Real-time optimization of a dynamic system (PV-BESS) integrated into a building for self-consumption*

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***Abstract*—This work proposes an Artificial Neural Network (ANN)-based approach to optimize, in real time, the power generation of a photovoltaic system integrated into a residential building (PV-BESS). The studied model combines a PV generator, a battery energy storage system, and DC–DC converters regulated by a Maximum Power Point Tracking (MPPT) algorithm. A multilayer feedforward ANN, trained using the Levenberg–Marquardt algorithm, is employed to accurately predict the optimal duty cycle and ensure maximum power extraction. The results demonstrate that the ANN-based MPPT model outperforms conventional methods such as Perturb and Observe (P&O) and Incremental Conductance (INC) by reducing power oscillations, improving response speed, and providing better energy stability, even under variable weather conditions. This approach contributes to the optimization of self-consumption and supports the transition toward sustainable energy development in Senegal.**

***Index Terms*—Artificial Neural Network (ANN), Photovoltaic System, MPPT, PV-BESS, Energy Management, Building-Integrated Photovoltaics (BIPV), Renewable Energy, Senegal.**

I. Introduction

The continuous growth of global energy demand, combined with the progressive depletion of fossil fuel resources and the increasing emission of greenhouse gases, is driving the transition toward more sustainable and environmentally friendly energy systems. In this context, renewable energy sources play a crucial role in modern energy policies, particularly solar photovoltaic (PV) energy, which is distinguished by its abundance, availability, and low environmental impact [3], [11]. Senegal possesses significant solar potential that can support the development of building-integrated photovoltaic systems. These systems enable the local generation of clean electricity while reducing dependence on fossil fuels and lowering energy costs in residential and commercial buildings. Consequently, the integration of photovoltaic technologies into buildings represents a promising solution for improving energy efficiency and supporting the sustainable energy transition in Senegal [4], [12]. However, the performance of photovoltaic systems remains highly dependent on climatic conditions such as solar irradiance, temperature, humidity, and weather fluctuations. These factors cause significant variations in power generation and can considerably reduce the energy efficiency of PV installations. To enhance maximum power extraction, several conventional Maximum Power Point Tracking (MPPT) techniques have been developed, including Perturb and Observe (P&O) and Incremental Conductance (INC). Despite their simplicity, these methods exhibit limitations such as oscillations around the maximum power point and slow response under rapidly changing weather conditions [5]. To overcome these limitations, Artificial Intelligence (AI) techniques, particularly Artificial Neural Networks (ANNs), have emerged as powerful solutions for the modeling, prediction, and optimization of photovoltaic systems. Owing to their ability to learn complex nonlinear relationships, ANNs can improve the accuracy of photovoltaic power prediction, optimize energy efficiency, and enhance the stability of building-integrated

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photovoltaic systems [6], [7]. Furthermore, recent advances in Deep Learning and smart grid technologies have enabled the development of more efficient energy management strategies for intelligent buildings and residential microgrids. Several studies have demonstrated that deep learning models, such as Long Short-Term Memory (LSTM) networks and advanced artificial intelligence techniques, provide superior performance in energy forecasting and photovoltaic system optimization [13]–[15]. In this context, this paper proposes an Artificial Neural Network-based approach for optimizing the performance of building-integrated photovoltaic systems in order to contribute to the sustainable energy transition in Senegal. The main objective is to develop an intelligent model capable of improving photovoltaic power prediction, maximizing energy efficiency, and enhancing the operational stability of building-integrated PV systems. The remainder of this paper is organized as follows. Section II presents the system architecture and mathematical modeling of the PV-BESS system. Section III describes the proposed ANN-based MPPT methodology. Section IV discusses the simulation results and performance evaluation. Finally, Section V concludes the paper and outlines future research perspectives.

