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Research article

Assessing PV inverter efficiency degradation under semi-arid conditions: A case study in Morocco

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ABSTRACT

The worldwide shift towards renewable energy sources, including solar and wind, is progressing rapidly. This change is driven by decreasing prices and technical advancements that are becoming more centralized. The objective is to develop a cutting-edge approach and technology that seamlessly incorporates photovoltaic (PV) energy sources into a power network while ensuring grid stability. This research evaluates the lifetime and degradation of PV inverters under real operating conditions, focusing on semi-arid climate scenarios. Current papers demonstrate a yearly failure rate of 1–15% for PV inverters, highlighting the need for a thorough reliability evaluation. This investigation research applied a unique technique that included continuous monitoring of PV inverter performance parameters by comparing the measured with the predicted normal operating output. The results show that Sandia's inverter performance model is highly suitable for accurately modeling normal PV inverter behavior. Furthermore, weighted efficiency dropped by 3.96%, 0.63% and 1.29% respectively for 7 kW, 15 kW and 20 kW photovoltaic systems over the five years. These findings have implications for comprehensive maintenance strategies, including regular inspections, safety protocols, and remote monitoring solutions. Ultimately, this research paper sheds light on the causes of declining solar inverter performance and provides suggestions for enhancing PV plant maintenance and reliability. It also represents an outstanding reference given the literature shortage.

1. Introduction

Renewable energy, particularly solar photovoltaic (PV) technology, has been on a meteoric rise in the last decade, to accelerate the energy transition and create a circular economy, which are two key priorities for many countries to change the face of the energy industry worldwide. This development is shown in the 2021 report [1] by the International Renewable Energy Agency (IEA), which reveals a global solar installation capacity of 942 GW. Forecasts show an additional 1,500 GW by 2030, according to [2]. Aligning with ambitious worldwide ambitions targeted at a future dominated by renewable energy by 2050, the increasing feasibility of solar energy has reached grid parity in numerous nations. Central to these aspirations is optimizing energy harvesting from PV systems,

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which is vital for maximizing energy yield and reducing system downtime [3]. PV panels, designed with a lifespan of 20–25, are juxtaposed with the shorter expected lifetime of PV inverters, typically less than 15 years [4].

Various external conditions, including changes in humidity, temperature, dust, and rain, continuously challenge the operational efficacy of these systems. These circumstances may contribute to potential failures, including delamination, hot spots, cell cracks, glass soiling, and corrosion [5–7]. Managing Maximum Power Point Tracking (MPPT) and combining the direct current (DC) output from PV plants into usable alternating current (AC) are two of the inverter's most essential functions [8]. Therefore, it is critical to guarantee the system's effectiveness and dependability [9]. Despite their vital relevance, the enormous dependability challenges PV inverters encounter are shown by the annual failure rates, which range from 1% to 15% [10].

In light of these differences, it is clear that the installation site's specific environmental conditions need a proactive and all-encompassing maintenance strategy. The essential components of inverters include cooling fans, DC contactors, insulated-gate bipolar transistor (IGBT) power module solder connections, DC bus capacitors, and IGBTs. When these parts fail, it may significantly impact system downtime and energy consumption [11–13].

The inverter load ratio (ILR) hugely affects solar PV system dynamics, which was thoroughly investigated in the reference [14]. Therefore, ILR has become an important indicator that significantly affects system performance. It indicates the power of a photovoltaic field concerning the inverter's power. This research deeply analyzed the complex correlation between the inverter load ratio and crucial performance metrics. These indicators include clipping occurrence, seasonal and daily patterns, temporal resolution of the data, ambient conditions, and module degradation. Through these assessments, researchers have conclusively demonstrated that increasing ILR increases inverter operating potential, decreases costs per kilowatt-hour of AC power, and affects system performance during peak production phases. Furthermore, this study unequivocally indicates that higher ILRs contribute to more consistent generation patterns, even when associated with high solar-related ramp rates.

This work [15] addresses the complex dynamics between the location problem and PV module degradation, emphasizing the substantial influence on solar inverter durability and reliability. Furthermore, this research analyzes the impact of critical factors, including the state of degradation of photovoltaic modules and strategic positioning. Notably, the temporal degradation of PV modules, an inevitable consequence of prolonged exposure to ambient elements, is paramount due to its impact on PV inverters' overall reliability and operational longevity.

The environmental conditions in which the UPS operates are also crucial to its performance. Numerous investigations have confirmed that inverter performance and downtime are closely linked to local climate and usage profiles. Several studies have highlighted the significant impact of the installation site on inverter performance and durability. This research suggests that the inverter load profile, determined by solar irradiation and ambient temperature, varies according to geographical location. For instance, areas near the equator, including South America and Africa, typically experience high solar irradiation levels throughout the year with minimal seasonal fluctuations [15].

A further aspect relating to photovoltaic panel sizing significantly impacts inverter reliability in colder climates, such as Denmark [16]. Indeed, the same authors point out in [17] that earlier research has neglected the impact of photovoltaic module breakdown, prompting the present study to assess inverter lifetime by incorporating both mission profiles and panel degradation rates. Assessments performed in Denmark and Arizona have demonstrated the substantial effect of rapid panel degradation, mainly in hot climates, including Arizona. Excluding such degradation can result in a significant 54% discrepancy in photovoltaic inverter lifetime predictions, highlighting the crucial role of comprehensive analyses in accurately assessing system reliability, particularly in severe climates.

1.1. Contribution

In light of the literature findings, this study utilizes Morocco as a case study to investigate a hitherto uncharted territory in the context of photovoltaic inverter performance and degradation of solar inverters in semi-arid climates. The article aims to refine maintenance strategies that improve the dependability and efficiency of not only inverters but entire photovoltaic systems. The main contributions of this study are twofold:

- Firstly, the research delves into the operational degradation of solar inverters, especially in semi-arid climates where the yearly failure rate is significant. The inverter performance is monitored continuously and compared with forecasts of typical operations in this study.
- Secondly, this research proves that Sandia's inverter performance model accurately predicts photovoltaic inverter behavior. It highlights the contribution of modeling to understanding inverter degradation and developing a thorough maintenance strategy for PV plants.

Ultimately, several factors motivated this project: Filling a crucial knowledge gap by examining the impact of harsh environmental conditions and conducting a comparative analysis of the three inverter models (Sandia, PVWatts, and Driesse). This investigation critically assessed inverter model performance and established an outstanding reference for researchers and experts in the field.

1.2. Paper organization

The authors have chosen this structure to present the paper clearly.

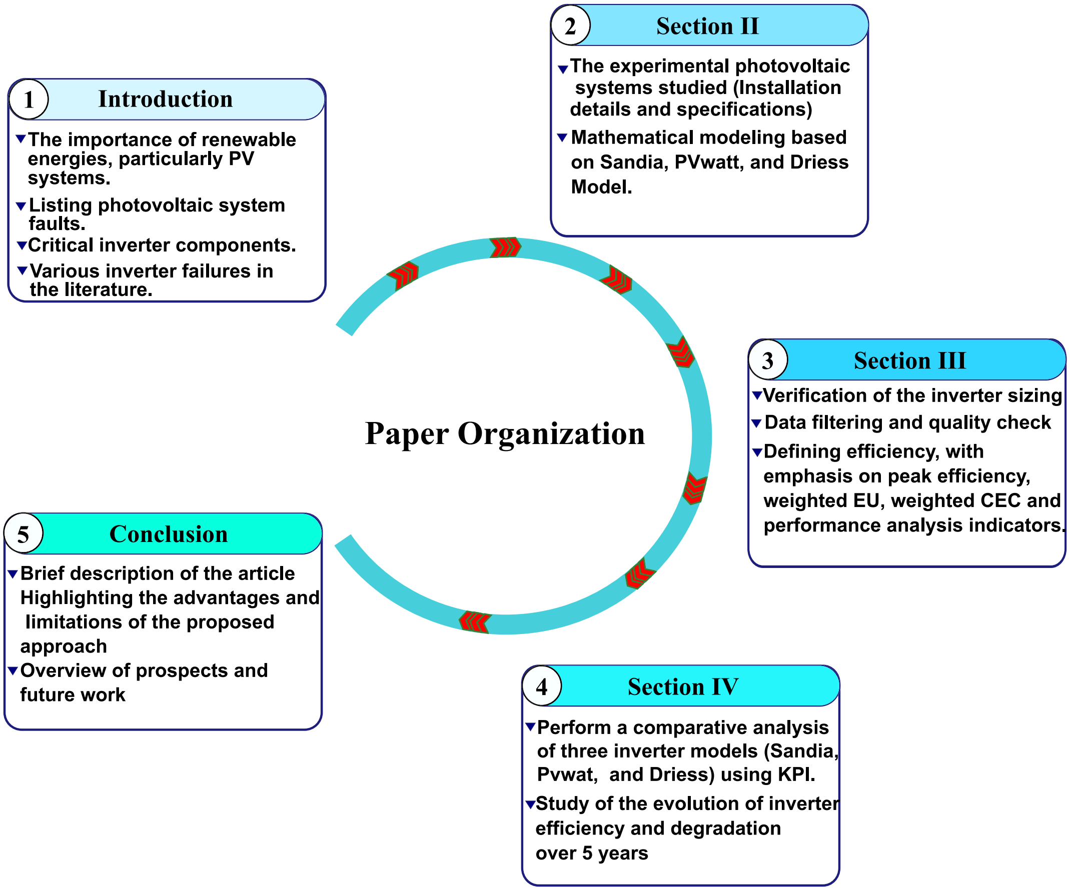

Fig. 1. Paper organization.

