The autoencoder was trained on healthy-only sequences from the training partition; the anomaly detection threshold was selected to maximise the F1-score on the validation set, with a sensitivity analysis reported in Section 3.2.2.

3. RESULTS AND DISCUSSION

This section reports the validation results of the proposed photovoltaic (PV) emulator by reproducing standard electrical characteristics and accelerated ageing tests specified in IEC 61215. Emulator performance is evaluated under standard test conditions, controlled environmental variations, durability test sequences, and electrical fault scenarios. The emulator outputs are compared against manufacturer specifications (for the Madison-based reference module) and well-established analytical approaches, in particular the Sandia single-diode model.

3.1. Emulator validation and reproduction of IEC 61215 tests

Figure 2 presents the current–voltage (I – V) and power–voltage (P – V) characteristics generated by the emulator under standard test conditions (STC: irradiance of 1000 W/m² and cell temperature of 25 °C). The results are benchmarked against the reference curves from the Madison manufacturer's datasheet (reference module) and the Sandia single-diode model. The emulator accurately reproduces the overall shape of the I – V and P – V curves, including the short-circuit current (I_{sc}), open-circuit voltage (V_{oc}), and the maximum power point (MPP). The deviation between the emulator and the Sandia model remains below typical modelling uncertainties reported in the literature, with relative errors generally limited to a few per cent for V_{oc} , I_{sc} , and P_{max} . The close alignment of the emulator-generated curves with the reference models confirms the correctness of the parameter identification and the numerical implementation of the single-diode model. Minor discrepancies observed around the knee region of the I – V curve can be attributed to differences in resistive parameterisation and the absence of manufacturer-specific secondary effects, which are commonly neglected in analytical PV models.

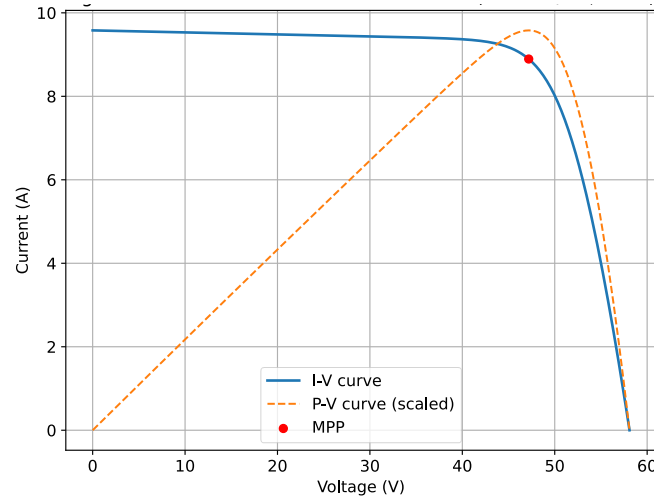


Fig. 2. I-V and P-V characteristics at STC (1000 W/m^2 , 25°C)

3.1.1. Performance under variable environmental conditions

To evaluate the emulator's ability to reproduce realistic operating conditions, Figure 3 shows families of I - V and P - V curves simulated under multiple irradiance levels (1000 , 800 , 600 , and 400 W/m^2) and cell temperatures (25 , 45 , and 65°C).

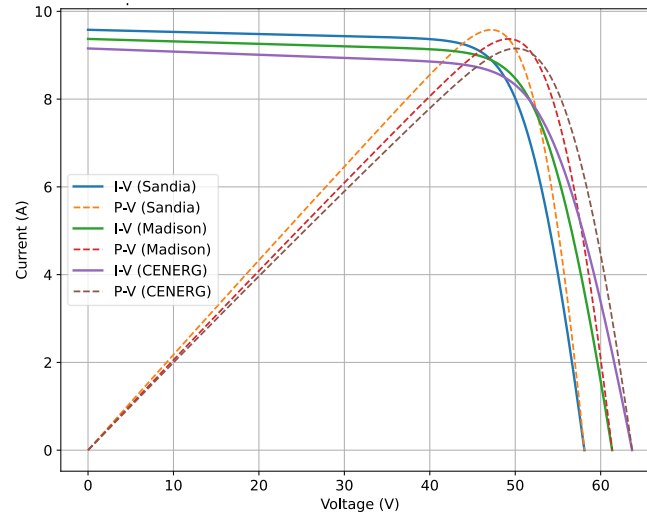


Fig. 3. Curves under varying irradiance and temperature

As expected from PV theory, a decrease in irradiance primarily affects the short-circuit current, which is approximately linearly dependent on incident irradiance. By contrast, increasing cell temperature mainly reduces the open-circuit voltage (V_{oc}) due to enhanced recombination effects and increased intrinsic carrier concentration in the semiconductor junction. The emulator successfully captures these trends across the full operating range, maintaining physically consistent curve shapes and realistic shifts of the maximum power point. These results demonstrate the suitability of the emulator for studying PV system behaviour under fluctuating environmental conditions, such as those encountered in outdoor installations and grid-connected applications.

3.1.2. Simulation of IEC 61215 durability tests

Figure 4 illustrates the evolution of key electrical performance parameters (P_{max} , V_{oc} , and I_{sc}) during a simulated thermal cycling test, in accordance with IEC 61215-2 requirements. Thermal cycling is known to induce mechanical stress, solder joint fatigue, and interconnection degradation, which ultimately affect the electrical performance of PV modules.

