



(RESEARCH ARTICLE)



## RULE-BASED ENERGY MANAGEMENT OF A STANDALONE PV-BATTERY SYSTEM UNDER ONE-MONTH SOLAR RESOURCE VARIABILITY: A CASE STUDY IN SENEGAL

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### ABSTRACT

Energy management is a key factor in the reliability and performance of photovoltaic (PV) systems coupled with battery storage for rural electrification. Unlike studies based on representative days, this work investigates the operation of a PV–battery system over a continuous 28-day period (672 h) to assess the influence of day-to-day weather variations on its behaviour. The system consists of a 36.6 kWp PV generator, a battery storage system (648 Ah, 200 V), and a bidirectional buck–boost converter exchanging energy between the DC bus and the batteries. Simulations were carried out in MATLAB/Simulink using hourly solar irradiation and temperature profiles measured in Senegal in February 2005, and a domestic load profile. Maximum power point tracking is performed with the incremental conductance algorithm, while a PI controller maintains the DC bus voltage at its 395 V reference. A rule-based energy management strategy coordinates PV generation, storage and load supply according to the instantaneous power balance and the battery state of charge (SOC). Results show that the DC bus voltage remains globally close to its reference despite fluctuations in solar irradiation, apart from a transient drop to about 260 V around 275 h. The battery SOC stays close to 50% over the whole month, indicating stable operation of the strategy under the simulated conditions. This study provides a basis for analysing the sizing and operation of PV–battery systems in the sub-Saharan African context.

**Keywords:** Photovoltaic-battery system; Energy management; Rural microgrid; Solar water pumping; Battery storage; MPPT control

## 1 INTRODUCTION

Access to reliable and sustainable electricity is now an essential factor for the economic and social development of rural areas, particularly in remote regions where the expansion of conventional power grids remains constrained by technical and economic limitations. According to the International Energy Agency, sub-Saharan Africa continues to face a significant electricity access deficit, which directly affects economic activities, education, healthcare services, as well as industrial and agricultural development [1]. In this context, decentralized energy systems based on renewable energy sources emerge as a suitable solution for improving energy access in remote areas while reducing dependence on fossil fuels [2], [3], [4].

Among the various renewable energy sources available, solar photovoltaic (PV) energy is of particular interest in regions with high solar potential, particularly in West Africa. Its modular nature, ease of installation, and the progressive reduction in investment costs have made it a widely adopted technology for standalone rural applications [2],[5]. However, the intermittent nature of photovoltaic power generation, which is directly related to variations in solar irradiation and weather conditions, represents a major limitation to ensuring a continuous and reliable electricity supply [6], [3].

In agricultural rural areas, access to energy is also closely linked to the availability of water for irrigation [7]. Solar photovoltaic water pumping has emerged as a sustainable alternative to diesel-powered systems, with reported benefits for agricultural productivity, greenhouse gas emissions and operating costs [8],[9]. When rural electrification and pumping needs coexist, energy flow management becomes essential to make the best use of the available photovoltaic energy [10], [11].

To mitigate the intermittency of photovoltaic power generation, battery energy storage is a widely adopted solution in standalone microgrids [12]. Batteries store the excess energy generated during periods of high irradiation and supply it when photovoltaic generation becomes insufficient. However, the overall performance of a PV-battery system strongly depends on the energy management strategy, which must balance supply continuity, utilization of the generated energy and battery lifetime [13], [14], [15]. Recent studies also show that battery degradation, input data quality and the temporal horizon of the analysis significantly affect the evaluation of energy management strategies [16], [17].

Furthermore, improving the performance of photovoltaic systems relies on maximum power point tracking (MPPT) algorithms capable of continuously extracting the maximum available power despite climatic variations [18],[19]. Among the techniques proposed in the literature, the incremental conductance method remains one of the most effective approaches due to its fast convergence and accuracy under varying irradiation conditions. In parallel, power electronic converters and their control strategies play a crucial role in regulating the DC bus and coordinating energy exchanges between the photovoltaic generator, the energy storage system and the loads [20], [21].

Although extensive research has been devoted to standalone photovoltaic systems and energy management strategies, many studies analyze system behavior over short periods, typically a representative day or a few specific weather scenarios [22],[23]. Such an approach evaluates the instantaneous behavior of the system but does not capture its response to successive variations in the solar resource [24]. Analysis over a longer period, such as a complete month of measured data, allows the evolution of the battery state of charge and the stability of the DC bus to be assessed under realistic day-to-day weather variability [25],[26].

In a previous study [12], we proposed an energy management strategy for a 36.6 kWp PV-battery system supplying rural loads and agricultural pumping, assessed over two 48-hour scenarios, one with a clear sky and one with an overcast sky. The present paper builds on this system and strategy, described in detail in [12], to address a different question: how the system behaves under successive day-to-day variations of the solar resource over a continuous 28-day period, using measured irradiation and temperature data.

The objective of this study is to examine, over 28 consecutive days, the behavior of the DC bus voltage, the power flows and the battery state of charge of a standalone PV-battery system under measured weather conditions in Gandon, Senegal. The contributions of this paper are:

- A continuous 28-day (672 h) simulation of the PV-battery system of [12] using measured irradiation and temperature data;

- An analysis of the DC bus voltage and of the battery state of charge under successive weather variations, complementing the 48-hour scenarios of [12];
- A qualitative analysis of the influence of irradiance and temperature variations on the PV power and on the energy exchanges between the PV generator, the battery and the load.

The remainder of this paper is organized as follows: Section 2 presents the system architecture, the modeling of the PV generator and the battery, and the MPPT control and energy management strategy. Section 3 presents and discusses the simulation results. Section 4 concludes the paper and outlines future work.

## 2 MATERIALS AND METHODS

## 2.1 Description of the Proposed System

Figure 1 presents the architecture of the proposed PV-battery hybrid system for standalone microgrids. The photovoltaic generator constitutes the primary energy source. Voltage and current measurements are used by the incremental conductance MPPT algorithm to control the Boost converter and maximize the extracted power. The DC bus distributes energy to the load and the energy storage system. The battery, connected through a bidirectional Buck-Boost converter, is charged when photovoltaic generation exceeds the demand and discharged in the event of an energy deficit. Finally, the energy management system (EMS) supervises the overall system by controlling the converters to maintain DC bus stability and ensure a reliable and continuous power supply to the load.