II. Methodology and Materials

A. Description of the Studied System

The studied system consists of a Building-Integrated Photovoltaic Battery Energy Storage System (PV-BESS) designed to supply the electrical demand of a residential building. The proposed architecture integrates a photovoltaic (PV) generator, a DC–DC boost converter, a battery energy storage system (BESS), and a load representing the building's electrical consumption. The photovoltaic generator converts solar irradiance into electrical energy. Since the output power of the PV array varies according to environmental conditions such as solar irradiance and temperature, a Maximum Power Point Tracking (MPPT) controller is employed to ensure operation at the maximum power point. In this work, an Artificial Neural Network (ANN)-based MPPT algorithm is used to predict the optimal duty cycle of the DC–DC converter and maximize power extraction from the PV array. The DC–DC boost converter interfaces the PV generator with the DC bus and regulates the operating voltage of the photovoltaic system. The converter switching signal is generated through Pulse Width Modulation (PWM), where the duty cycle is provided by the ANN-MPPT controller. The battery energy storage system plays a crucial role in balancing power generation and consumption. It stores excess photovoltaic energy during periods of high solar production and supplies energy when the photovoltaic generation is insufficient to meet the load demand. This enhances system reliability, improves self-consumption, and reduces dependence on the utility grid. The residential load represents the electrical appliances and energy requirements of the building. The energy management strategy aims to maximize the utilization of photovoltaic energy while maintaining power balance and ensuring stable operation under varying weather conditions. Figure **??** illustrates the overall architecture of the proposed PV-BESS system integrated into a residential building.

B. MRER Modeling

1. Photovoltaic Generator : A photovoltaic generator (PVG) is a device composed of an array of identical solar modules connected in series and/or parallel (Figure 2). It is modeled as a current source in parallel with a diode. To account for internal losses and dissipation effects, two resistances are included in the model: a series resistance and a shunt resistance [14].

$$I_{PV} = I_{ph} - I_0 \left[\exp\left(\frac{V_{PV} + R_S I_{PV}}{n V_t} \right) - 1 \right] - \frac{V_{PV} + R_S I_{PV}}{R_{sh}} \tag{1}$$

where I_{ph} is the photocurrent generated by the PV module, I_0 is the reverse saturation current of the diode, n is the diode ideality factor $(1 \leq n \leq 1.5)$, V_t is the thermal voltage, R_s is the series resistance, R_{sh} is the shunt resistance, V_{PV} is the photovoltaic panel voltage, and I_{PV} is the photovoltaic panel current. 2. Boost Converter Modeling : The boost converter, also known as a DC–DC boost converter, is used to increase the voltage produced by the photovoltaic array to a higher DC output voltage. It consists of an input capacitor, an inductor, a semiconductor switch, a diode, and an output capacitor [15]. The boost converter plays a crucial role in photovoltaic energy conversion systems by regulating the operating voltage of the PV generator and ensuring efficient power transfer to the load or the energy storage system. The switching operation is controlled by a Pulse Width Modulation (PWM) signal generated by the MPPT controller, which adjusts the duty cycle to maximize power extraction from the photovoltaic array.

$$L_h \frac{dI_L}{dt} = V_{PV} - (1 - \alpha) V_{ch} \tag{2}$$

$$C_2 \frac{dV_{ch}}{dt} = (1 - \alpha) I_L - I_{ch} \tag{3}$$

where L_h is the boost inductor, C_2 is the output capacitor, I_L is the inductor current, V_{PV} is the photovoltaic voltage, V_{ch} is the output voltage, I_{ch} is the load current, and α is the duty cycle. Under steady-state conditions, the voltage conversion ratio of the boost converter is given by:

$$V_{ch} = \frac{V_{PV}}{1 - \alpha} \tag{4}$$

where L_h is the boost converter inductance, I_L is the inductor current, V_{PV} is the photovoltaic generator voltage, α is the duty cycle, V_{ch} is the DC bus voltage, C_2 is the output capacitor, and I_{ch} is the load current. 3. Bidirectional Converter Modeling (Buck–Boost) : The bidirectional converter is responsible for energy exchange between the battery energy storage system and the DC bus [16]. It enables the storage of excess energy when photovoltaic generation exceeds the load