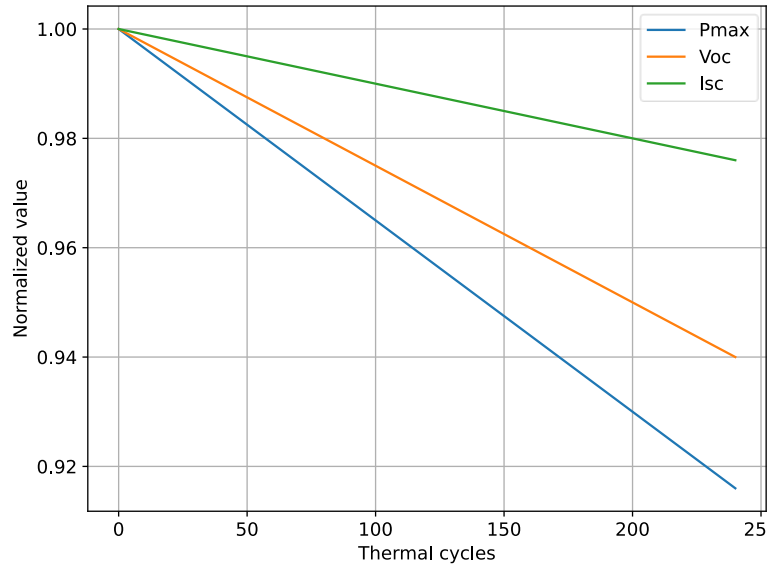


Fig. 4. Performance degradation during thermal cycling test

The simulation results reveal a progressive degradation of the maximum power output, accompanied by a noticeable reduction in open-circuit voltage, while the short-circuit current remains comparatively less affected. This behaviour is consistent with experimentally observed ageing mechanisms reported in the literature, in which increases in series resistance and recombination losses predominantly affect voltage-related parameters. The emulator's ability to reproduce such degradation trends highlights its potential as a virtual test bench for accelerated lifetime analysis and reliability studies, reducing the need for time-consuming and costly experimental campaigns.

3.1.3. Reproduction of electrical faults and defects

The emulator's capability to simulate electrical faults is demonstrated in Figure 5, which compares the $I-V$ and $P-V$ characteristics of a PV module operating under normal conditions and with a simulated hot-spot fault. The emulator's capability to simulate electrical faults is illustrated in Figure 5, which compares the $I-V$ and $P-V$ characteristics of a PV module under normal operation and under a simulated hot-spot fault. The hot-spot is modelled as a localised reduction in the shunt resistance (R_{sh}), resulting in a marked distortion of the $I-V$ curve and a pronounced reduction in the maximum extractable power. The affected curves exhibit a softened knee region and increased power losses, which are characteristic signatures of hot-spot and mismatch phenomena observed in real PV modules. These results confirm that the emulator can realistically reproduce fault-induced performance degradation, making it a valuable tool for developing and validating fault detection, diagnosis, and protection algorithms in PV systems.

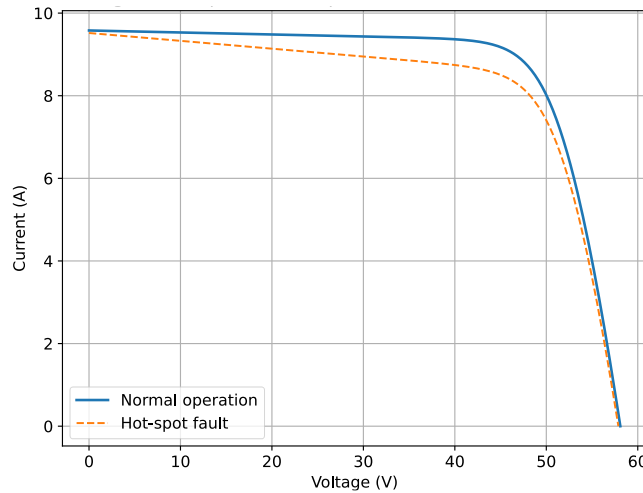


Fig. 5. Impact of hot-spot fault on I-V characteristics

3.1.4. Quantitative comparison of electrical parameters

Table 2 summarises a quantitative comparison of the key electrical parameters (V_{oc} , I_{sc} , P_{max} , and fill factor FF) obtained from the emulator against reference values derived from the manufacturer's datasheet (Madison-based reference) and the analytical Sandia model under different irradiance and temperature conditions.

Tab. 2. Quantitative comparison of emulator electrical parameters against Sandia and Madison references under varying irradiance and temperature conditions

	Model	Irradiance (W/m^2)	Temperature ($^{\circ}\text{C}$)	V_{oc} (V)	I_{sc} (A)	P_{max} (W)	FF (-)
0	Sandia	1000	25	58.094260	9.579473	419.640536	0.754054
1	Sandia	800	25	57.581632	7.666857	337.846834	0.765277
2	Sandia	1000	45	54.275191	9.679259	386.279056	0.735288
3	Madison	1000	25	61.341216	9.371365	424.590049	0.738609
4	Madison	800	25	60.784211	7.501663	342.493827	0.751112
5	Madison	1000	45	57.070413	9.467073	388.387081	0.718850
6	Cennerg	1000	25	63.679263	9.154229	416.207738	0.713987
7	Cennerg	800	25	63.078100	7.330677	336.869138	0.728515
8	Cennerg	1000	45	58.897239	9.243781	377.197408	0.692826

Overall, the emulator exhibits strong agreement with the Sandia model, which is used here as the analytical benchmark. Slightly larger discrepancies are observed with the Madison-based reference, mainly due to datasheet simplifications and manufacturing tolerances. Variations in the fill factor are primarily driven by differences in the assumed series and shunt resistances among the models considered.

Figure 6 provides a direct graphical comparison of the I - V and P - V characteristics obtained from the Sandia, Madison, and CENERG models under standard test conditions (STC). While all three models exhibit similar open-circuit voltages, noticeable differences arise near the maximum power point.