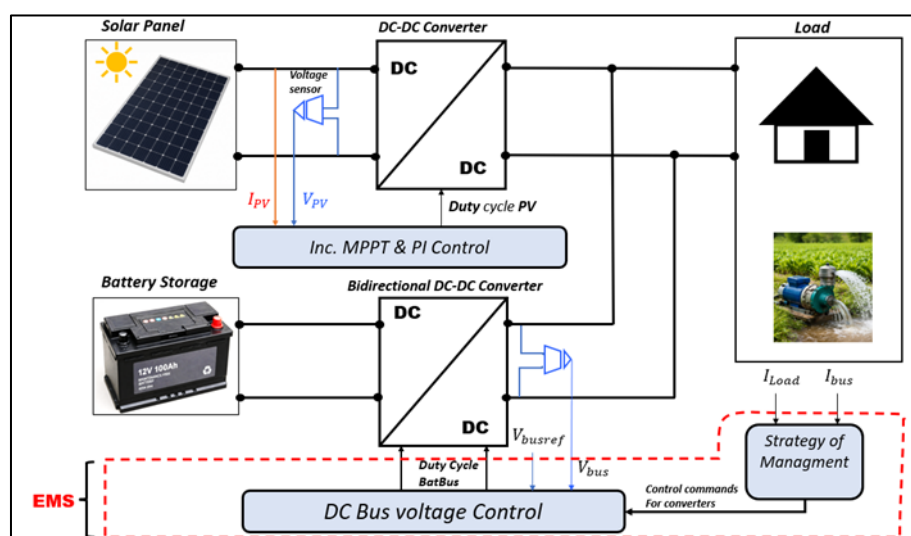


**Figure 1: Synoptic diagram of the system studied.**

## 2.2 Description of the study area

The study area is located in Gandon, a locality in northwestern Senegal, in the Saint-Louis region. This area has significant solar potential, characterized by high solar radiation availability and seasonal variability in solar irradiation. These conditions make it a relevant site for studying and managing photovoltaic systems.

In this study, the solar data used were measured directly at the Gandon site during February 2005. These measured data constitute the main inputs to the model for analyzing the behavior of the photovoltaic–battery system and assessing its ability to meet local energy requirements. Figure 2 presents the study site.

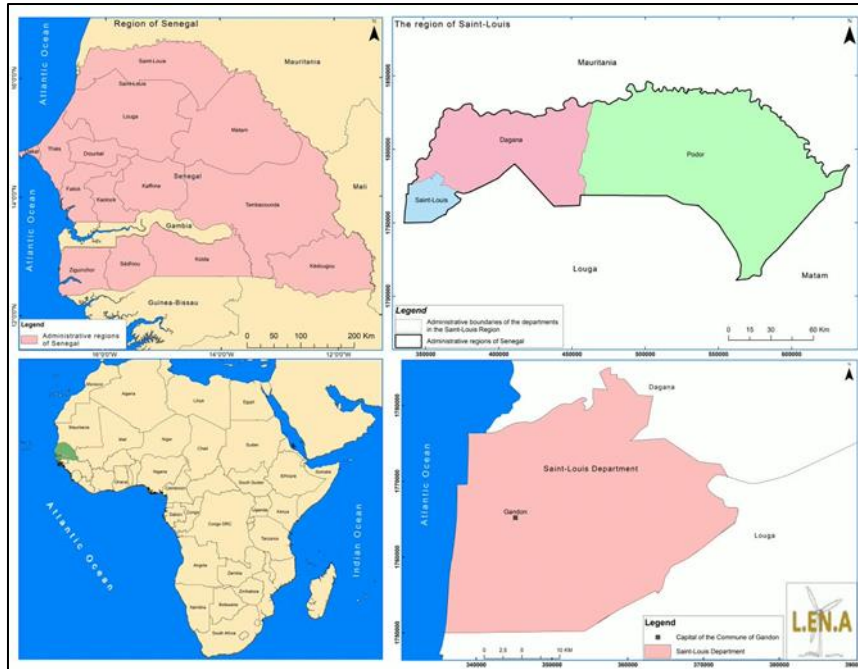


Figure 2: Location of the study site

### 2.3 Modeling the PV

The photovoltaic generator is represented by a **simplified Single-Diode Model (SDM)**, as illustrated in Fig. 3. This model is widely used to reproduce the nonlinear electrical behavior of photovoltaic cells and modules, particularly through their current-voltage ( $I$ - $V$ ) and power-voltage ( $P$ - $V$ ) characteristics. It provides an appropriate trade-off between modeling accuracy and computational simplicity, making it particularly suitable for the simulation and analysis of photovoltaic systems [27],[28],[29].

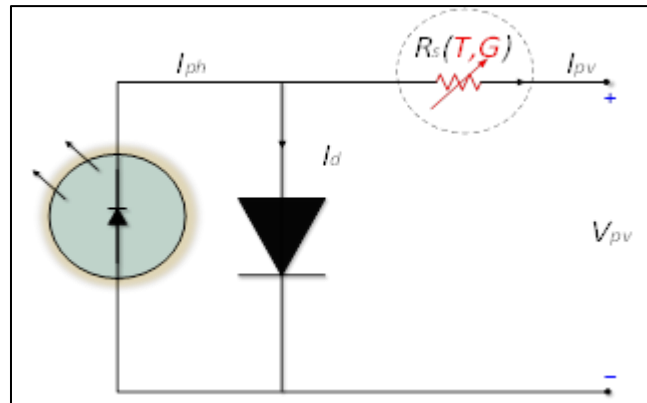


Figure 3: Single-diode PV model

The equivalent circuit considered consists of a photo-generated current source  $I_{ph}$ , a diode representing the nonlinear behavior of the photovoltaic junction, and a series resistance  $R_s$ . The latter accounts for the ohmic losses associated with semiconductor materials, metallic contacts, and module interconnections. In the adopted model, the series resistance is considered dependent on the operating conditions and is expressed as  $R_s(T, G)$ .

where  $T$  represents the cell temperature and  $G$  the solar irradiance. Recent studies show, in particular, that  $I_{ph}$ ,  $I_0$ ,  $n$  and  $R_s$  play an important role in determining the characteristics of the photovoltaic module [27],[28].