- The second section highlights the experimental photovoltaic systems studied and details the model-driven algorithm mathematically.
- The third section of this paper is dedicated to verifying inverter sizing, data filtering, quality control, and related efficiency metrics.
- The fourth section presents an exhaustive comparative analysis of the findings relating to the three proposed inverter models (Sandia, PVWatt, and Driess) through the degradation and efficiency assessment over five years.

Finally, a comprehensive and concise conclusion is presented, including an outline of the proposed method's advantages and suggestions for potential research avenues (see Fig. 1).

2. Experimental PV systems and model driven algorithms

2.1. *Experimental PV systems*

This study was conducted at the Green Energy Park research platform and focused on evaluating three different grid-connected PV systems. These systems had capacities of 7.2 kWp (first system), 16.56 kWp (second system), and 22.23 kWp (third system). The first system comprised 60 CIGS modules, the second system comprised 69 monocrystalline modules, and the third system contained 114 monocrystalline modules. Fig. 2 visually represents these PV arrays. The solar panels are installed on fixed open racks, facing south at an angle of 32°. Table 1 presents the specific details of each PV module. Additionally, each system is connected to its own inverter, which is monitored through a PV string monitoring unit, as depicted in Fig. 3. Table 2 lists the technical specifications of these inverters. A holistic and structured approach is applied to conduct the analysis. The outdoor test facility incorporates a data acquisition system recording electrical parameters on system operating performance such as (AC and DC power, AC and DC current, AC and DC voltage, frequency, etc.). Data loggers are interconnected to each system, enabling data recording with a sampling time of two minutes. Data acquisition is an essential preliminary step involving careful processing, correction, and cleaning of the acquired data. This preparation is necessary for effective real-time monitoring of PV systems. Subsequently, the data is stored in a database with a maintenance history. The aim is to develop predictive algorithms and use machine learning methods to automate the operation and maintenance (O&M) duties, hence enhancing the efficiency of solar systems, namely inverters.

Fig. 2. (a) 22.23 kWp Mono-Si System, (b) 16.56 kWp Mono-Si System, (c) 7.2 kWp CIGS System.

Table 1
Technical characteristics of the studied PV systems.

Characteristics	First system	Second system	Third system
Installed PV power (kW)	7.2	16.56	22.23
Panel power (W)	120	240	195
Module inclination (deg)	32	32	32
Module orientation	South	South	South
Number of modules	60	69	114
Number of strings	5	3	6
PV Technology	CIGS	Mono-Si	Mono-Si
Year of installation	2017	2017	2017

2.2. Model driven algorithms

Accurate modeling of PV inverters is essential for optimizing their efficiency and monitoring the performance of PV systems. Inverters are the primary elements of solar power systems and are responsible for converting DC to AC, which is suitable for electrical grids. Therefore, detailed and precise modeling is essential for continuous performance tracking, evaluating degradation over time, and developing effective maintenance strategies. This is particularly important in the context of prognostic and health management systems implemented in PV installations, as the system's overall efficacy is contingent on the inverters' long-term functionality and optimal performance [18].

Inverter failures can be categorized into several distinct types, including flaws in manufacturing and design, control system issues, and failures of electrical components. These failures highlight the complex relationship between the operational conditions, system illumination, thermal regulation, and heat dissipation mechanisms. In particular, control issues related to the complex dynamics between the inverter's interaction with the AC side grid and the DC side's PV panel highlight the diverse and intricate challenges of ensuring inverter reliability [19]. Photovoltaic systems present several challenges. Factors such as environmental variables and inverter efficiency contribute to the complexity of accurately simulating realistic performances. In common modeling approaches, inverter efficiency is oversimplified as a constant factor, assuming linearity throughout the operating range. Simplifying inverter performance may result in misleading findings since the inverter's efficiency is directly related to the input voltage and load frac-

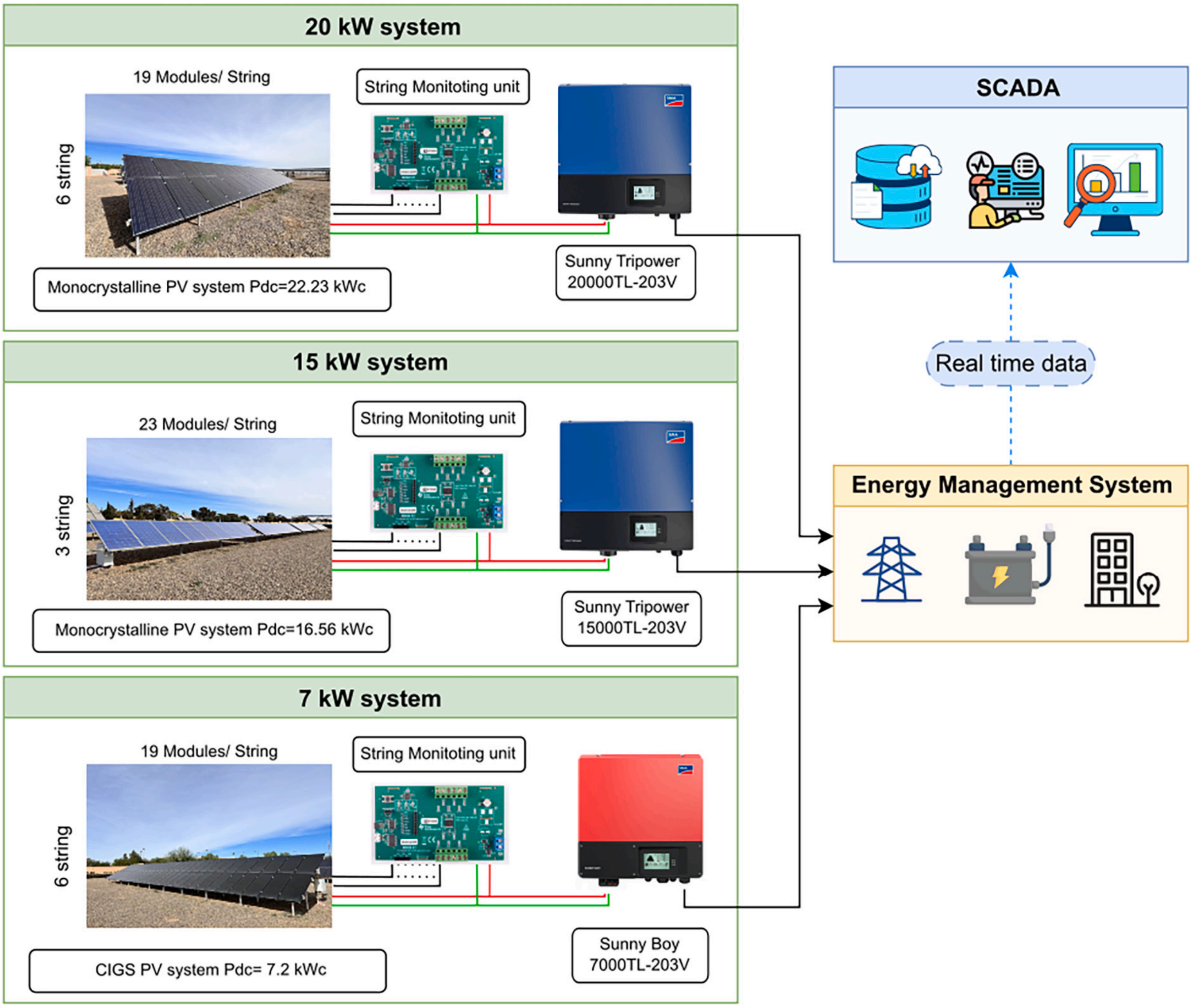

Fig. 3. PV systems architecture and data collection at the Green Energy Park platform.

Table 2
Technical specifications of the studied inverters.

Technical data	Sunny Boy 7000T-230 V	Sunny Tripower 15000TLEE	Sunny Tripower 20000TLEE
Input (DC)			
Max. DC power (@ cos $\varphi = 1$)	7300 W	15260 W	20450 W
Max. input voltage	600 V	1000 V	1000 V
MPP voltage range/rated input voltage	345 V–480 V/379 V	580 V–800 V/580 V	580 V–800 V/580 V
Min. input voltage/initial input voltage	345 V/360 V	570 V/620 V	570 V/620 V
Max. input current	21.1 A	36 A	36 A
Max. input current per string	21.1 A	36 A	36 A
Number of independent MPP inputs	1	1	1
Strings per MPP input & Combiner Box	6	6	6
Output (AC)			
Rated power/max. apparent AC power	7000 W/7000 VA	15 000 W/15 000 VA	20 000 W/20 000 VA
Nominal AC voltage	240 V/211 V	3/N/PE, 230 V/400 V	3/N/PE, 230 V/400 V
nominal AC voltage range	229 V	160 V–280 V	160 V–280 V
AC power frequency/range	50 Hz, 60 Hz/ − 6 Hz, +5 Hz	50 Hz, 60 Hz/ − 6 Hz, +5 Hz	50 Hz, 60 Hz/ − 6 Hz, +5 Hz
Rated power frequency/rated grid voltage	50 Hz/230 V	50 Hz/230 V	50 Hz/230 V
Max. output current	29.2 A	24 A	29 A
Power factor at rated power	1	1	1
Feed-in phases/connection phases	1/2	3/3	3/3
Efficiency CEC efficiency/max. efficiency	98.5%/98.7%	98.5%/98.3%	98.5%/98.2%

tion. Thus, the requirement for more nuanced performance characteristics is highlighted, providing engineers and analysts with a comprehensive understanding of the inverter power conversion performance [20].