The Sandia-based model, used as an analytical benchmark, exhibits the sharpest knee in the I - V curve and the highest peak power, reflecting optimised resistive parameters and minimal internal losses. The Madison model, derived from manufacturer datasheet information, shows a slightly reduced fill factor, primarily due to higher effective series resistance and simplified assumptions in parameter extraction. The Cennerg model presents a more pronounced deviation, with a smoother knee region and a lower maximum power output. This behaviour is consistent with increased series resistance and reduced shunt resistance, which are commonly associated with ageing effects, material degradation, or non-ideal operating conditions. The corresponding P - V curve highlights a broader, flatter maximum-power region, indicating reduced conversion efficiency and increased internal dissipation.

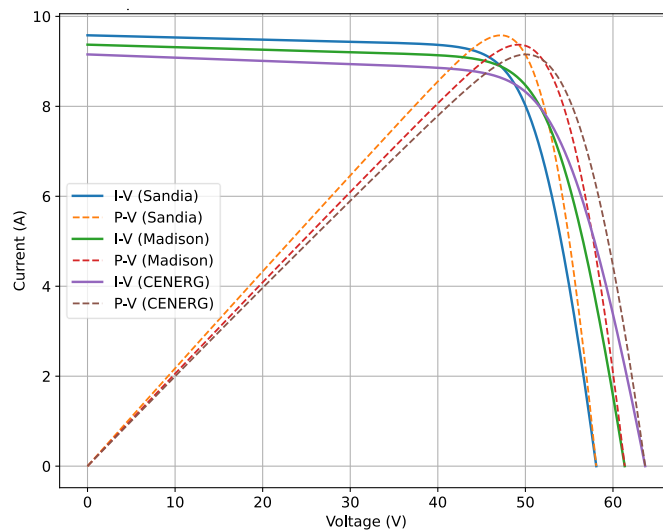


Fig. 6. Comparison of I - V and P - V for different PV models at STC

These graphical observations are fully consistent with the quantitative results reported in Table 2, where the Sandia model yields the highest fill factor and maximum power, while the Madison and Cenerg models exhibit progressively lower performance indicators. The combined use of numerical metrics (Table 2) and comparative $I-V/P-V$ curves (Figure 6) provides comprehensive validation of the emulator's ability to accurately reproduce and distinguish among different PV modelling approaches.

These quantitative results further validate the accuracy and robustness of the proposed emulator across a wide range of operating conditions.

3.2. Performance of the autoencoder-based predictive maintenance module

This section evaluates the performance of the proposed predictive maintenance module, which is based on an unsupervised autoencoder architecture. The autoencoder is designed to learn a compact representation of healthy PV operating conditions and to detect deviations from this normal behaviour through reconstruction error analysis. The assessment combines qualitative and quantitative indicators, covering reconstruction accuracy, anomaly discrimination capability, and robustness under varying environmental conditions.

3.2.1. Autoencoder reconstruction performance under healthy conditions

Figure 7 presents a visual comparison between representative healthy input data and their corresponding reconstructions generated by the trained autoencoder. The results show a strong overlap between the original and reconstructed signals, particularly in the region around the maximum power point, which is the most sensitive area for PV performance assessment.

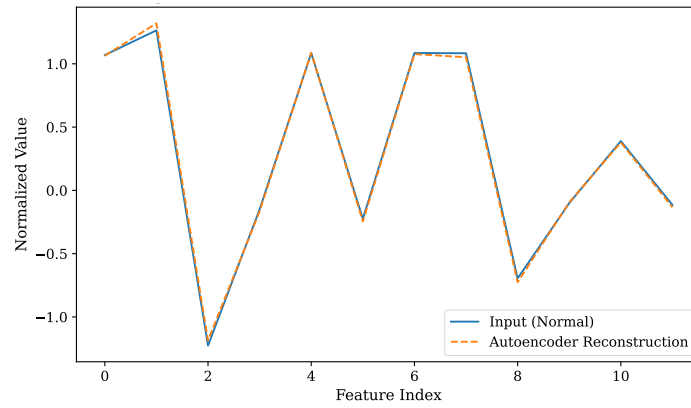


Fig. 7. Normal sample reconstruction (Input vs Output)

The autoencoder accurately preserves the overall shape of the $I-V$ characteristics, including the short-circuit current and open-circuit voltage regions. Minor reconstruction discrepancies are mainly observed in high-voltage, low-current regions, where measurement noise and model non-linearities are more pronounced. These deviations remain within acceptable margins and do not affect the overall diagnostic capability.

Quantitatively, the mean reconstruction error computed over the healthy training dataset remains low, indicating that the autoencoder has successfully learned a stable latent representation of nominal PV behaviour. This low baseline error provides a reliable reference for subsequent anomaly detection.

3.2.2. Distribution of reconstruction errors and threshold selection

Figure 8 illustrates the distribution of reconstruction errors for healthy and anomalous datasets. The healthy data exhibit a narrow, sharply peaked distribution centred around low error values, reflecting the stability and consistency of nominal operating conditions learned during training. By contrast, anomalous data produce a significantly broader distribution, shifted toward higher reconstruction errors.

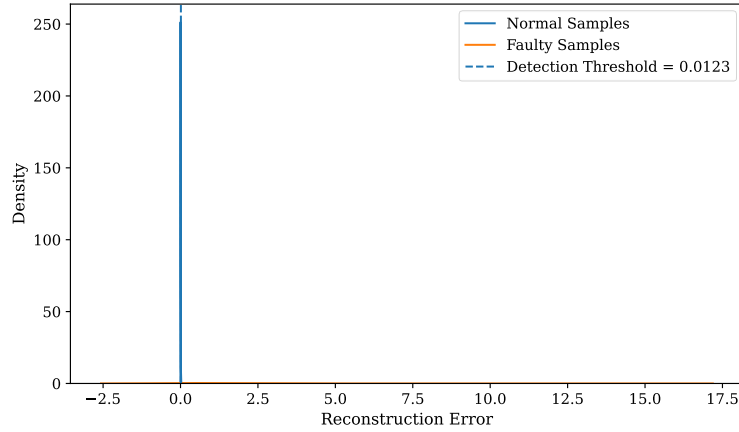


Fig. 8. Reconstruction Error Distribution

The clear separation between the two distributions enables the definition of a robust anomaly detection threshold. The selected threshold, indicated in Figure 8, is chosen to minimise false positives while ensuring high sensitivity to abnormal behaviour. This threshold-based strategy is consistent with common practice in unsupervised anomaly detection for PV systems and industrial monitoring applications. The strong contrast between the two distributions confirms the discriminative power of the reconstruction error as an effective anomaly score.