By applying Kirchhoff's current law to the equivalent circuit, the current delivered by the photovoltaic generator is expressed by Equation (1) :

$$I_{pv} = I_{ph} - I_d \quad (1)$$

Where  $I_d$  denotes the current flowing through the diode.

Using the Shockley equation, this current is given by Equation (2):

$$I_d = I_0 \left[ \exp \left( \frac{V_{pv} + I_{pv} R_s (T, G)}{n N_s V_T} \right) - 1 \right] \quad (2)$$

Where  $I_0$  denotes the diode reverse saturation current,  $n$  is the ideality factor,  $N_s$  represents the number of cells connected in series, and  $V_T$  is the thermal voltage. The latter is defined by Equation (3):

$$V_T = \frac{kT}{q} \quad (3)$$

where  $k$  is the Boltzmann constant,  $q$  is the elementary charge, and  $T$  is the absolute cell temperature.

Consequently, the characteristic equation of the considered photovoltaic model can be formulated as follows:

$$I_{pv} = I_{ph} - I_0 \left[ \exp \left( \frac{V_{pv} + I_{pv} R_s (T, G)}{n N_s V_T} \right) - 1 \right] \quad (4)$$

This equation illustrates the nonlinear and implicit nature of the model, as the photovoltaic current  $I_{pv}$  appears both outside and within the exponential term. Consequently, determining the current corresponding to a given voltage requires the numerical solution of the governing equation. In recent studies, numerical approaches and optimization techniques have been widely employed to estimate the parameters of the single-diode model and to accurately reproduce the experimental current-voltage characteristics of photovoltaic (PV) modules [27],[29].

The photogenerated current primarily depends on the solar irradiance and the cell temperature. It can be estimated from the reference conditions using Equation (5):

$$I_{ph}(G, T) = [I_{ph,ref} + K_I(T - T_{ref})] \frac{G}{G_{ref}} \quad (5)$$

where  $I_{ph,ref}$  denotes the photogenerated current under reference conditions,  $K_I$  is the temperature coefficient of the current,  $T_{ref}$  is the reference temperature, and  $G_{ref}$  is the reference irradiance. This dependence enables the model to accurately reproduce variations in the current-voltage (I-V) characteristics under different environmental conditions. A recent study published in *Results in Physics* highlighted the importance of accounting for both temperature and irradiance when simulating the single-diode model [27].

Finally, the electrical power generated by the photovoltaic generator is calculated using Equation (6):

$$P_{pv} = V_{pv} I_{pv} \quad (6)$$

The maximum power point (MPP) corresponds to the operating point  $(V_{mpp}, I_{mpp})$  at which the photovoltaic power  $P_{pv}$  reaches its maximum value [30], as expressed by Equation (7):

$$P_{mpp} = V_{mpp} I_{mpp} \quad (7)$$

### Technical Specifications of the Photovoltaic Module

Table 1 presents the main technical specifications of the photovoltaic module under study. It highlights the key electrical parameters, including the maximum power, voltage, and current. The temperature coefficients are also provided to characterize the module's behavior under varying climatic conditions.

**Table 1: PV parameters**

| Parameter                               | Value                                  |
|-----------------------------------------|----------------------------------------|
| Module                                  | Advance Solar Hydro Wind Power API-150 |
| Number of Cells (Ncell)                 | 72                                     |
| Maximum Power Output (W)                | 150.075                                |
| Current at Maximum Power Point (Imp, A) | 4.35                                   |
| Voltage at Maximum Power Point (Vmp, V) | 34.5                                   |
| Short-Circuit Current (Isc, A)          | 5.05                                   |
| Open-Circuit Voltage (Voc, V)           | 41.8                                   |
| Temperature Coefficient of Isc (%/°C)   | 0.096                                  |
| Temperature Coefficient of Voc (%/°C)   | -0.419                                 |

## 2.4 Modeling of the battery energy storage chain

### 2.4.1 Storage battery

The battery constitutes the energy storage component of the photovoltaic system. It absorbs the excess energy generated by the PV generator and supplies energy when solar power production becomes insufficient. For photovoltaic applications, an equivalent electrical model can be used to represent the battery behavior while providing a good compromise between modeling accuracy and computational simplicity [31], [32].

In this study, the battery is modeled using an open-circuit voltage that depends on the state of charge (SOC), together with an internal resistance. The terminal voltage [33] is expressed by Equation (8):

$$V_{bat}(t) = V_{oc}(SOC(t)) - R_{int} \times I_{batt}(t) \quad (8)$$

where  $V_{bat}$  is the battery terminal voltage,  $V_{oc}$  is the open-circuit voltage,  $R_{int}$  is the internal resistance, and  $I_{batt}$  is the battery current.

The open-circuit voltage is considered to be a function of the state of charge:

$$V_{oc} = f(SOC) \quad (9)$$

This relationship accounts for the variation in the battery voltage as a function of its state of charge [34].

The state of charge (SOC) represents the amount of charge available in the battery relative to its nominal capacity [35], [36]. It is defined by Equation (10):

$$SOC(t) = \frac{Q(t)}{Q_{nom}} \times 100 \quad (10)$$

where  $Q(t)$  represents the charge available at time  $t$ , and  $Q_{nom}$  denotes the nominal capacity of the battery.

The evolution of the state of charge (SOC) is determined using the ampere-hour counting method [37],[38]:

$$SOC(k+1) = SOC(k) - \frac{100 \Delta t}{Q_{nom}} \begin{cases} \eta_c I_{batt}(k), & \text{if } I_{batt}(k) < 0, \\ \frac{I_{batt}(k)}{\eta_d}, & \text{if } I_{batt}(k) \geq 0. \end{cases} \quad (11)$$

where  $Q_{nom}$  is the nominal battery capacity (Ah),  $\Delta t$  is the time step (h),  $I_{batt}$  is the battery current (positive during discharge and negative during charge), and  $\eta_c$  and  $\eta_d$  are the coulombic charge and discharge efficiencies, respectively.