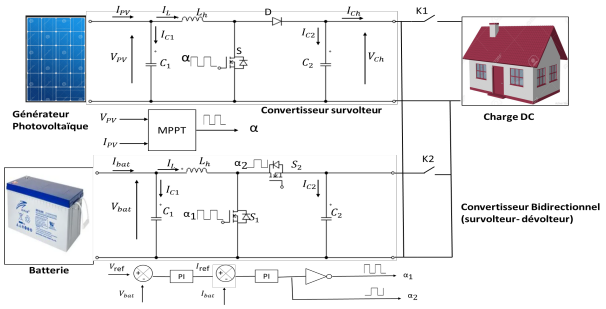

Fig. 1. Architecture of the Proposed ANN-Based PV-BESS System

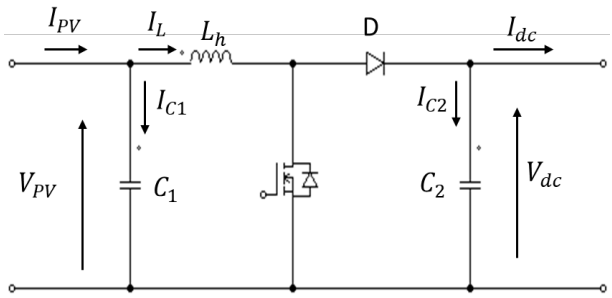

Fig. 2. Electrical Circuit of the Boost Converter

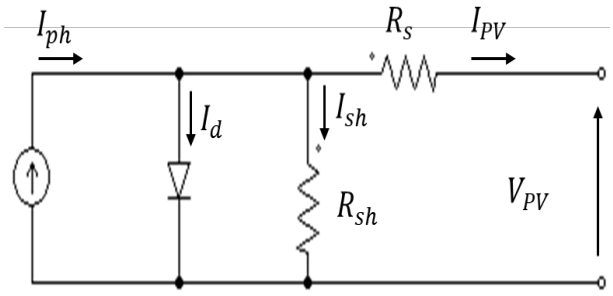

Fig. 3. Equivalent Circuit of a Photovoltaic Cell Using the Single-Diode Model

demand and supplies energy back to the DC bus when photovoltaic production is insufficient to meet the required demand [17]. The converter operates in two modes. In buck mode, the excess energy generated by the photovoltaic system is used to charge the battery. In boost mode, the battery discharges and provides energy to support the load or stabilize the DC bus voltage. This bidirectional power flow capability enhances the reliability, flexibility, and energy management performance of the PV-BESS system. The bidirectional converter is controlled according to the battery state of charge (SOC), the photovoltaic power generation, and the load demand to ensure efficient energy utilization and stable system operation. The dynamics of the bidirectional converter operating in battery mode are given by:

$$L_h \frac{dI_{Lb}}{dt} = \Delta V_{ch} - V_{bat} \tag{5}$$

$$C_1 \frac{dV_{bat}}{dt} = I_{Lb} - I_{bat} \tag{6}$$

where L_h is the inductor, C_1 is the battery-side capacitor, I_{Lb} is the inductor current, V_{bat} is the battery voltage, I_{bat} is the battery current, and ΔV_{ch} is the voltage difference on the DC bus.

$$V_{bat} = \alpha V_{ch} \tag{7}$$

where α is the duty cycle and V_{ch} is the DC bus voltage.

4. Battery Modeling : The battery is the energy storage element of the system. Its model must allow tracking of the state of charge (SOC) and representation of internal losses. A simple equivalent electrical model is adopted, consisting of a SOC-dependent voltage source in series with an internal resistance [18]. The battery state of charge (SOC) can be expressed as:

$$V_{bat} = E_b(SOC) - R_i I_{bat} \tag{8}$$

$$\frac{dSOC}{dt} = -\frac{I_{bat}}{C_{bat}} \tag{9}$$

$$SOC(t) = SOC(0) - \frac{1}{C_{bat}} \int I_{bat}(t)\, dt \tag{10}$$

where V_{bat} is the battery terminal voltage, $E_b(SOC)$ is the open-circuit voltage as a function of the state of charge, R_i is the internal battery resistance, I_{bat} is the battery current, SOC is the state of charge, C_{bat} is the nominal battery capacity, and $SOC(0)$ is the initial state of charge.