To assess the sensitivity of the detection performance to the threshold choice, Table 3 reports precision, recall, F1-score, and false positive rate across three threshold configurations: a conservative threshold ($\tau - 20\%$, maximising recall), the optimal threshold τ (maximising F1-score on the validation set), and a restrictive threshold ($\tau + 20\%$, minimising false positives). The results confirm that the selected threshold τ provides a balanced operating point. In operational PV monitoring contexts such as Cameroon, where maintenance resources are limited and unplanned outages impose high costs, a recall-maximising configuration (lower threshold) may be preferred at the expense of increased inspection frequency. The final choice of threshold should therefore be tailored to the deployment's specific cost structure.

Tab. 3. Threshold sensitivity analysis for the autoencoder-based anomaly detector

Threshold configuration	Precision	Recall	F1-score	False positive rate (%)
$\tau - 20\%$ (conservative)	0.74	0.96	0.84	18.2%
τ (optimal, selected)	0.82	0.90	0.86	9.3%
$\tau + 20\%$ (restrictive)	0.91	0.79	0.85	3.1%

3.2.3. Detection of simulated anomalies

To further illustrate the detection capability of the proposed method, specific anomaly scenarios are analysed. These include performance degradation due to soiling and the appearance of localised hot-spot faults. The temporal evolution of the reconstruction error shows stable, low-level behaviour during normal operation, followed by a sharp increase upon anomaly detection. When the reconstruction error exceeds the predefined threshold, the system successfully triggers an anomaly detection event. The detection delay remains limited, demonstrating the autoencoder's ability to identify faults at an early stage. Table 4 summarises representative anomaly detection cases, including the type of defect, the time of detection, and the corresponding anomaly score. The results indicate that severe faults, such as hot-spots, are detected more rapidly and with higher reconstruction error peaks, whereas gradual degradations, such as soiling, produce a slower but clearly detectable increase in the anomaly score.

Tab. 4. Representative autoencoder-based anomaly detection cases: defect type, detection time, and anomaly score (reconstruction error)

Anomaly Type	Mean Anomaly Score
Short Circuit	12.578
Open Circuit	12.413
Increased Series Resistance	1.389
Decreased Shunt Resistance	0.700
Degradation	0.063
Soiling	0.055

The quantitative performance of the autoencoder-based detection framework is reported in Table 5, using standard classification metrics: precision, recall, F1-score, and the area under the ROC curve (AUC). These metrics are computed on a validation dataset containing both healthy and anomalous samples.

Tab. 5. Quantitative performance of autoencoder-based anomaly detection on the validation dataset (Precision, Recall, F1-score, and AUC)

Metric	Value
Precision	0.817
Recall	0.896
F1-Score	0.855
AUC	0.967

The high-precision values indicate a low false-alarm rate, which is essential for practical deployment in PV monitoring systems. At the same time, the high recall demonstrates the method's strong sensitivity to anomalies, ensuring that most fault events are correctly detected. The resulting F1-score reflects a balanced trade-off between precision and recall.

AUC values close to unity confirm the autoencoder's excellent discriminative capability across a wide range of detection thresholds, highlighting its robustness and reliability as an unsupervised anomaly detection tool.

3.3. Results of fault classification models

3.3.1. Learning behaviour and convergence analysis

This subsection analyses the learning dynamics, convergence properties, and generalisation capability of the proposed sequence-based fault classification models. The evaluated architectures include GRU, BiGRU, deep LSTM, GRU enhanced with an attention mechanism, and a simplified Transformer-based model. The analysis is conducted on three independent datasets (Madison, Sandia, and Cenerg) to assess robustness and dataset independence under realistic photovoltaic operating conditions.

From the loss curves (Figure 9, left), the GRU, BiGRU, and deep LSTM architectures exhibit a rapid and monotonic decrease in training loss, reaching near-zero values after approximately 15–25 epochs. The close alignment between training and validation loss curves indicates a stable optimisation process and limited overfitting. Among these models, the BiGRU architecture demonstrates the fastest convergence, which can be attributed to its bidirectional structure, enabling it to exploit both past and future temporal dependencies within the input sequences.

The GRU model augmented with an attention mechanism shows a more gradual reduction in loss. This behaviour reflects the increased representational complexity introduced by the attention module, which requires additional training epochs to learn discriminative temporal weighting effectively. Nevertheless, the validation loss closely follows the training trend, confirming that the attention mechanism improves feature extraction without compromising generalisation.

In contrast, the simplified Transformer-based architecture exhibits nearly constant and relatively high loss values throughout training, indicating an inability to learn meaningful temporal representations from the dataset. This limitation is primarily attributed to the moderate dataset size, limited temporal resolution, and the lack of explicit positional encoding, which are known to hinder Transformer-based models in time-series classification when data availability is constrained.

The accuracy curves (Figure 9, right) further confirm these observations. The BiGRU model rapidly reaches near-perfect classification accuracy on both training and validation sets within fewer than 15 epochs. GRU and deep LSTM models also achieve high accuracy levels, albeit with slightly slower convergence. The GRU-Attention model converges more progressively but ultimately attains comparable accuracy, highlighting its ability to emphasise relevant temporal segments. Conversely, the Transformer-based model remains close to random classification performance. Figure 10 presents the learning curves obtained on the MADISON dataset, providing additional insight into the robustness and reproducibility of the observed learning behaviours across datasets.