The power exchanged by the battery is calculated from its voltage and current [39]:

$$P_{bat}(t) = V_{bat}(t) \times I_{batt}(t) \quad (12)$$

According to the adopted convention,

$P_{bat} > 0$  corresponds to **discharging**, whereas

$P_{bat} < 0$  corresponds to **charging**.

Thus, excess photovoltaic generation can be stored in the battery and subsequently supplied when the PV power becomes insufficient.

To ensure operation within an admissible range, the SOC is subject to the following constraint:

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \quad (13)$$

The power exchanged with the battery is also limited by:

$$-P_{ch,max} \leq P_{bat}(t) \leq P_{dis,max} \quad (14)$$

where  $P_{bat}$  denotes the instantaneous power exchanged by the battery,  $P_{ch,max}$  the maximum charging power, and  $P_{dis,max}$  the maximum discharging power. According to the adopted convention, negative power corresponds to battery charging, whereas positive power corresponds to battery discharging.

These constraints prevent battery overcharging and excessive discharge. They are particularly important in the analysis of the monthly variability of the solar resource, as the SOC level reached during a given month directly influences the system's ability to meet the demand during periods of low photovoltaic generation.

The developed model thus makes it possible to determine the main electrical quantities of the storage system, including voltage, current, exchanged power, and state of charge. It provides the basis for evaluating the energy management strategy of the PV-battery system under the different monthly solar resource conditions considered.

#### 2.4.2 Bidirectional DC-DC Converter Architecture

Figure 4 illustrates the structure of a bidirectional buck–boost converter that provides the interface between the battery and the DC bus. The battery, with voltage  $V_{bat}$ , is connected to the bus  $V_{bus}$  through an inductance  $L_{batt}$ , two power switches  $S_1$  and  $S_2$ , as well as a capacitor  $C_{bus}$ . The inductance  $L_{batt}$  enables control and limitation of the variations in the battery current ( $I_{batt}$ ). Switch  $S_1$ , driven by the control signal  $Q_{boost}$ , operates in boost mode during energy transfer from the battery to the bus. Switch  $S_2$ , driven by the control signal  $Q_{buck}$ , operates in buck mode during energy transfer from the bus to the battery. The associated diodes ensure the necessary conduction paths during the commutation phases. The capacitor  $C_{bus}$ , connected to the DC bus, contributes to smoothing  $V_{bus}$  and absorbing rapid power fluctuations. This structure therefore enables bidirectional power transfer between the battery and the bus, while ensuring control of both  $I_{batt}$  and  $V_{bus}$ .

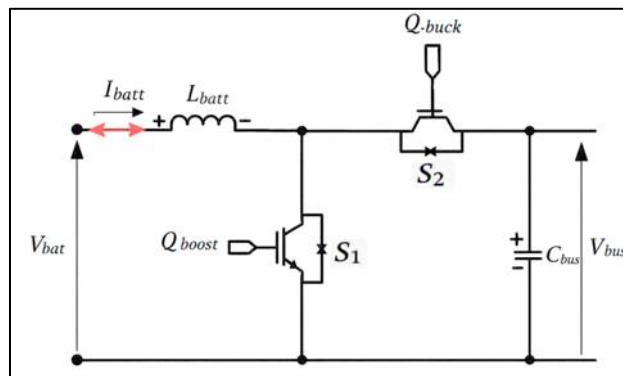


Figure 4: Buck-Boost bidirectional DC-DC converter [12]

#### 2.4.3 System electrical parameters

For the study of the storage system, the main electrical parameters of the battery and the bidirectional DC-DC converter are defined based on representative values of a medium-power storage application. The battery is described by the electrical model presented previously, with parameters allowing the reproduction of its charge and discharge characteristics. The bidirectional converter ensures the energy exchange between the battery and the DC bus and

includes, in particular, a filtering inductance, a bus capacitor, and a switching frequency adapted to the control strategy. Table 2 presents all the electrical parameters used for modeling and simulations.

**Table 2: Electrical parameters used for the modeling of the bidirectional battery–converter system**

| System component              | Parameter                      | Symbol        | Value              |
|-------------------------------|--------------------------------|---------------|--------------------|
| Battery                       | Rated capacity                 | $(Q)$         | 648 Ah             |
|                               | Nominal voltage                | $(E_0)$       | 200 V              |
|                               | Polarization coefficient       | $(K)$         | 0.0029             |
|                               | Internal resistance            | $(R_b)$       | 0.0038 $\Omega$    |
|                               | Exponential-zone amplitude     | $(A_b)$       | 21.16              |
|                               | Exponential-zone time constant | $(B)$         | 0.094              |
|                               | Initial state of charge        | $(SOC_{bat})$ | 50%                |
| Bidirectional DC–DC converter | DC-bus capacitance             | $(C_{bus})$   | 3300 $\mu\text{F}$ |
|                               | Battery-side inductance        | $(L_{bat})$   | 1 mH               |
|                               | Switching frequency            | $(f)$         | 10 kHz             |

#### 2.4.4 PI controller parameter tuning

In order to ensure a satisfactory compromise between response speed, tracking accuracy, and system stability, the gains of the PI controllers have been carefully determined for the current and voltage loops. The selected parameters are summarized in Table 3.

**Table 3: Selected gains of the PI control loops**

| Control loop       | Gain                          | Value |
|--------------------|-------------------------------|-------|
| Current controller | Proportional gain, $(k_{pi})$ | 0.05  |
|                    | Integral gain, $(k_{ii})$     | 0.01  |
| Voltage controller | Proportional gain, $(k_{pv})$ | 100   |
|                    | Integral gain, $(k_{iv})$     | 1100  |

Figure 5 presents the control scheme implemented to ensure the regulation of the DC bus voltage.