5. Proportional-Integral (PI) Control : The stability of the DC bus is ensured by a dual-loop control structure consisting of an outer voltage loop and an inner current loop. Proportional-Integral (PI) controllers are used to maintain the DC bus voltage at its reference value despite variations in power generation and load demand [19].

$$e_v(t) = V_{dc}^{ref} - V_{dc}(t) \tag{11}$$

$$I_{ref}(t) = K_{pv} e_v(t) + K_{iv} \int e_v(t)\, dt \tag{12}$$

$$e_i(t) = I_{ref}(t) - I_L(t) \tag{13}$$

$$\alpha(t) = K_{pi} e_i(t) + K_{ii} \int e_i(t)\, dt \tag{14}$$

where $e_v(t)$ is the DC-link voltage error, V_{dc}^{ref} is the reference DC-link voltage, $V_{dc}(t)$ is the measured DC-link voltage, $I_{ref}(t)$ is the reference current generated by the outer voltage loop, K_{pv} and K_{iv} are the proportional and integral gains of the voltage PI controller, $e_i(t)$ is the current error, $I_L(t)$ is the measured inductor current, $\alpha(t)$ is the duty-cycle control signal, and K_{pi} and K_{ii} are the proportional and integral gains of the current PI controller. 6. Energy Management of the MRER : The energy management of the microgrid is based on a decision-making logic that relies on the comparison between generated power, consumed power, and the battery state of charge (SOC). When the photovoltaic power generation exceeds the load demand, the surplus energy is used to charge the battery, provided that the SOC remains below its maximum limit. Conversely, when the PV generation is insufficient, the battery discharges to compensate for the power deficit, as long as its SOC remains above a minimum threshold. This strategy ensures energy balance, protects the battery against overcharging and deep discharging, and guarantees supply continuity.

- K_1: typically controls the connection of the photovoltaic generator to the DC bus.
- K_2: controls the battery interaction mode (charging or discharging).

Table I presents the switching logic of the energy management strategy based on the battery state of charge and PV availability. 6. Artificial Neural Network (ANN)-Based MPPT Control : Artificial Neural Networks (ANNs) are an artificial intelligence technique inspired by the functioning of the human brain. They consist of input layers, hidden layers, and an output layer, interconnected through adjustable weights that allow the system to learn from data. For the implementation of the MPPT control in the PV–BESS system, an ANN-based model has been developed [21]. The implemented program relies on simulated photovoltaic voltage and current data, enabling the calculation of PV power and the associated optimal duty cycle. This duty cycle is then smoothed to ensure better control stability. The photovoltaic power is given by:

TABLE I
ENERGY MANAGEMENT SWITCHING LOGIC

Source	Battery Charge/Discharge	Battery Full
PV	$K_1 = 1$	$K_1 = 1$
Battery	$K_2 = 1$	$K_2 = 0$

$$P_{PV} = V_{PV} I_{PV} \tag{15}$$

The selected neural network is a multilayer feedforward network composed of two hidden layers (15 and 10 neurons) and one output layer. The activation functions used are *tansig* in the hidden layers to capture system nonlinearities, and *purelin* in the output layer, which is suitable for continuous outputs such as the duty cycle. The training of the network is based on minimizing the Mean Squared Error (MSE), which measures the difference between predicted and target values:

$$MSE = \frac{1}{N} \sum (y_i - \hat{y}_i)^2 \tag{16}$$

where y_i is the target (actual) value and $\hat{y}_i$ is the predicted output of the model. Several training algorithms can be used, including gradient descent and the Levenberg–Marquardt algorithm. Gradient descent adjusts the network weights by following the slope of the cost function; although simple to implement, it suffers from slow convergence and may become trapped in local minima, limiting its effectiveness for highly nonlinear systems such as photovoltaic systems [23]. In contrast, the Levenberg–Marquardt algorithm combines the advantages of gradient descent and the Gauss–Newton method. By using the Jacobian matrix to estimate the curvature of the error function, it accelerates convergence and improves learning accuracy [24]. Thus, the Levenberg–Marquardt algorithm is chosen for this model due to its speed, stability, and ability to handle nonlinearities efficiently. It enables the neural network to accurately predict the optimal duty cycle and ensure reliable optimization of power generation. The weight update rule of the Levenberg–Marquardt algorithm is given by:

$$w_{k+1} = w_k - (J^T J + \mu I)^{-1} J^T e \tag{17}$$

where J is the Jacobian matrix, e is the error vector, and μ is the damping parameter. This equation updates the network weights iteratively to progressively reduce prediction error.