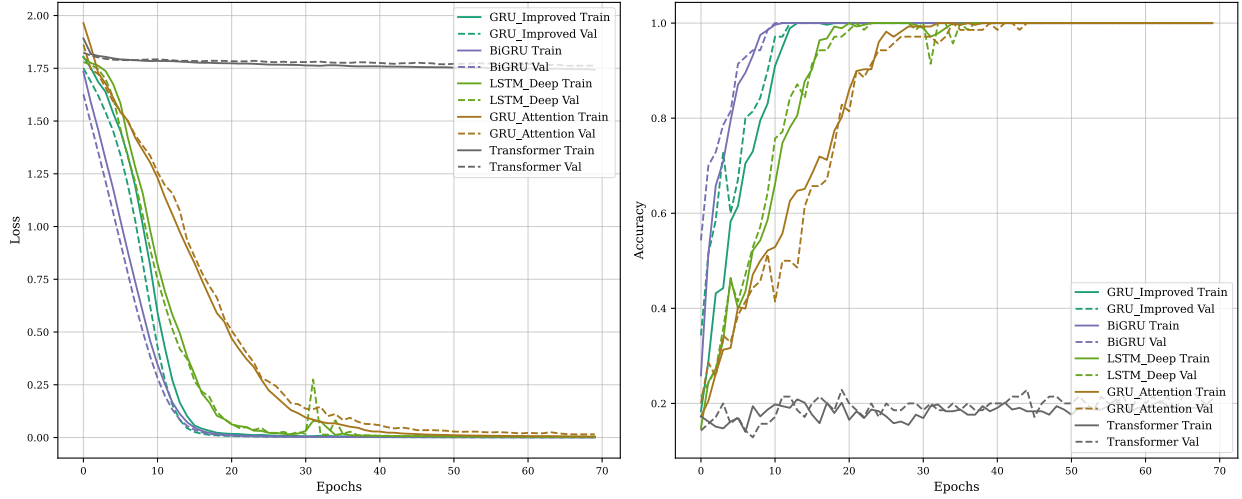


Fig. 9. Learning Curves on the SANDIA Dataset (Training and validation loss and accuracy)

The trends observed in Figure 10 are fully consistent with those reported in Figure 9. The GRU, BiGRU, and deep LSTM models again demonstrate rapid convergence, characterised by a sharp decrease in loss during the initial training epochs followed by stable saturation. The close overlap between training and validation curves confirms strong generalisation capability and indicates that these models do not suffer from significant overfitting on the MADISON dataset.

The BiGRU architecture maintains its leading position, achieving near-optimal accuracy in fewer epochs than the other recurrent models. This behaviour reinforces the value of bidirectional temporal modelling for photovoltaic fault signatures exhibiting delayed or asymmetric temporal patterns.

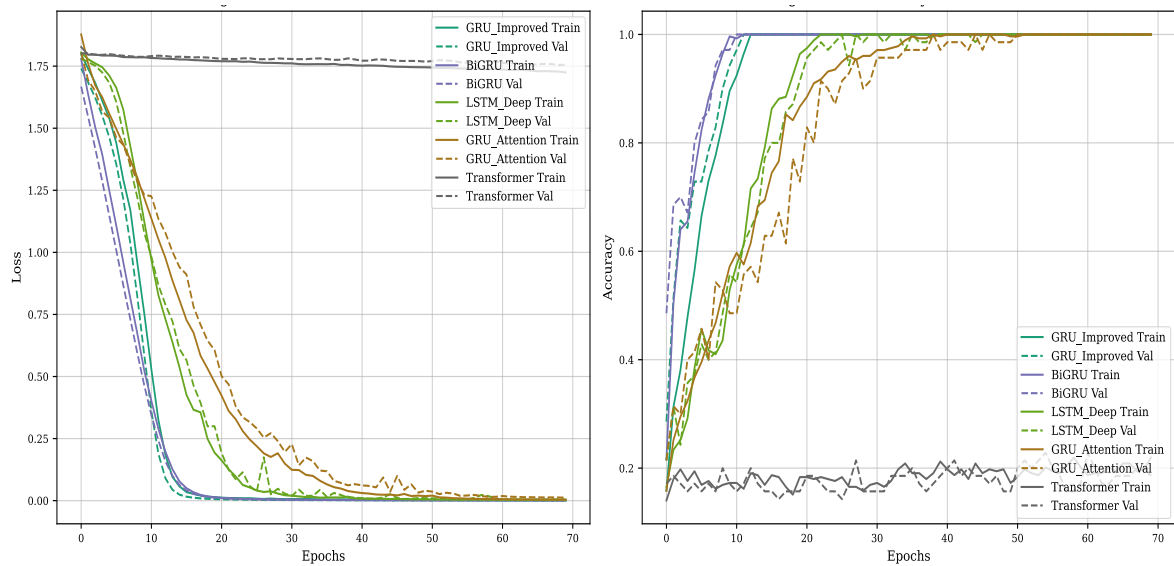


Fig. 10. Learning Curves on the MADISON Dataset (Training and validation loss and accuracy)

Consistent with previous observations, the simplified Transformer-based architecture again fails to demonstrate effective learning. Both loss and accuracy curves remain largely flat, confirming that Transformer-style models without deep stacking or positional encoding are not well-suited for photovoltaic fault classification under moderate data availability.

The GRU with attention mechanism displays a slower yet steady convergence profile. While its learning dynamics are less aggressive, the final validation accuracy closely matches that of the recurrent-only models, highlighting the effectiveness of attention mechanisms in selectively emphasising informative temporal segments, particularly relevant for datasets such as MADISON, where fault-related information may be sparsely distributed over time.

Figure 11 illustrates the learning behaviour of the evaluated models on the CENERG dataset, which is characterised by higher variability and more realistic operational conditions.