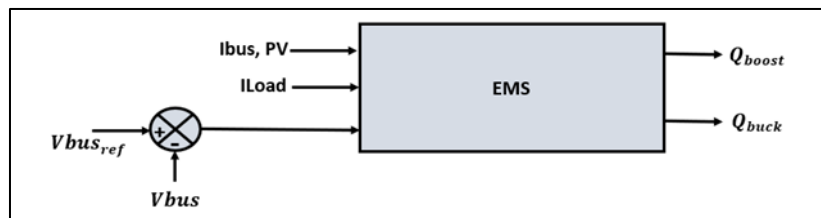


**Figure 5: Strategy for DC bus voltage regulation**

#### 2.4.5 Incremental conductance method for MPPT

The Incremental Conductance (IncCond) method is adopted to ensure Maximum Power Point Tracking (MPPT) of the photovoltaic generator. It is based on the analysis of the slope of the power–voltage characteristic of the generator. At the maximum power point, the derivative of the power with respect to the voltage is equal to zero.

$$\frac{dP_{PV}}{dV_{PV}} = 0 \quad (15)$$

Since  $P_{PV} = V_{PV} \times I_{PV}$ , this condition can be expressed according to equation (16):

$$\frac{\Delta I_{PV}}{\Delta V_{PV}} = -\frac{I_{PV}}{V_{PV}} \quad (16)$$

Thus, the algorithm compares the instantaneous conductance  $\frac{I_{PV}}{V_{PV}}$  with the incremental conductance  $\frac{\Delta I_{PV}}{\Delta V_{PV}}$ . Depending on the sign of their difference, the operating voltage is either increased or decreased in order to bring the generator closer to its maximum power point. This method has the advantage of being more suitable for rapid variations in irradiance than methods based solely on successive perturbations, which makes it relevant for photovoltaic systems subjected to variable solar conditions.

In the studied system, the signal generated by the IncCond-MPPT algorithm is transmitted to the control of the DC-DC converter to adjust the operating point of the PV generator and continuously extract the maximum available power. Figure 6 illustrates the maximum power point tracking (MPPT) algorithm based on the incremental conductance method.

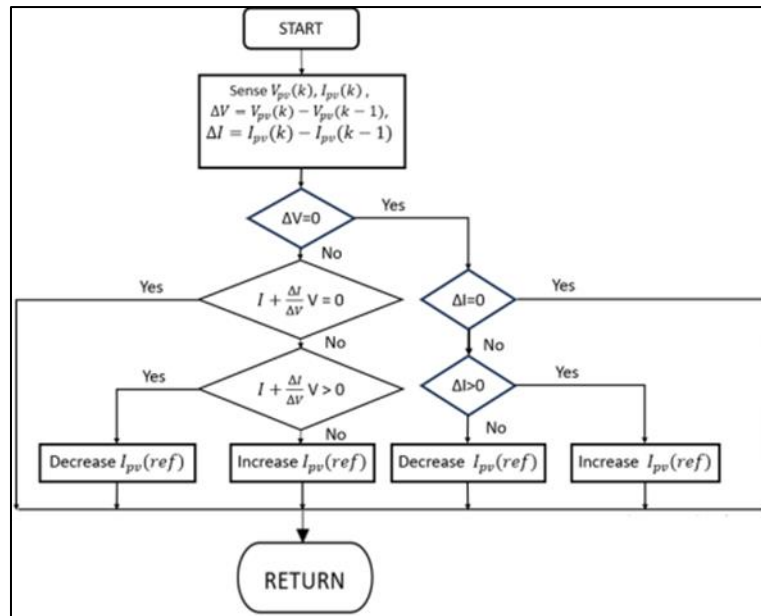


Figure 6: Incremental conductance-based algorithm [12].

#### 2.4.6 Energy management strategy of the photovoltaic–battery system

The energy management strategy (Figure 7) aims to ensure, in real time, the balance between the available photovoltaic power, the microgrid demand, and the battery. Based on the microgrid data, the power balance is determined by equation (17) :

$$S = I_{Load} - I_{buspv} \quad (17)$$

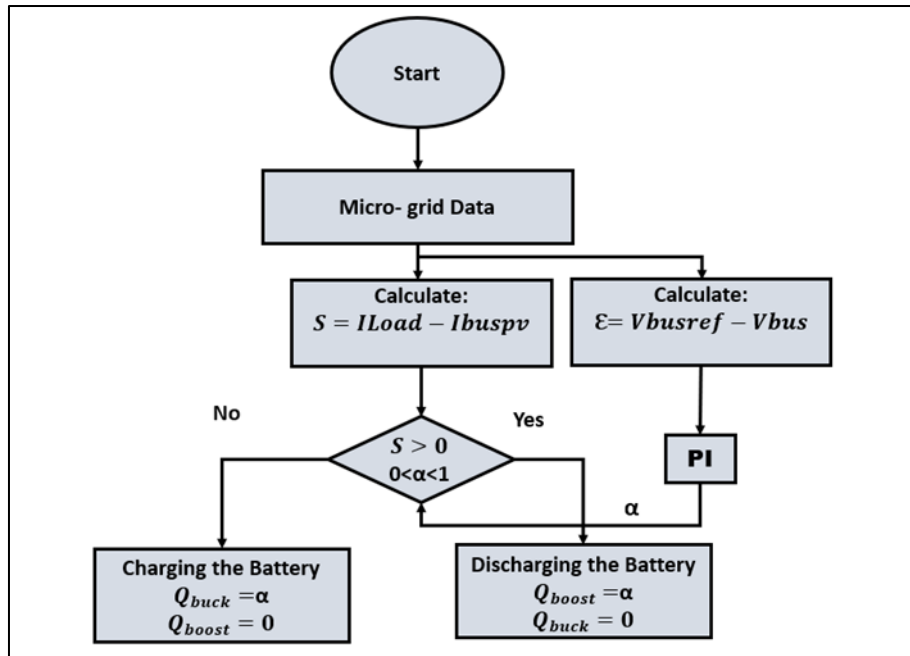


**Figure 7: Energy management algorithm for a PV-battery microgrid**

Figure 7 presents the flowchart of the proposed energy management strategy for the photovoltaic–battery microgrid. Based on the system data, the power deviation is determined by

$$S = I_{Load} - I_{buspv}, \text{ while the DC bus voltage error is calculated as : } \varepsilon = V_{busref} - V_{bus}.$$

When  $S > 0$ , the power demand exceeds the photovoltaic production, and the battery is discharged through the bidirectional converter operating in boost mode. Conversely,

when  $S \leq 0$ , the photovoltaic surplus is directed to the battery to ensure charging in buck mode.