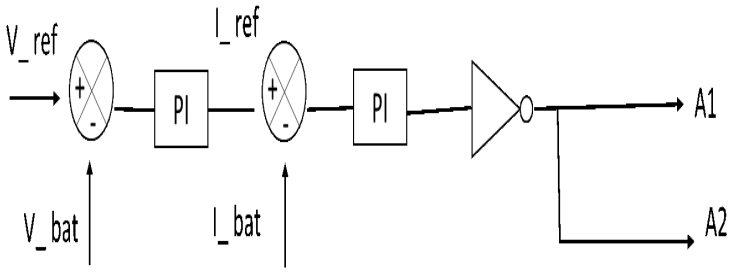

Fig. 4. Cascade Control for PI Regulation of the Bidirectional Converter

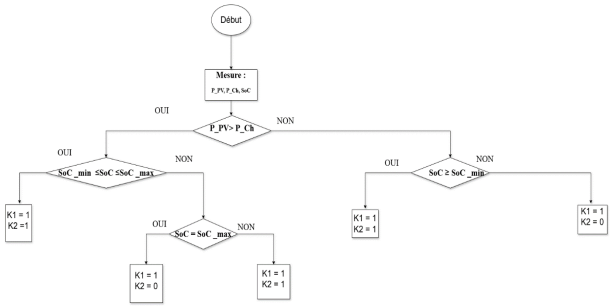

Fig. 5. Integrated Energy Management and Control Strategy

III. Results and discussion

A. Simulation

Solar Irradiation and Temperature Data (Bokhol Power Plant) : The solar irradiation and ambient temperature (Figures 9) data used in this study are obtained from the Bokhol solar power plant, located in the Saint-Louis region of Senegal. This photovoltaic installation, with a capacity of 15.7 MW and commissioned in 2018, produces approximately 25 GWh of electricity per year. It supplies nearly 160,000 people and helps avoid about 25,000 tons of CO_2 emissions annually. For the purposes of modeling and real-time optimization of the PV–BESS system, the collected data cover a period of three days. They include:

- The hourly variation of solar irradiation (W/m^2),
- The variation of ambient temperature (C),
- The representative power output under local climatic conditions (W).

Table II summarizes the electrical characteristics of the photovoltaic (PV) module used in this study.

Table III presents the inductance value of the boost converter used in the PV system.

Table IV lists the main parameters of the boost DC–DC converter used in the system.

TABLE II
Photovoltaic Module Characteristics

Parameter	Value
P_m	213.15 W
V_{mp}	29 V
I_{mp}	7.35 A

TABLE III
Boost Converter Inductance

Parameter	Value
Inductance L	1.5 mH
Input Capacitor C_e	330 μF
Output Capacitor C_s	470 μF
Duty Cycle α	0.5

TABLE IV
Boost Converter Parameters

Parameter	Value
Inductance L	2 mH
Input Capacitor C_e	470 μF
Output Capacitor C_s	860 μF
Duty Cycle α	0.5

Table V presents the electrical characteristics and operating limits of the battery used in the PV-BESS system. The main parameters of the photovoltaic module, DC–DC converters, and battery system are summarized in the following tables. These parameters are used for simulation and performance evaluation of the proposed ANN-based PV-BESS system.