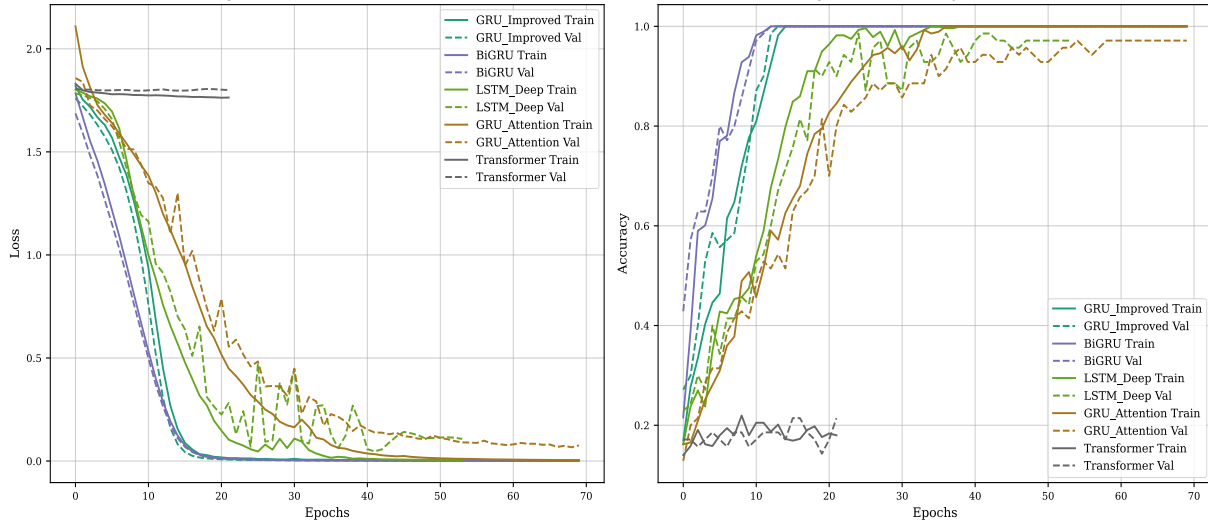


Fig. 11. Learning Curves on the CENERG Dataset (Training and validation loss and accuracy)

From the loss convergence curves (Figure 11, left), the GRU, BiGRU, and deep LSTM architectures again exhibit rapid and stable convergence, with training loss decreasing sharply within the first 15–20 epochs. The validation loss closely tracks the training loss, confirming strong generalisation despite the increased variability inherent to real-world datasets such as CENERG.

Among all evaluated models, the BiGRU architecture consistently demonstrates the fastest convergence and the earliest stabilisation at low loss values. This behaviour highlights its effectiveness at capturing bidirectional temporal dependencies in photovoltaic fault evolution under non-stationary operating conditions. The GRU-Attention model shows a more oscillatory and progressive reduction in loss, reflecting the increased optimisation complexity induced by the attention mechanism. Nevertheless, the alignment between training and validation curves confirms that the added flexibility does not degrade generalisation performance. The Transformer-based model again fails to learn meaningful representations, with both loss and accuracy remaining nearly constant throughout training. This observation further reinforces the conclusion that Transformer architectures are less suitable than recurrent models for photovoltaic fault classification in low-to-moderate data regimes. The accuracy curves (Figure 11, right) corroborate these findings. The BiGRU model achieves near-perfect accuracy on both the training and validation sets in fewer than 15 epochs, closely followed by the GRU and LSTM models. The GRU-Attention model converges more slowly but ultimately achieves comparable accuracy. In contrast, the Transformer-based model remains close to random classification levels.

Across all three datasets, a consistent ranking of the evaluated models emerges. The BiGRU architecture consistently outperforms the other approaches in convergence speed, training stability, and classification accuracy. Its ability to leverage bidirectional temporal context proves particularly advantageous for distinguishing fault types with similar instantaneous signatures but distinct temporal evolution.

The GRU-Attention model appears to be a competitive alternative, offering enhanced representational capacity and potential interpretability at the expense of greater training complexity. However, the consistently

poor performance of the simplified Transformer-based architecture indicates that attention-only models require larger datasets and more elaborate designs to outperform recurrent-based approaches in this application.

3.3.2. Confusion matrix analysis and class-wise performance evaluation

This subsection provides a detailed evaluation of the fault classification performance of the selected BiGRU model through confusion matrix analysis and class-wise metrics. While global accuracy offers an overall indication of model performance, confusion matrices allow a finer inspection of misclassification patterns and class discrimination capability, which is critical for practical photovoltaic fault diagnosis.

Figure 12 presents the confusion matrix obtained for the BiGRU-based classifier evaluated on the synthetic fault dataset. The fault classes considered include decreased shunt resistance, degradation, increased series resistance, open circuit, short circuit, and soiling. A strong dominance of diagonal elements can be observed, indicating a very high rate of correct classification across all fault categories. This result confirms the BiGRU architecture's excellent discriminative capability when applied to temporally structured photovoltaic fault signatures.

For the decreased shunt-resistance and increased series-resistance fault classes, perfect classification is achieved, with all samples correctly assigned to their respective categories. This highlights the BiGRU model's ability to capture subtle yet distinctive temporal patterns associated with variations in resistive parameters in photovoltaic systems. The open-circuit and short-circuit fault classes also exhibit flawless classification, with no observable confusion with other fault types. This is particularly relevant operationally, as these fault modes correspond to severe electrical anomalies that require immediate intervention.

The soiling class shows near-perfect performance, with only a single misclassification, in which one sample is incorrectly assigned to the degradation class. This limited confusion can be attributed to the partially overlapping long-term temporal effects of soiling and degradation on photovoltaic output characteristics, especially under slowly varying environmental conditions.