The regulation of the DC bus voltage is achieved by a PI controller, whose output ( $\alpha$ ) defines the duty cycle applied to the converter. This strategy thus enables the dynamic adaptation of power flows between the photovoltaic generator, the battery, and the load, while contributing to maintaining the DC bus voltage around its reference value.

### 3 RESULTS AND DISCUSSION

This section reports the simulation results of the PV- battery system under Gandon solar conditions. The analysis highlights the impact of irradiance variability on PV generation, battery SOC, and load supply, followed by a discussion assessing the efficiency of the proposed energy management strategy in maintaining microgrid stability.

#### 3.1 Weather conditions and solar irradiation profiles

Figure 8 shows the evolution of solar irradiance and ambient temperature over a period of 28 days (672 h). The irradiance exhibits a daily cyclic variation, with zero values during nighttime and daytime maxima ranging approximately between 600 and 850 W/m<sup>2</sup>. More pronounced fluctuations are observed on certain days, reflecting the variability of weather conditions. The temperature also follows a daily cycle, with values ranging approximately between 14 and 40 °C. These variations therefore constitute representative operating conditions for evaluating the performance of the photovoltaic system and its energy management strategy.

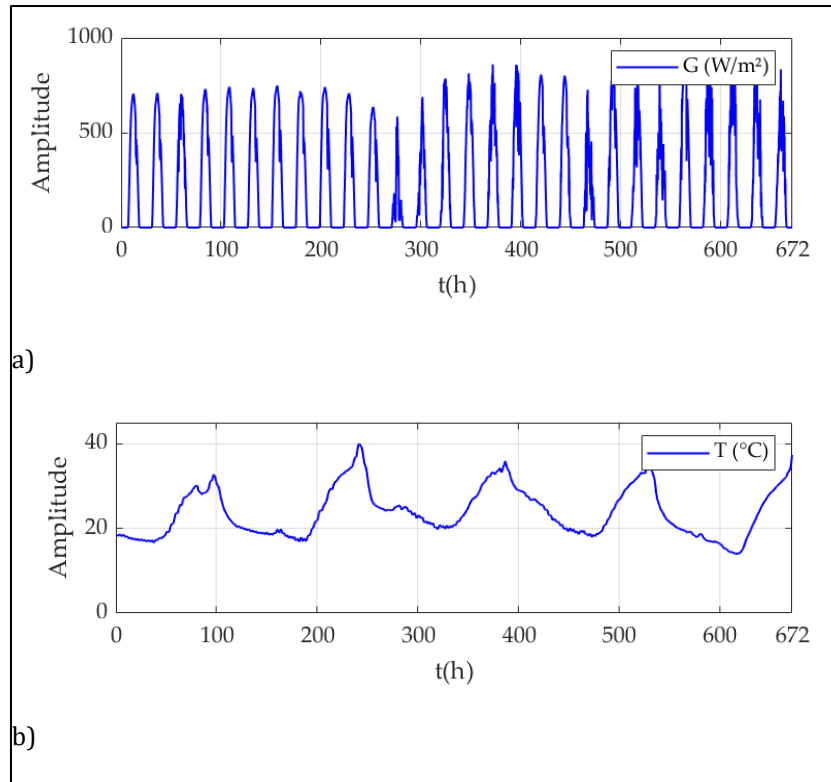


**Figure 8: Time profiles of solar irradiance and ambient temperature during the study period**

### 3.2 Analysis of the photovoltaic current and its reference

Figure 9 shows the tracking of the photovoltaic current with respect to its reference, allowing the evaluation of the performance of the implemented control strategy.

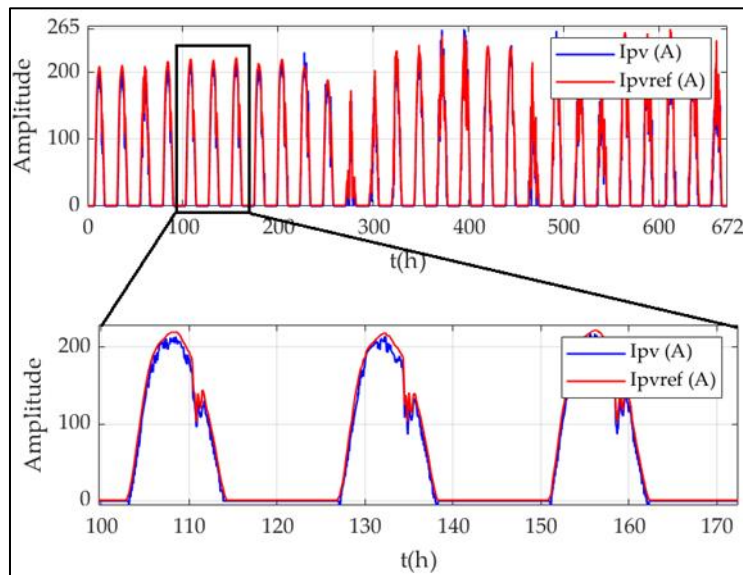


**Figure 9: Tracking of the photovoltaic current and its reference**

Figure 9 presents the evolution of the actual photovoltaic current  $I_{pv}$  and the reference current  $I_{pvref}$  over a 28-day period corresponding to February 2005. The curves exhibit a cyclic pattern linked to the day–night alternation, with nearly zero current during nighttime and values exceeding 200 A during periods of high solar production. The magnified view highlights a good agreement between  $I_{pv}$  and  $I_{pvref}$ . Despite some minor deviations and oscillations during rapid current variations, the actual current correctly follows its reference. These results therefore demonstrate the good performance of the control strategy and its satisfactory ability to track the reference despite the variability of the solar resource.

### 3.3 Analysis of the PV current injected into the DC bus over time

Figure 10 presents the temporal evolution of the photovoltaic current  $I_{buspv}$  over a period of 672 hours.