Significant research has been devoted to developing empirical performance models for grid-connected PV inverters in response to these challenges. Extensive literature reviews, illustrated in [21] and [22], outline various modeling approaches, ranging from simple performance approximations based on the manufacturer's data sheets to more sophisticated analytical methods incorporating impedance models. An outstanding technique in this field is the performance-modeling approach, exemplified by the Sandia Array Performance Model. This approach, presented in this ref [23], offers an empirical perspective that accurately reproduces the energy-delivery characteristics of the DC–AC inversion process. Moreover, the paper under consideration introduces a PV array conditions monitoring system utilizing the Sandia Array Performance Model. This model accurately predicts PV arrays' power production and energy output. It highlights the importance of using performance models based on empirical data to monitor inverter performance continuously during system operation. This significantly contributes to assessing the health of PV systems and planning for maintenance [24].

2.2.1. Mathematical modeling based on Sandia model

The Sandia model applied a specific equation to describe the AC power output (P_{ac}) of a PV inverter as a function of the DC power input (P_{dc}) [20]. The formula is given by Eq. (1).

$$P_{\mathrm{ac}} = \left(\frac{P_{\mathrm{aco}}}{A - B} - C \cdot (A - B) \right) \cdot (P_{\mathrm{dc}} - B) + C \cdot (P_{\mathrm{dc}} - B)^2 \tag{1}$$

P_{aco} denotes the maximum AC power output under standard test conditions. Meanwhile, A, B, and C are coefficients that describe the inverter's performance (refer to Eqs. (2), (3), and (4)). These coefficients were determined empirically and varied among the different inverter models. Eq. (1) considers the nonlinear relationship between the AC power output and DC power input, providing a more accurate reflection of real-world inverter behavior, particularly under varying operational conditions [25].

$$A = P_{\mathrm{dco}} \cdot \left(1 + C1 \cdot (V_{\mathrm{dc}} - V_{\mathrm{dco}})\right) \tag{2}$$

$$B = P_{\mathrm{so}} \cdot \left(1 + C2 \cdot (V_{\mathrm{dc}} - V_{\mathrm{dco}})\right) \tag{3}$$

$$C = C_o \cdot \left(1 + C3 \cdot (V_{\mathrm{dc}} - V_{\mathrm{dco}})\right) \tag{4}$$

Where:

- P_{ac}: AC power output from inverter based on input power and voltage, (W).
- P_{dc}: DC power input to inverter, typically assumed to be equal to the PV array maximum power, (W).
- V_{d}: DC voltage input, typically assumed to be equal to the PV array maximum power voltage, (V).
- P_{aco}: Maximum ac-power "rating" for inverter at reference or nominal operating condition, assumed to be an upper limit value, (W).
- P_{dco}: DC power level at which the ac-power rating is achieved at the reference operating condition, (W).
- V_{dco}: DC voltage level at which the AC-power rating is achieved at the reference operating condition, (V).
- P_{so}: DC power required to start the inversion process, or self-consumption by inverter, strongly influences inverter efficiency at low power levels, (W).
- P_{nt}: AC power consumed by the inverter at night (night tare) to maintain circuitry required to sense PV array voltage, (W).
- C_{o}: Parameter defining the curvature (parabolic) of the relationship between ac-power and dc-power at the reference operating condition, a default value of zero gives a linear relationship, (1/W).
- C_1: Empirical coefficient allowing Pdco to vary linearly with dc-voltage input, the default value is zero, (1/V).
- C_2: Empirical coefficient allowing Pso to vary linearly with dc-voltage input, the default value is zero, (1/V).
- C_3: Empirical coefficient allowing Co to vary linearly with dc-voltage input, the default value is zero, (1/V).

These eight parameters (P_{aco}, P_{dco}, P_{so}, V_{dco}, C_0, C_1, C_2, and C_3) need to be estimated to prove the Sandia model's applicability for accurately modeling the behavior of inverters in photovoltaic systems.

2.2.2. Mathematical modeling based on PVWatt model

The California Energy Commission (CEC) provided data on inverters manufactured after 2010 to create the PVWatts V5 inverter model. This involved analyzing the average part-load efficiency curve based on the data and then selecting an inverter with the efficiency curve that closely matched this average. The efficiency data of the chosen inverter was then fitted to a quadratic loss model. The efficiency curve is scaled based on a user-specified nominal efficiency (η_{nom}), with the inverter's reference efficiency (η_{ref}), (see Eq. (5)).

$$\eta = \frac{\eta_{\mathrm{nom}}}{\eta_{\mathrm{ref}}} \left(-0.0162 \cdot \zeta + 0.9858 \cdot \zeta - \frac{0.0059}{\zeta} \right) \tag{5}$$

Where

$$\zeta = \frac{P_{dc}}{P_{dco}} \tag{6}$$

$$P_{do} = \frac{P_{aco}}{\eta_{\text{nom}}} \tag{7}$$

The AC power rating P_{aco} is determined from the system's DC power rating and DC/AC ratio. This approach enables the PVWatts V5 model to be a flexible and accurate tool for simulating inverter performance in photovoltaic systems by incorporating real-world data and sophisticated statistical analysis [26].

$$P_{\text{AC}} = \begin{cases} \eta P_{\text{dc}} & \text{if } 0 < P_{\text{dc}} < P_{\text{dco}} \\ P_{\text{aco}} & \text{if } P_{\text{dc}} \geq P_{\text{dco}} \\ 0 & \text{if } P_{\text{dc}} = 0 \end{cases} \tag{8}$$

2.2.3. Mathematical modeling based on Driess model

The electrical conversion efficiency (η) of an inverter is an indicator of the efficiency of converting input power (P_{in}) into output power (P_{out}), the difference corresponding to the power loss (P_{loss}), which is typically dissipated as heat inside the inverter. Hence, this efficiency is expressed mathematically as a power level function, frequently using a quadratic formula, as shown in Eq. (9) [27]:

$$P_{\text{loss}} = a_0 + a_1 \cdot P_{\text{out}} + a_2 \cdot P_{\text{out}}^2 \tag{9}$$

This quadratic expression corresponds to empirical data and is interpretable by physical phenomena. In grid-connected inverters, where the output voltage is constant, P_{out} is directly proportional to the output current I_{out}. The quadratic equation terms are understood as follows:

1. **Self-consumption** $a_{\mathbf{o}}$ refers to constant losses from internal inverter processes, such as drive and auxiliary circuits, regardless of output power.
2. **Fixed voltage drop losses** $a_{\mathbf{1}}$. Such losses correspond to I_{out} resulting from constant voltage drops between the semiconductors inside the inverter.
3. **Ohmic losses are denoted as** $a_{\mathbf{2}}$ are characterized by their quadratic nature and proportionality to the square of the output current (I_{out^2}). These losses arise due to the presence of resistance within the inverter circuits.

The linear term a_1 accounts for switching losses occurring during the transition of power semiconductors from turning on to turning off and vice versa. These losses are approximately proportional to the current when the switch is on and the voltage when it is turned off. It is crucial to note that while each coefficient (a_0, a_1, a_2) typically identifies a different physical loss mechanism and is expected to be positive, there are several cases in which a negative value is observed a_1. This pattern may arise in multistage inverters when an increase in power leads to a variation in the internal bus voltage. Furthermore, this challenges the assumption that the internal currents are consistently proportional to the power level. This could explain the negative coefficient [27]. To calculate the efficiency from P_{loss}, Eq. (10) is applied.

$$\eta = \frac{P_{\text{out}}}{P_{\text{out}} + P_{\text{loss}}} \tag{10}$$

This equation reflects the proportion of input power converted to output power, with the remainder released mostly as heat due to various inefficiencies within the inverter's components and operations.

3. Methodology and approach

3.1. Verification of the inverter sizing

A photovoltaic system's optimal performance depends on several critical factors during inverter sizing. Initially, the inverter's capacity should be aligned with the overall PV plant capacity. This ensures that the system's energy output is unrestricted by under-sizing, which may result in reduced efficiency and superfluous costs. Furthermore, the inverter's efficiency and power monitoring capabilities influence the PV system's global energy yield and performance ratio. Thus, measuring foreseeable variations in solar irradiation and ambient site temperature is essential to identify an inverter resistant to shading and temperature. Moreover, it is crucial to thoroughly evaluate the inverter's compatibility with the grid standards and regulations of the particular nations to ensure seamless integration. In addition, the inverter's protection characteristics, reliability, and maintenance requirements are essential to ensure photovoltaic systems' long-term functionality and durability. Addressing these critical factors optimizes the PV system performance and profitability by deploying appropriate inverter sizing. Table 3 presents each system's specifications to verify the inverter's sizing.