Similarly, the degradation class exhibits very few misclassified samples, mainly confused with soiling. This observation is physically consistent, as both phenomena may induce progressive performance degradation rather than abrupt transient signatures. Nevertheless, the extremely low misclassification rate demonstrates that the BiGRU model effectively separates these fault mechanisms by exploiting temporal dependencies in the input sequences.

The confusion matrix indicates near-unity precision and recall values for all fault classes, confirming that the BiGRU model maintains both high sensitivity and high specificity. The absence of systematic off-diagonal patterns further suggests that misclassifications are isolated and not indicative of structural weaknesses in the model. Importantly, the balanced performance across all fault categories demonstrates that the classifier does not suffer from class bias, even when the number of samples differs between fault types. This robustness can be attributed to the bidirectional recurrent structure, which enables the model to capture both short-term transients and long-term temporal trends characteristic of different photovoltaic fault mechanisms.

3.3.3. Implications for diagnostic reliability

The results illustrated in Figure 12 confirm that the BiGRU model achieves highly reliable fault discrimination under synthetic operating conditions. The excellent class-wise performance indicates that the proposed architecture is well-suited for deployment in real-time photovoltaic monitoring systems, where accurate identification of both abrupt and progressive faults is essential for timely maintenance and system protection. Combined with the convergence and generalisation analysis presented in Section 3.3.1, these findings further validate the selection of the BiGRU architecture as the core classification module of the proposed hybrid diagnostic framework. Table 6 reports the quantitative performance metrics of the selected BiGRU classifier, including precision, recall, and F1-score computed for each fault category, along with the overall classification accuracy. These metrics, derived from the confusion matrix in Figure 12, provide a comprehensive assessment of the model's diagnostic reliability at the class level.

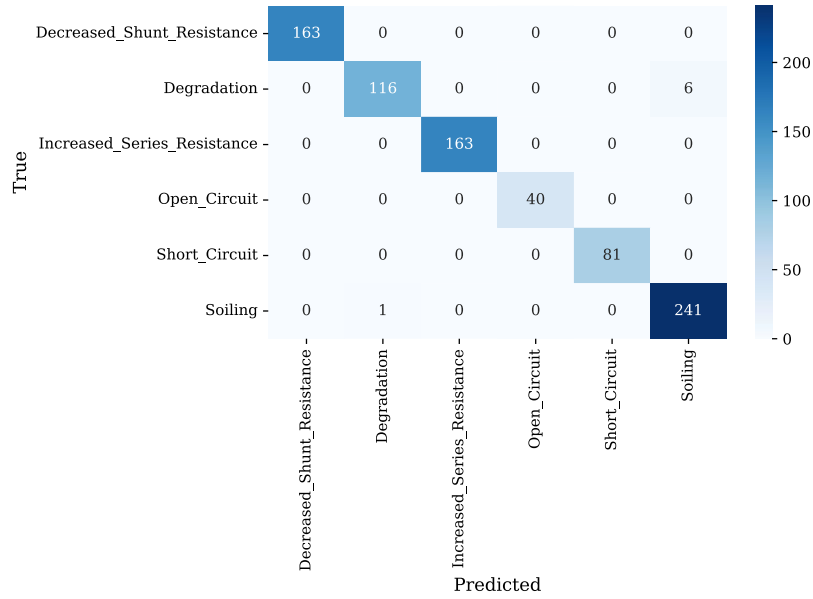


Fig. 12. Confusion Matrix of the BiGRU Model on the Synthetic Dataset (True vs. predicted fault classes)

Tab. 6. Class-wise Accuracy Metrics of the BiGRU Fault Classification Model (Values reported in percentage.)

Fault class	Precision (%)	Recall (%)	F1-score (%)
Decreased shunt resistance	100.0	100.0	100.0
Degradation	99.1	95.1	97.1
Increased series resistance	100.0	100.0	100.0
Open circuit	100.0	100.0	100.0
Short circuit	100.0	100.0	100.0
Soiling	97.6	99.6	98.6
Overall accuracy	-	-	99.3

The results presented in Table 6 demonstrate the excellent diagnostic performance of the BiGRU classifier across all photovoltaic fault types considered.

Perfect precision, recall, and F1-score values are achieved for shunt-resistance decrease, series-resistance increase, open-circuit, and short-circuit faults. This confirms that the proposed model accurately detects both parametric degradations and severe electrical anomalies without ambiguity.

For the degradation and soiling classes, slightly reduced recall and precision values are observed. These minor performance reductions are consistent with the limited confusion identified in the confusion matrix and can be attributed to the partially overlapping temporal signatures of progressive faults. Nevertheless, F1-scores remain above 97%, indicating robust and reliable discrimination.

The overall classification accuracy of 99.3% confirms the high effectiveness of the BiGRU architecture and aligns with the convergence and generalisation behaviour discussed in Section 3.3.1.

From a practical perspective, the balanced performance across all fault categories is particularly important for photovoltaic monitoring applications, where both abrupt failures (e.g., short circuit, open circuit) and slowly evolving faults (e.g., degradation, soiling) must be identified with high confidence. The consistently high F1-scores demonstrate that the proposed model maintains an optimal trade-off between sensitivity and specificity. These results further validate the selection of the BiGRU architecture as the reference classifier within the proposed hybrid diagnostic framework.

3.4. Comparative discussion with recent literature

To contextualise the performance of the proposed framework, this section positions the reported results against recent related work on PV fault diagnosis and predictive maintenance. Recent reviews (Li et al., 2021; El-Banby et al., 2023; Hamza et al., 2025) survey a broad range of machine-learning and deep-learning approaches for PV fault detection, covering ANNs, SVMs, CNNs, LSTMs, and hybrid architectures. Reported overall classification accuracies on balanced synthetic or semi-real datasets typically range from 88% to 98%, depending on the number of fault classes, the data generation strategy, and the model complexity. Within this

range, recurrent architectures (GRU, LSTM) and hybrid two-stage pipelines tend to occupy the upper end, particularly when temporal dependencies in electrical signals are explicitly exploited (Hamza et al., 2025; Al-Humairi et al., 2025). Table 7 summarises a selection of representative approaches, along with the results of the present work.