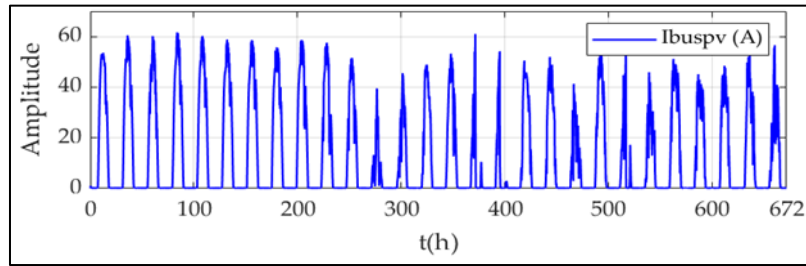


**Figure 10: Temporal evolution of the photovoltaic current ( $I_{buspv}$ )**

Figure 10 presents the temporal evolution of the amplitude of the photovoltaic current  $I_{buspv}$  over the study period. The signal exhibits a strongly periodic behavior, characterized by rapid rising phases followed by an almost instantaneous return to zero amplitude. The maximum values generally reach 50-60 A, with amplitude variations observed throughout the considered period. A decrease in signal regularity as well as the appearance of more pronounced fluctuations are particularly noticeable between 250 and 400 h, and beyond 450 h. These variations can be attributed to changes in the operating conditions of the system, notably to fluctuations in the photovoltaic resource and the electrical demand.

### 3.4 Analysis of DC bus voltage regulation over time

Figure 11 presents the evolution of the DC bus voltage ( $V_{bus}$ ) and its reference ( $V_{busref}$ ), allowing the evaluation of the quality of voltage regulation during the studied period.

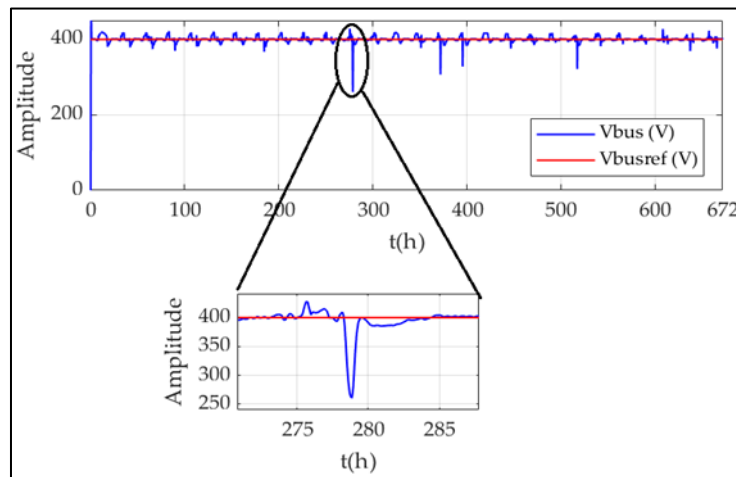


**Figure 11: Tracking of DC bus voltage and its reference**

Figure 11 presents the evolution of the DC bus voltage ( $V_{bus}$ ) as well as its reference ( $V_{busref}$ ) over a 672-hour period. The bus voltage remains generally close to its reference value, set around 395 V, which indicates good regulation of the system. Some occasional disturbances are observed during the studied period, particularly around 275-280 h, where  $V_{bus}$  undergoes a significant drop to about 260 V before gradually returning to its reference value. This disturbance remains transient, and the voltage subsequently recovers stable operation. Overall, the tracking of the reference remains satisfactory, despite a few occasional variations linked to the system's operating conditions.

### 3.5 Analysis of battery currents and their temporal evolution

Figure 12 presents the evolution of the currents  $I_{bat}$  (curve a) and  $I_{busbat}$  (curve b) over a 672-hour period. Both curves exhibit a periodic and oscillatory behavior, characterized by alternating charging and discharging phases of the battery. For curve (a), the current varies approximately between  $-100$  and  $110$  A, while curve (b) shows a lower amplitude, ranging between about  $-55$  and  $55$  A. Despite a gradual decrease in amplitude during the study period, both signals maintain a similar evolution. These results highlight a consistent dynamic between the battery current and the bus-associated current, with variations mainly driven by changes in the system's operating conditions, particularly fluctuations in the photovoltaic resource and electrical demand.

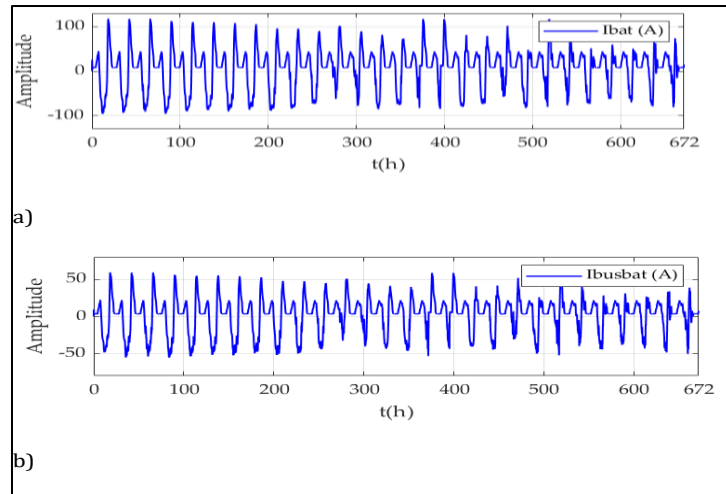


**Figure 12: Temporal evolution and dynamics of battery and bus currents**

### 3.6 Evolution of the battery state of charge under solar variability

The analysis of the storage system makes it possible to evaluate the evolution of the battery state of charge (SOC) and its ability to balance photovoltaic production with energy demand.

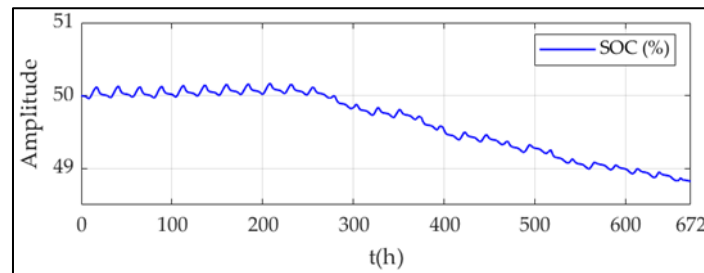


**Figure 13: Evolution of the battery state of charge (SOC)**

Figure 13 presents the evolution of the battery state of charge (SOC) over a 672-hour period corresponding to the month of February. The SOC remains generally close to 50%, with small periodic oscillations linked to alternating charging and discharging phases. A slight decrease is nevertheless observed during the study period, with the SOC dropping from about 50.1% to 48.8%. This trend reflects a moderate cumulative energy deficit, while indicating that the battery remains within a relatively stable operating range. The energy management system thus ensures a satisfactory balance between photovoltaic production and microgrid demand despite the variability of the solar resource.