3.2. Data filtering and quality check

The study's dataset spans five years, from January 2018 to August 2023. The winter and autumn seasons are included in this dataset. During these times, there are significant changes in solar irradiance, temperature, and the difficulty of making predictions. Figs. 4–9 illustrates a visual representation of the production of DC and AC power for each system between 2018 and 2023.

Table 3
PV systems characteristics.

Characteristics	First system	Second system	Third system
V_{mpp} Voltage at Maximum Power (V)	44.9	30.6	37.1
I_{mpp} Current at Maximum Power (A)	2.68	7.84	5.25
V_{oc} Open circuit voltage (V)	57.4	37.2	45.6
I_{sc} Short circuit current (A)	3.13	8.37	5.56
Maximum mpp voltage (V)	538.8	703.8	704.9
Max. input current (A)	13.4	23.52	31.5
P Total maximum power (Wc)	7200	16 500	22 200
Max. DC power at the inverter level (W)	7300	15 260	20 450

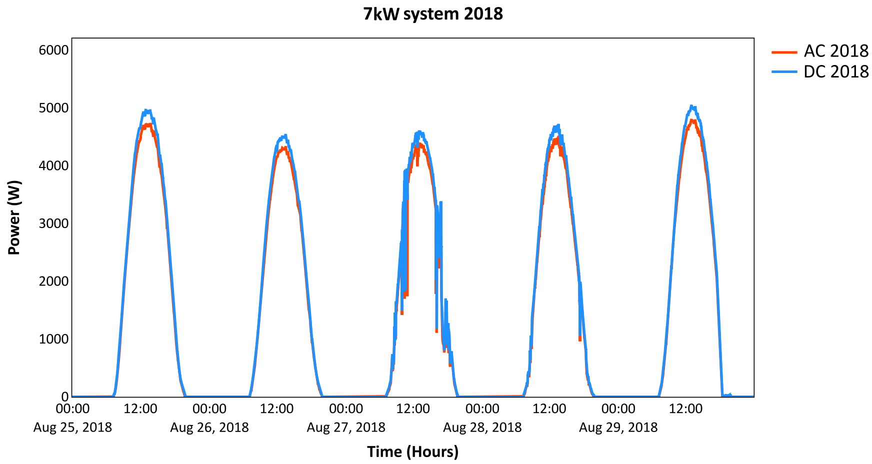

Fig. 4. Visual representation of the production of DC and AC power for 7 kW System in 2018.

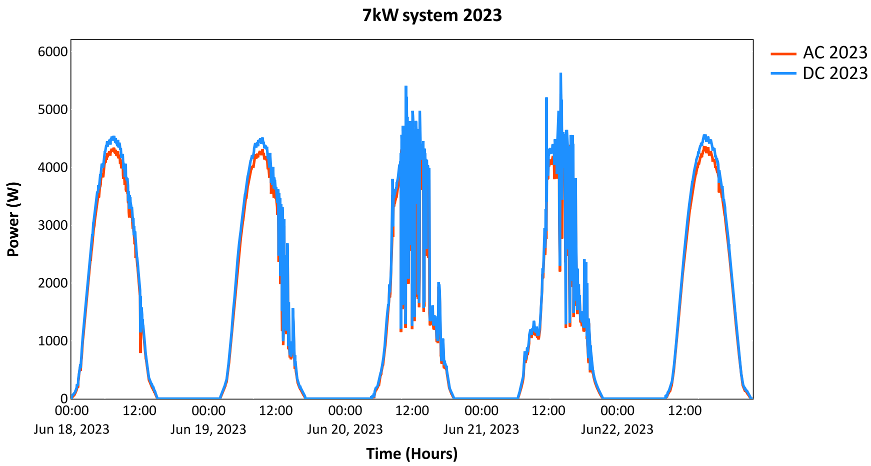

Fig. 5. Visual representation of the production of DC and AC power for 7 kW System in 2023.

Pre-processing raw data is essential for removing outliers and abnormal recordings before examining the recorded measurements. Implementing existing data preprocessing techniques requires in-depth knowledge of the data source architecture and setup. The initial step is to resample and synchronize the data sources. Next, a series of filters are implemented to purify the unprocessed data. The filters first eliminated negative PAC values and negative chain currents by replacing them with zero. Furthermore, whenever the PDC and PAC were equal to zero, the UDC values were replaced by zero. Subsequently, a filter was implemented to eliminate inaccurate data points, particularly those with power values that exceeded the system's maximum peak power. Moreover, a standard behavior filter was implemented to eradicate the energy management system, restricting the inverter's power. Fig. 10 provides an overview of these procedures.

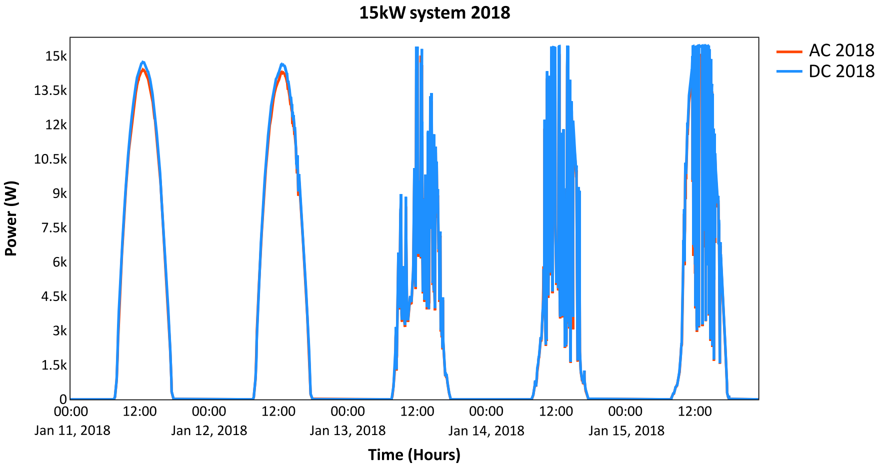

Fig. 6. Visual representation of the production of DC and AC power for 15 kW System in 2018.

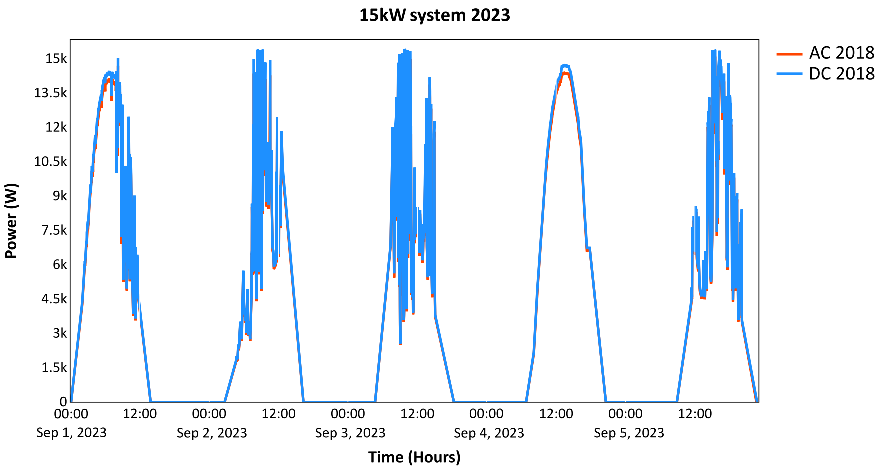

Fig. 7. Visual representation of the production of DC and AC power for 15 kW System in 2023.

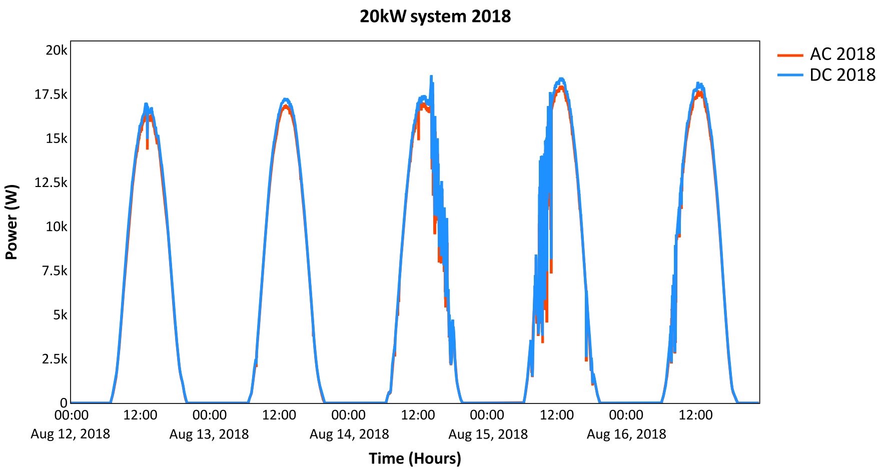

Fig. 8. Visual representation of the production of DC and AC power for 20 kW System in 2018.