Tab. 7. Comparison of the proposed framework with representative recent PV fault diagnosis approaches.

Reference	Method	Data type	Classes	Accuracy/ AUC	Notes
Li et al. (2021)	ANN variants	Simulated/experimental	3–5	90–97%	Review: range across reviewed works
El-Banby et al. (2023)	DL incl. AE-based	Mixed	3–6	88–97% / AUC 0.87–0.95	Review: threshold sensitivity is rarely analysed
Al-Humairi et al. (2025)	ML ensemble	Synthetic/semi-real	4–5	92–96%	Balanced datasets; no tropical context
Hamza et al. (2025)	CNN/LSTM/hybrid	Synthetic	4–6	94–98%	Two-stage pipelines; review
This work	BiGRU + Autoencoder (two-stage)	Synthetic (3-model emulator)	6	99.3% / AUC 0.967	Threshold sensitivity analysed; tropical context

The BiGRU classifier achieves an overall accuracy of 99.3% across six fault classes, which places it at the upper end of the performance range reported in the reviewed literature. This result is consistent with the observation that bidirectional recurrent architectures, which exploit temporal dependencies in both directions, offer a structural advantage over feedforward or unidirectional models for time-series fault classification. It is important to note, however, that this high accuracy is obtained on balanced, synthetically generated data; real-world accuracy may be lower due to class imbalance, sensor noise, and distribution shift, as discussed in the Limitations section.

For the anomaly detection component, the autoencoder achieves an AUC of 0.967, which exceeds the typical range of 0.87–0.95 reported for reconstruction-error-based unsupervised detectors in recent reviews (El-Banby et al., 2023). A distinguishing feature of the present work is the explicit threshold sensitivity analysis (Section 3.2.2), which quantifies the precision-recall trade-off across three operating configurations. This analysis, rarely reported in comparable studies, provides actionable guidance for deployment in contexts such as Cameroon, where the asymmetric costs of missed faults and false alarms must be explicitly considered.

Beyond raw performance metrics, the proposed framework presents several distinguishing characteristics relative to the surveyed literature. First, the simultaneous use of three complementary PV models (Sandia, Madison, Cenerg) for dataset generation ensures that the training data covers a broader range of operating conditions and parameter variability than single-model approaches, improving robustness and generalisability. Second, the two-stage unsupervised-then-supervised architecture explicitly separates anomaly detection from fault classification, which reduces dependence on exhaustive fault labelling and improves resilience to unforeseen anomaly types. Third, the framework is explicitly designed for tropical and resource-constrained environments, a deployment context that remains underrepresented in the existing PV diagnostics literature (Sepúlveda-Oviedo et al., 2023; Hamza et al., 2025).

The present work relies on data generated through analytical PV models (Sandia, Madison, Cenerg) and the software emulator. This approach provides a controlled, reproducible, and cost-effective validation environment, which is particularly relevant for resource-constrained contexts such as Cameroon, where access to labelled field datasets is limited. However, it does not fully substitute for field data validation. The classification and detection metrics reported (BiGRU accuracy $\geq 99\%$, autoencoder AUC ≈ 0.97) must therefore be interpreted in the context of synthetic data; real-world performance may differ due to sensor noise, measurement uncertainty, unmodelled degradation pathways, and environmental non-stationarities not captured by the analytical models. No cross-validation on an independent external dataset was performed. These limitations do not invalidate the contribution of the proposed framework as a reproducible laboratory-grade platform for algorithm development and comparative evaluation, but they define the scope within which the reported results should be generalised.

4. CONCLUSIONS

This paper proposed and validated a hybrid, data-driven framework for photovoltaic (PV) system monitoring that combines a PV emulator, an unsupervised autoencoder-based anomaly-detection module, and a supervised BiGRU fault classifier. The emulator accurately reproduces standard electrical characteristics, environmental dependencies, ageing effects, and fault-induced distortions under selected IEC 61215-inspired test scenarios, and serves as a complementary tool rather than a replacement for formal IEC 61215 certification. Its strong agreement with analytical benchmarks and manufacturer-based references confirms its suitability as a reliable platform for generating data for intelligent diagnostic algorithms.

The autoencoder proved highly effective for early anomaly detection, achieving strong discrimination (AUC close to unity) with robustness to irradiance and temperature variability, enabling reliable detection without excessive false alarms. The BiGRU classifier further achieved an overall accuracy exceeding 99%, exploiting bidirectional temporal dependencies to reliably discriminate both abrupt electrical faults and progressive mechanisms such as degradation and soiling.

The key contribution of this work lies in integrating unsupervised and supervised learning into a unified two-stage diagnostic framework: the autoencoder serves as a robust first-line detector, while the BiGRU provides precise fault identification once sufficient temporal evidence is available. This strategy improves generalisation, reduces reliance on labelled fault data, and offers a scalable, cost-effective predictive maintenance solution particularly suited to resource-constrained environments such as Cameroon. The scope and limitations of this validation approach are discussed in detail in Section 3.4; these should be taken into account when interpreting the reported results and directly motivate the future research directions outlined below.

Future work will focus on: (i) large-scale field validation on real PV installations in Cameroon; (ii) collection of labelled field data and benchmarking against publicly available datasets such as PVDAQ (Sandia) or similar open repositories; (iii) transfer-learning strategies to adapt the trained models to real operational conditions; (iv) the integration of explainable AI (XAI) techniques to improve model interpretability for maintenance operators; and (v) the extension toward probabilistic and adaptive temporal models.

Conflicts of Interest

The authors declare no conflict of interest

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