### 3.7 Analysis of the evolution of battery voltage

This section analyzes the evolution of the battery voltage ( $V_{bat}$ ) in order to assess its stability over 672 hours of operation.

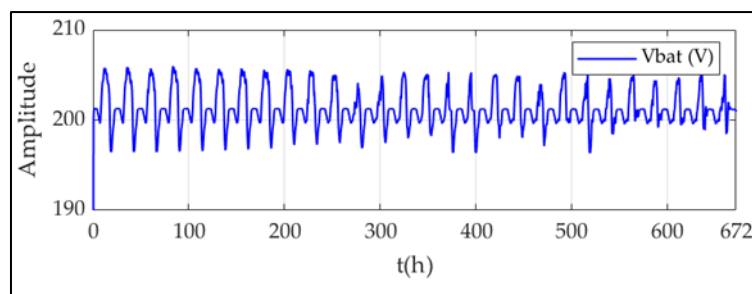


**Figure 14: Temporal evolution of battery voltage**

Figure 14 presents the evolution of the battery voltage ( $V_{bat}$ ) over a 672-hour period. The voltage remains generally stable around 200 V, with periodic oscillations of moderate amplitude. More pronounced variations are observed occasionally, particularly at the beginning and towards the end of the considered period. Despite these fluctuations, no

significant drift in the average voltage is detected, which reflects an overall stable behavior of the system throughout the study duration.

### 3.8 Analysis of power flows and system performance

This section presents the evolution of the main power flows of the system in order to evaluate its energy behavior and overall performance. The analysis focuses on photovoltaic, load, and battery powers, as well as their coordination throughout the studied period.

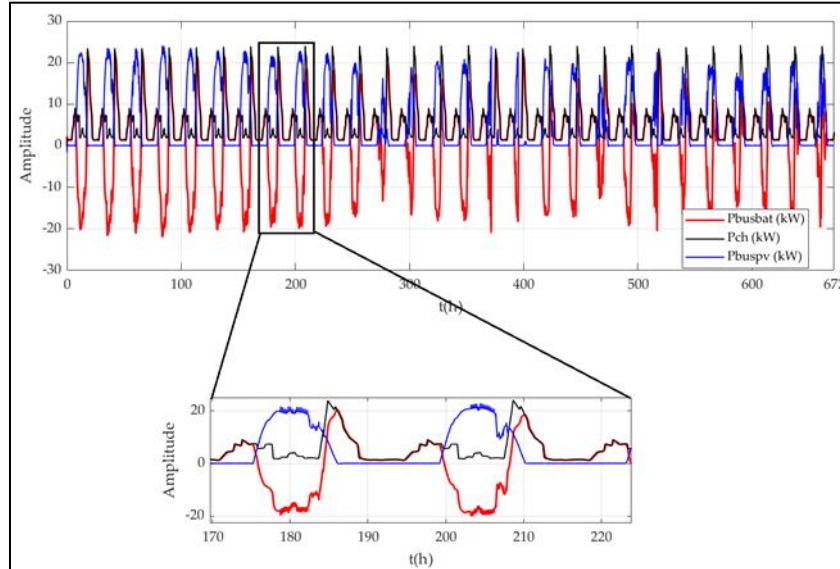


**Figure 15: Temporal evolution of power flows in the photovoltaic system and the battery**

Figure 15 presents the evolution of the powers  $P_{busbat}$ ,  $P_{ch}$ , and  $P_{buspv}$  over a 672-hour period. The three profiles exhibit a periodic behavior, characterized by a regular alternation of energy production, consumption, and storage phases. The photovoltaic power ( $P_{buspv}$ ) reaches its maximum values during solar production periods, while  $P_{busbat}$  shows positive and negative variations corresponding to the charging and discharging phases of the battery. The load power ( $P_{ch}$ ) remains generally low, with occasional variations linked to demand. This evolution highlights the good coordination of the different energy flows and confirms the satisfactory performance of the developed system in terms of energy management and distribution.

## 4 CONCLUSION AND PERSPECTIVES

This study analyzed the energy management of a standalone hybrid PV–battery system, taking into account the variability of solar conditions over a monthly period. The data measured in Gandon, Senegal, during February 2005, allowed the evaluation of the system's behavior over 28 days (672 hours). The results highlight the direct influence of solar irradiance and ambient temperature variations on the available photovoltaic power and on energy exchanges between the PV generator, the battery, and the load. The incremental conductance method allowed the PV current to follow its reference, and the DC bus voltage remained close to its 395 V reference, apart from a transient drop to about 260 V around 275–280 h. The battery absorbed the excess energy and supplied it when photovoltaic production became insufficient, with a state of charge staying close to 50% throughout the month. Since the simulation starts at 50% and the storage was only lightly stressed, these results do not show the behavior of the strategy near the SOC limits.

The monthly analysis complements the 48-hour scenarios of our previous work, from which the system and the strategy are taken. The study is limited to a single month at a single site, without water pumping, without comparison with another strategy and without quantitative performance indicators; it therefore provides a first, qualitative basis for analyzing PV–battery systems in the sub-Saharan African context.

Future work will focus mainly on extending the analysis to a full year to integrate seasonal variations of the solar resource. The use of real load profiles, including water pumping, will also allow the evaluation of the strategy under more representative operating conditions. Further studies may finally incorporate advanced energy management methods, including artificial intelligence and multi-objective optimization, to simultaneously optimize storage capacity, PV sizing, system reliability, and overall cost. Experimental validation on a real platform will also be an important step to confirm the performances obtained through simulation.

## STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

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### *Disclosure of conflict of interest*

The authors declare no conflicts of interest regarding this manuscript.

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