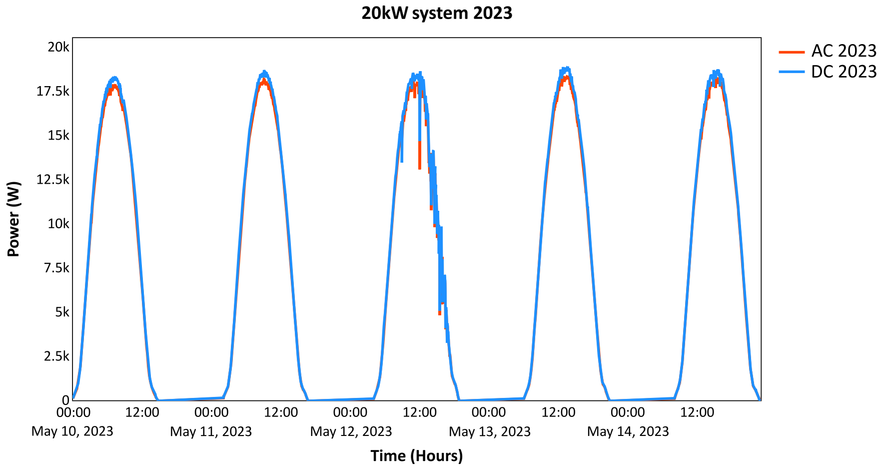

Fig. 9. Visual representation of the production of DC and AC power for 20 kW System in 2023.

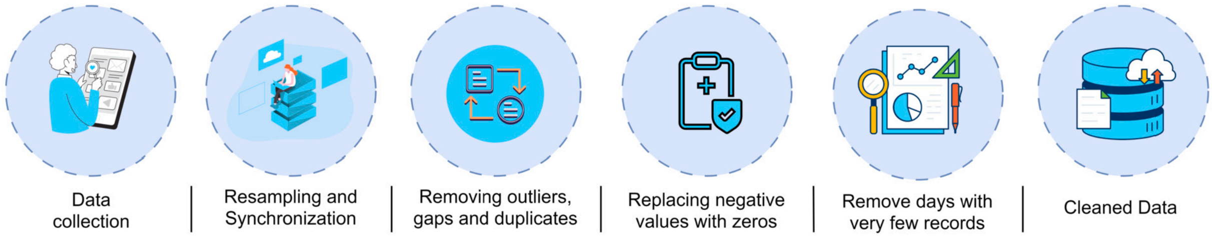

Fig. 10. Data processing procedure.

3.3. *Efficiency definition: CEC and EU*

The efficiency of photovoltaic inverters is multifaceted and extends beyond the usual power converter's output-to-input ratio. Efficiency in conversion and maximum power point tracking (MPPT) are two separate aspects of the inverter technology. The conversion efficiency represents the ratio of AC output energy to DC input energy over a given period. MPPT efficiency is the ratio between the energy harvested by the inverter and the optimum energy that can be extracted at the maximum power point (MPP), as provided by the PV simulator. The product of these two options defines the total efficiency of the photovoltaic inverter. In addition, conversion efficiency is subdivided into peak and weighted (or average) efficiency, which can be classified as European or CEC efficiency.

3.3.1. *Peak efficiency*

Peak efficiency, commonly known as nominal output efficiency, indicates the efficiency of photovoltaic inverters. Although this is prominently shown in inverter casings and data sheets, it is rarely, indeed never, achieved in actual operation. Following the IEC 61683:1999 standard, the maximum efficiency is defined as the ratio between the inverter's rated output power and its input power at this rated output, expressed as a percentage [28]. Mathematically, Reak's efficiency is represented by Eq. (11).

$$\eta_R = \frac{P_o}{P_i} \cdot 100 \tag{11}$$

Where:

η_R: Rated output efficiency (%).
P_o: Rated output power from the inverter (W).
P_i: Input power to inverter at rated output (W).

3.3.2. *Weighted EU*

Solar panel performance varies throughout the day. It typically decreases power production in the early morning and evening, whereas it increases in the afternoon. Consequently, inverters frequently fail to achieve their maximum efficiency. This finding led to the preference for weighted or average conversion efficiency as a more accurate indicator of photovoltaic inverter performance. Unlike peak efficiency, the weighted efficiency evaluates the inverter's performance over its entire operating range. Unlike peak efficiency, weighted efficiency assesses the inverter's operation across its entire operating range. As proposed by R. Hotopp [28], [29] the European efficiency is calculated using a formula that takes into account efficiencies at various operational points [30]:

$$\eta_{EU} = 0.03 \cdot \eta_{5\%} + 0.06 \cdot \eta_{10\%} + 0.13 \cdot \eta_{20\%} + 0.10 \cdot \eta_{30\%} + 0.48 \cdot \eta_{50\%} + 0.20 \cdot \eta_{100\%} \tag{12}$$

This method offers a more comprehensive view of the inverter's real-world efficiency.

3.3.3. Weighted CEC

California's Energy Commission developed a mathematical formula for evaluating the efficiency of solar inverters, known as the CEC efficiency. This formula is adapted to California's solar conditions, which involve a crucial solar potential similar to Morocco's climate in this context. Eq. (13) describes the efficiency of CEC [28].

$$\eta_{CEC} = 0.04 \cdot \eta_{10\%} + 0.05 \cdot \eta_{20\%} + 0.12 \cdot \eta_{30\%} + 0.21 \cdot \eta_{50\%} + 0.53 \cdot \eta_{75\%} + 0.05 \cdot \eta_{100\%} \tag{13}$$

This formula distinguishes from the European efficiency model by incorporating an extra efficiency point at 75% irradiation, enabling a more precise evaluation of efficiency in areas with abundant solar irradiation. Reference [28] provides a detailed description of the procedures used for these computations [31].

3.4. Performance analysis indicators

To objectively assess the performance of grid-connected photovoltaic systems. This necessitates adhering to the procedures laid forth in Task 13 of the International Energy Agency's Photovoltaic Power Systems Program (PVPS) [28]. While also integrating the requirements outlined in IEC 61 724 [29]. These include Root mean square Error (RMSE), Normalized Root Mean Square Error (NRMSE), Coefficient of Determination (R^2), and Mean Absolute Error (MAE).

3.4.1. Root mean square error

In several research studies, the Root Mean Square Error is commonly used as a standard statistical metric to measure model performance. It is widely applied in regression analysis, quantifying the difference between predicted and actual values, and is calculated using Eq. (14).

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2}{n}} \tag{14}$$

Where:

Y_i: Actual observed values from the dataset.
$\hat{Y}_i$: Predicted values.
n: Total number of observations.

3.4.2. Normalized root mean square error

The normalized root-mean-square error is a normalized measure of the prediction error indicator of the root-mean-square deviations between RMSE. Consequently, the model performed optimally when its NRMSE value is exceedingly low. Conversely, a model's performance is diminished by a high NRMSE value. Eq. (15) is used to determine the NRMSE.

$$\text{NMRSE} = \frac{\text{RMSE}}{|y_{\max} - y_{\min}|} \tag{15}$$

Where:

y_{max} represents the maximum value observed in the dataset.
y_{min} indicates the minimum value observed in the dataset.

3.4.3. Coefficient of determination

The coefficient of determination, is a statistical measure of fit quality. In the context of regression, it is a statistical measure of the approximation of the regression line to the actual data. It is graduated from 0 to 1, with 1 indicating a perfect match. Eq. (16) perfectly describes the mathematical framework of R^2.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n} (Y_i - \bar{Y})^2} \tag{16}$$

Where:

$\bar{Y}$: is the mean of the observed values Y_i.

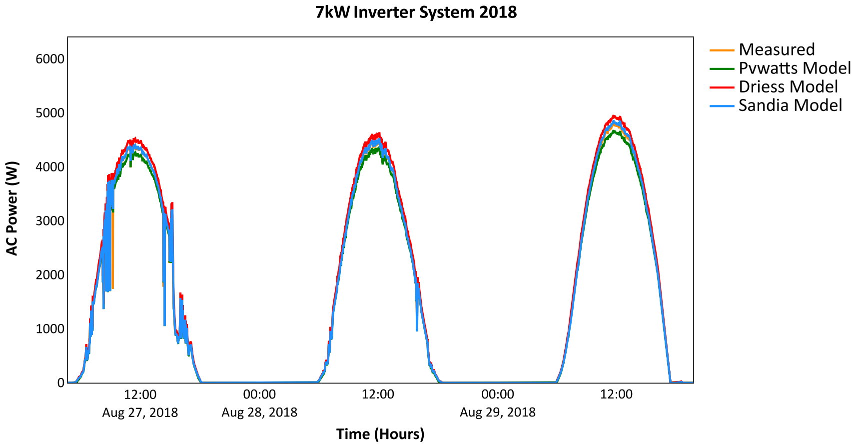

Fig. 11. Measured AC output power vs. modeled power for a 7 kW system in 2018.

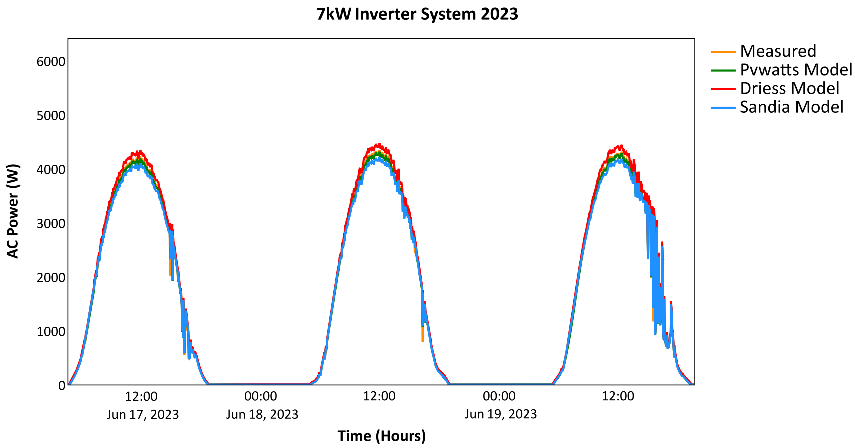

Fig. 12. Measured AC output power vs. modeled power for a 7 kW system in 2023.

3.4.4. Mean absolute error

Mean Absolute Error is a statistical measure used to evaluate the accuracy of a forecasting model, such as a regression or a time series model. It measures the average magnitude of errors between predicted and actual values in a dataset. It is expressed by Eq. (17).

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} |Y_i - \hat{Y}_i|}{n} \tag{17}$$

The MAE provides a direct measure of the closeness of predictions to actual values, irrespective of the direction of the errors. A lower MAE indicates that the model can predict with lower errors.

4. Results and discussion

4.1. Comparative analysis of the three inverter models (Sandia, PVWatt and Driess) using the metrics

Following an in-depth analysis under semi-arid climatic conditions, a comparative study was carried out on three physical models (Sandia, PVWatt, and Driess) to identify the model most accurately reflecting measured inverter AC output power among three PV plants by examining several key performance indicators between 2018 and 2023. Further analysis of the data presented in Table 4 revealed that the Sandia model outperformed the other two models regarding its ability to predict inverter AC output power (see Figs. 11–16). The Sandia model showed a lower RMSE for all systems and demonstrated a lower RMSE for all systems, suggesting a more precise fit to actual data. This model also demonstrated superiority in terms of normalized root-mean-square error (NRMSE), which, despite an upward trend, remained lower than those of the PVWatt and Driess models. Furthermore, the Sandia model's mean absolute error (MAE) is consistently lower, suggesting that its mean prediction errors were lower. Moreover, the Sandia model's coefficient of determination (R^2) was exceedingly high, approaching 1, indicating a robust correlation with the measured AC power. Overall, this comparative analysis shows unequivocally that the Sandia model outperforms the others in forecasting photovoltaic

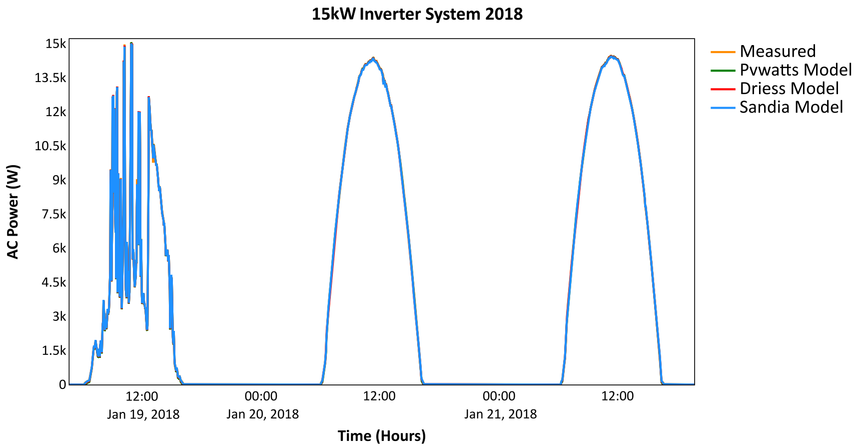

Fig. 13. Measured AC output power vs. modeled power for a 15 kW system in 2018.

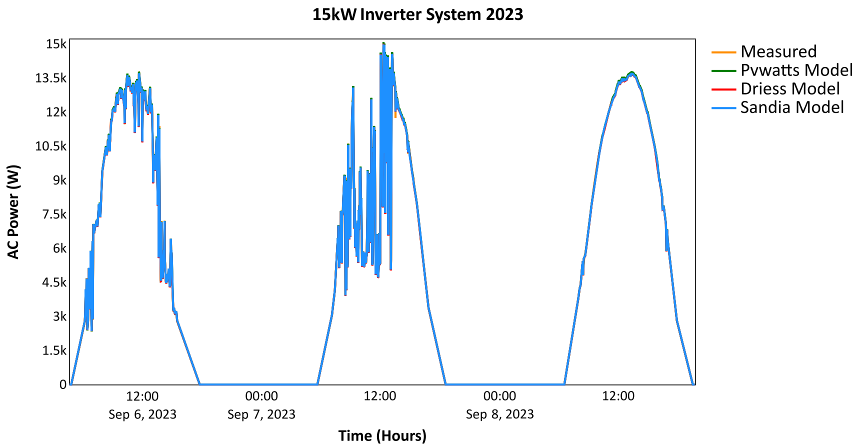

Fig. 14. Measured AC output power vs. modeled power for a 15 kW system in 2023.

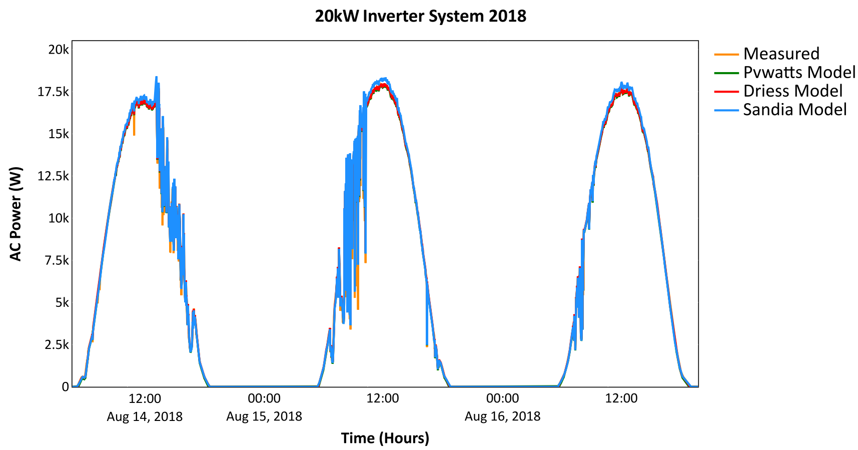

Fig. 15. Measured AC output power vs. modeled power for a 20 kW system in 2018.

inverter performance, with lower error measures and higher R^2 values. These data are critical for improving predictive maintenance techniques and increasing system efficiency in semi-arid regions, two areas where solar systems are particularly underdeveloped and understudied.

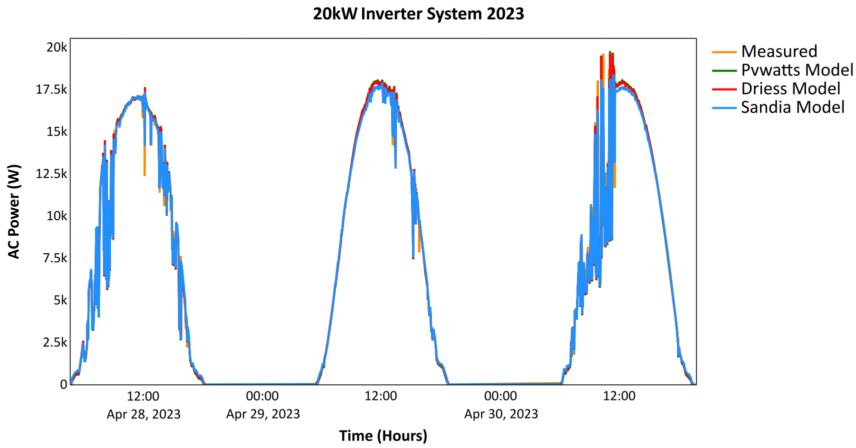

Fig. 16. Measured AC output power vs. modeled power for a 20 kW system in 2023.

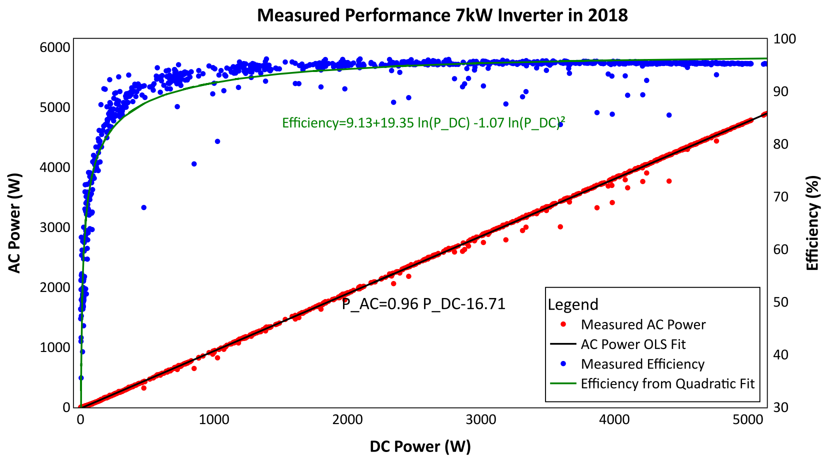

Fig. 17. Inverter efficiency and the correlation between AC and DC power over a five-year period for the 7 kW system in 2018.

4.2. Study of inverters efficiency over 5 years

In the context of assessing PV inverter degradation over five years (2018–2023), analysis of inverter efficiency using three different efficiency indicators including η_R (peak efficiency), η_{CEC} (California energy commission efficiency) and η_{EU} (European Union efficiency) for 7 kW, 15 kW and 20 kW systems offers illuminating revelations (see Figs. 17–22). For the 7 kW system, a notable decrease was observed in all three-efficiency metrics: η_R decreased from 95.38% to 94.70%, η_{CEC} from 94.57% to 92.46%, and η_{EU} from 93.11% to 89.15%. This degradation equates to efficiency reductions of 0.68%, 2.11%, and 3.96%, respectively (see Table 5). The 15 kW system experienced a slight decrease, with η_R dropping by 0.12% from 97.48% to 97.36%, η_{CEC} decreasing by 0.41% and η_{EU} decreasing by 0.63% from 97.80% to 97.17%. Finally, the 20 kW system showed a similar trend, with η_R reducing by 0.58% from 97.27% to 96.69%, η_{CEC} by 0.63% from 97.69% to 97.06%, and η_{EU} by 1.29% from 97.23% to 95.94%. These results indicate a progressive decline in inverter efficiency over time owing to the gradual nature of inverter degradation, which is related to the maintenance and longevity of photovoltaic systems.

4.3. Study of inverter degradation over 5 years

In this semi-arid climate study scenario, examining inverter efficiencies over five years (2018–2023) for the three systems provided a fundamental understanding of inverter degradation. While the efficiency measurements η_R, η_{CEC} and η_{EU} indicate a gradual decline in performance, suggesting degradation, more accurate quantification of this degradation was sought through the application of the Sandia model, which demonstrated superior performance to other physical models. Applying the 2018 Sandia model fitting parameters to the 2023 inverter data enabled a more precise quantification of the degradation (see Figs. 24–26). This approach enabled a direct comparison between the AC power predicted by the model and the actual AC power measured for each inverter. This benchmarking study revealed a slight degradation over the five years. This slight degradation, quantified more precisely by the Sandia model, underlines the nuanced nature of inverter performance over time. The results of this methodical approach are

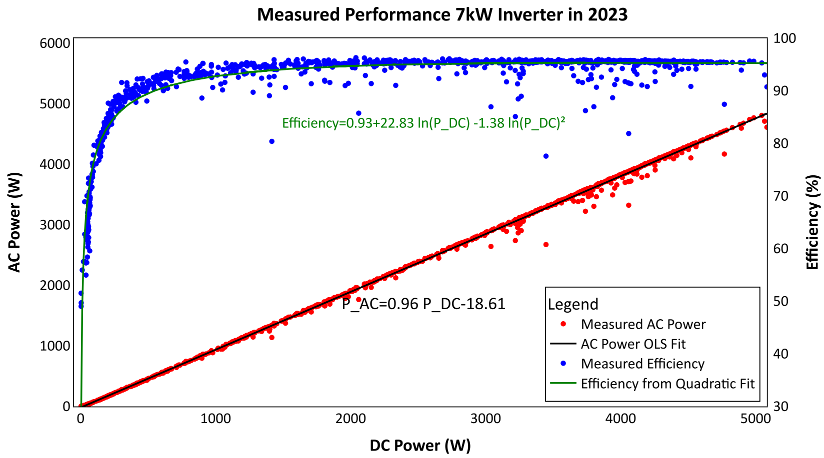

Fig. 18. Inverter efficiency and the correlation between AC and DC power over a five-year period for the 7 kW system in 2023.

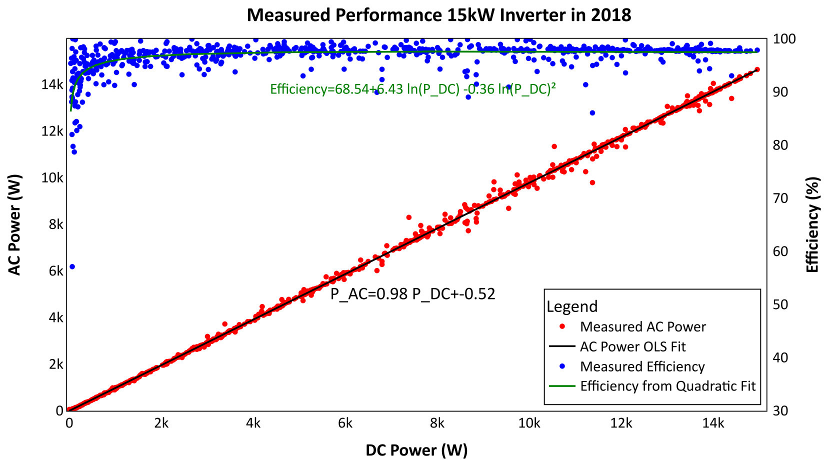

Fig. 19. Inverter efficiency and the correlation between AC and DC power over a five-year period for the 15 kW system in 2018.

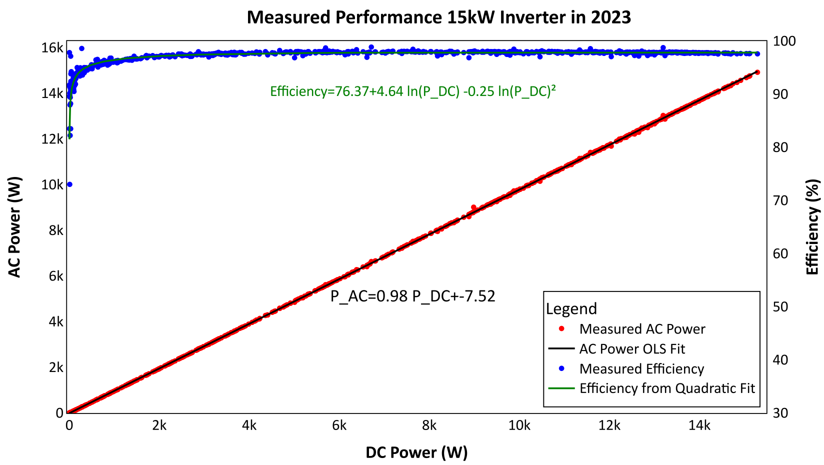

Fig. 20. Inverter efficiency and the correlation between AC and DC power over a five-year period for the 15 kW system in 2023.

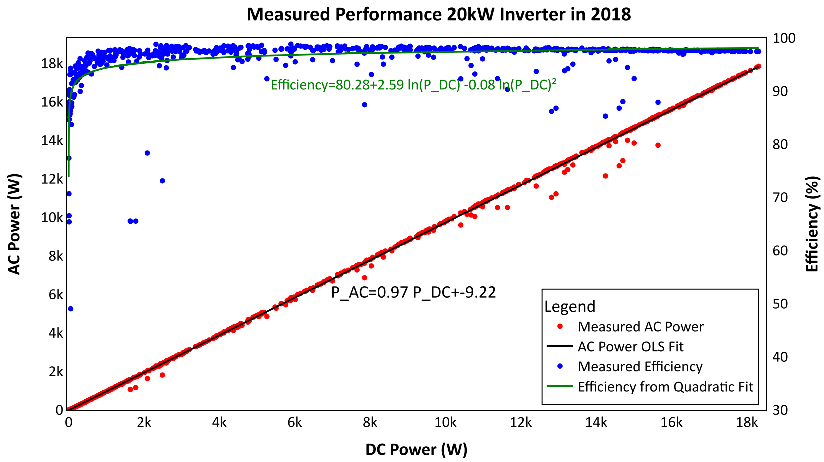

Fig. 21. Inverter efficiency and the correlation between AC and DC power over a five-year period for the 20 kW system in 2018.

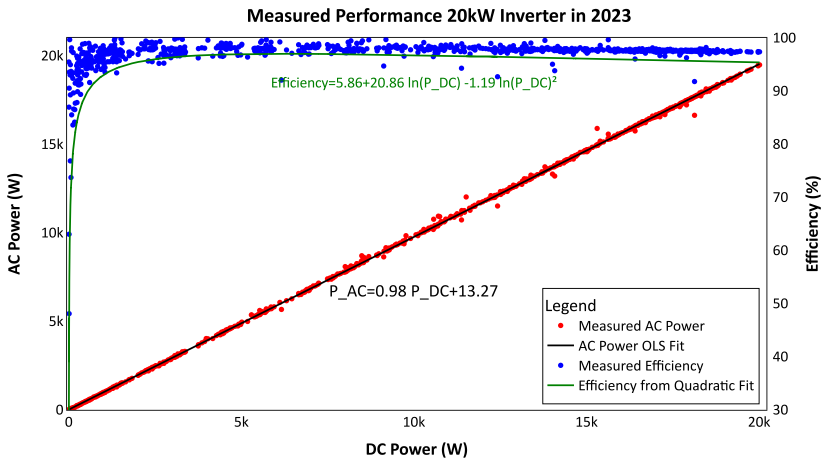

Fig. 22. Inverter efficiency and the correlation between AC and DC power over a five-year period for the 20 kW system in 2023.

crucial for a variety of reasons. First and foremost, they provide a more nuanced understanding of UPS degradation, surpassing the fundamental efficiency measurements. Second, the quantification of degradation is based on a reliable and accurate modeling framework, resulting from using a robust, high-performance model such as Sandia in this analysis. Finally, this data is valuable for developing predictive maintenance strategies and informing decisions on optimizing photovoltaic systems' long-term operation and efficiency. Traditional efficiency measurements indicated inverter degradation; applying the Sandia model for a more detailed analysis enabled more accurate quantification of this degradation, revealing a slight but substantial drop in inverter performance over five years. The main factors contributing to this degradation are dust and soiling, electrical stress, component aging, and a slight effect of humidity and corrosion, since the study takes place in a semi-arid climate. The accumulation of dust and particles on photovoltaic panels and inverters can obstruct air circulation, leading to overheating and inefficient cooling. Variations in the input power due to fluctuating solar irradiation can cause electrical stress on inverter components, particularly capacitors and semiconductor devices. In addition, natural wear and tear on internal components such as capacitors, insulated gate bipolar transistors (IGBTs), and diodes over extended periods of operation contributes significantly to performance degradation. While humidity fluctuations and exposure to moisture can lead to corrosion of electrical contacts and components, this effect is slight in a semi-arid environment. Notably, this study did not consider ambient temperature as a degradation factor, as all inverters are in an air-conditioned room (see Fig. 23).

5. Conclusion

The authors of this study effectively assessed the lifetime and degradation of three solar inverters connected to three PV stations. These stations are equipped with photovoltaic technology that varies in capacity and are connected to the grid of the Green Energy Park research platform. The authors applied these three inverter models (Sandia, PVWatt, and Driesse) to develop a reference model to serve as the foundation for their comparison. Moreover, weighted efficiency dropped by 3.96%, 0.63% and 1.29% respectively for 7 kW, 15 kW, and 20 kW photovoltaic systems over the five years. The authors of this study have derived several significant conclusions.

Fig. 23. Inverters in a temperature-controlled environment for optimal performance.

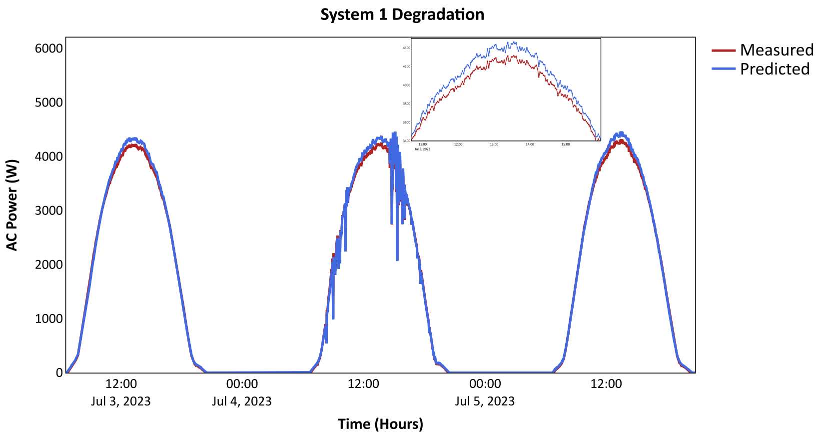

Fig. 24. Analysis of AC power output degradation over time in PV systems: comparison of measured vs. predicted data in 2023 for 7 kW system.

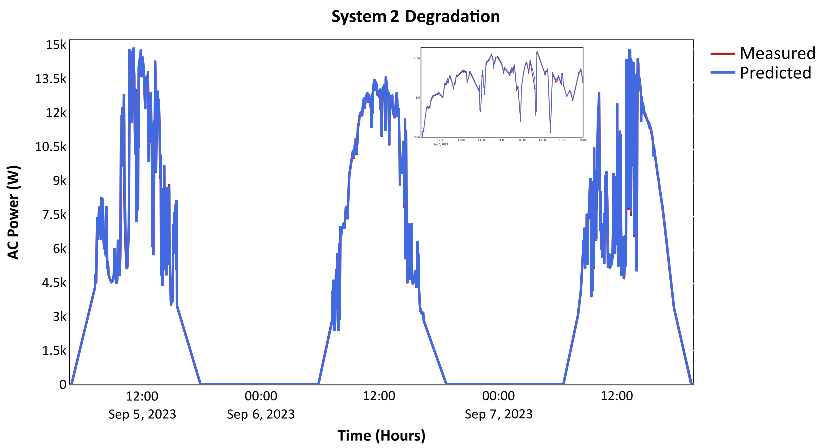

Fig. 25. Analysis of AC power output degradation over time in PV systems: comparison of measured vs. predicted data in 2023 for 15 kW system.

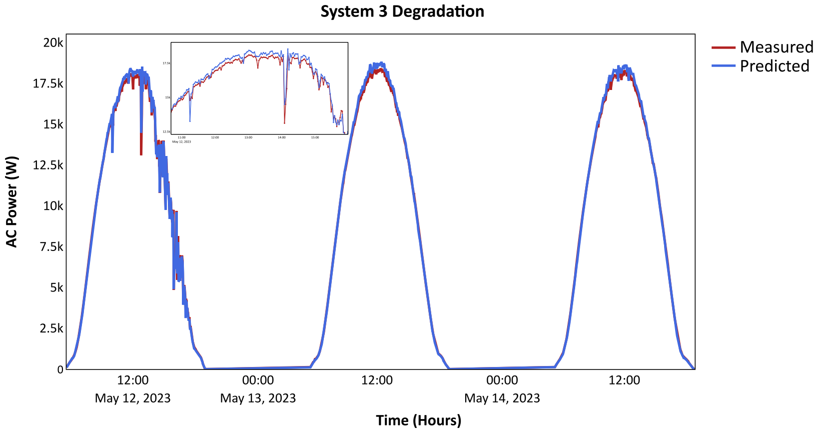

Fig. 26. Analysis of AC power output degradation over time in PV systems: comparison of measured vs. predicted data in 2023 for 20 kW system.

Table 4
Comparative performance analysis of photovoltaic systems: Sandia, PVWatts, and Driess models in 2018 and 2023.

PI	Sandia model						PVwatt model						Driess model					
	7 kW system		15 kW system		20 kW System		7 kW system		15 kW system		20 kW system		7 kW system		15 kW system		20 kW system	
	2018	2023	2018	2023	2018	2023	2018	2023	2018	2023	2018	2023	2018	2023	2018	2023	2018	2023
RMSE	82.01	131.68	54.72	86.91	347.93	384.50	91.82	121.03	59.62	90.49	333.20	354.34	104.76	154.29	55.76	92.13	329.73	347.88
NRMSE	0.01	0.02	0.00	0.01	0.02	0.02	0.02	0.02	0.00	0.01	0.02	0.02	0.02	0.03	0.01	0.01	0.02	0.02
MAE	16.84	62.49	12.29	25.17	66.90	178.62	37.88	35.95	17.80	31.20	61.56	112.26	43.09	80.76	15.18	39.76	38.94	84.01
R^2	0.997	0.993	0.991	0.995	0.996	0.993	0.997	0.994	0.992	0.996	0.997	0.992	0.996	0.99	0.993	0.99	0.997	0.992

Table 5
Efficiency metrics of PV inverters across different capacities (7 kW, 15 kW, 20 kW) in 2018 and 2023.

Inverter efficiency	7 kW System		15 kW System		20 kW System	
	2018	2023	2018	2023	2018	2023
η_R (%)	95.38	94.70	97.48	97.36	97.27	96.69%
η_{CEC} (%)	94.57	92.46	97.97	97.56	97.69	97.06
η_{EU} (%)	93.11	89.15	97.80	97.17	97.23	95.94

- Sandia's inverter performance model compared to others, including the PVWatt and Driesse model, predicting photovoltaic inverter failures with high accuracy in Morocco's semi-arid climate as a use case.
- Implications of the obtained results for global maintenance strategies, including regular inspections, safety protocols and remote monitoring solutions.

Consequently, this research is more suitable for the analysis of failures in general. Such approaches are worth exploring to detect thermal stress, fouling, humidity, corrosion, electrical stress and component aging. However, a significant limitation of these approaches is their inability to be applied until accurate data are available for comparison with the predicted data. Consequently, our forthcoming research will endeavor to provide a powerful tool for accurately detecting and diagnosing PV inverter malfunctions. Additionally, incorporating these models into a digital twin with duplicated hardware will provide additional advantages in the solar inverter industry.

CRediT authorship contribution statement

Oussama Idbouhouch: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Nabila Rabbah:** Writing – review & editing, Validation, Supervision, Resources, Investigation. **Nassim Lamrini:** Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Data curation. **Hicham Oufettoul:** Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Data curation, Conceptualization. **Ibtihal Ait Abdelmoula:** Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Mourad Zegrari:** Writing – review & editing, Supervision, Resources, Investigation.

Declaration of competing interest

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

Data availability

The data that has been used is confidential.
The authors do not have permission to share data.
The authors do not have any conflicts of interests/competing interests.

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