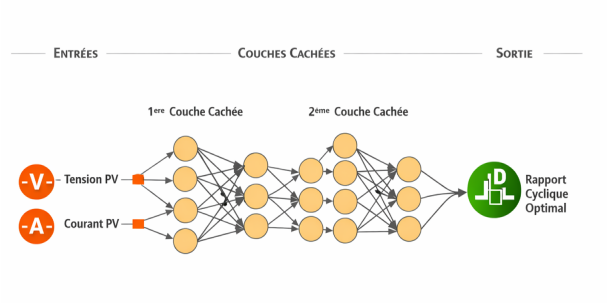

Fig. 6. Two-Hidden-Layer Neural Network Architecture for PV MPPT

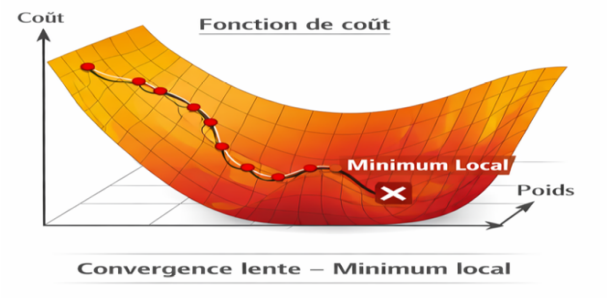

Fig. 7. Gradient Descent Optimization

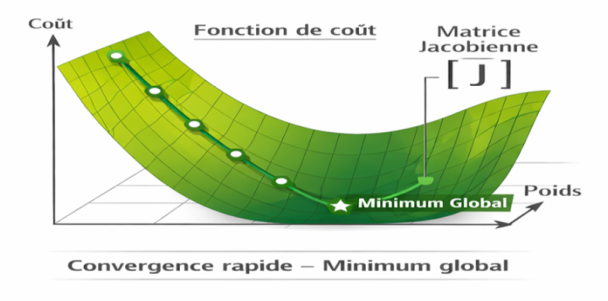

Fig. 8. LevenbergMarquardt Algorithm

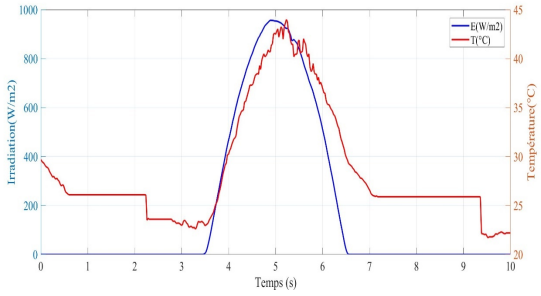

Fig. 9. Variation of solar irradiance E (W/m) and temperature T (C) versus time.

B. Results

The curves (Figures 11 and 12) compare the actual photovoltaic system power with the power predicted by the ANN-based MPPT model under two weather conditions: clear sky and cloudy sky. Under cloudy conditions (Figure 11), the actual power exhibits significant oscillations due to rapid variations in solar irradiance, whereas the ANN-predicted power remains smoother and more stable. This demonstrates the robustness of the ANN model, which is capable of filtering fluctuations and maintaining a consistent power output despite

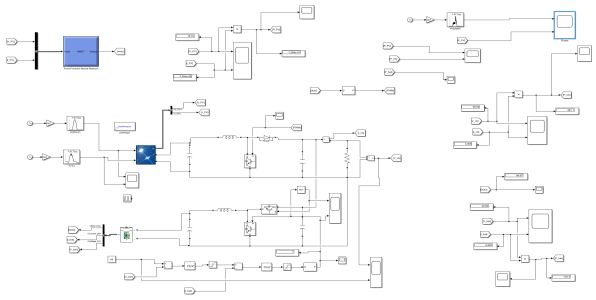

Fig. 10. Simulink model of the microgrid based renewable energy system (MRER)

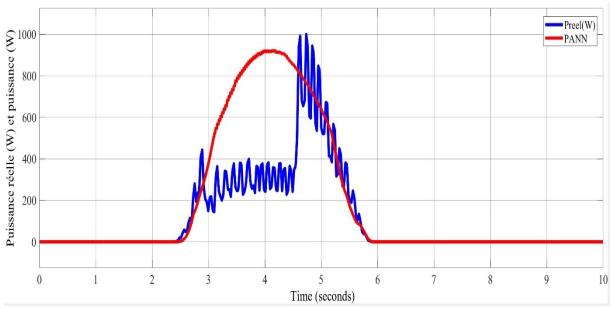

Fig. 11. Comparison between the actual power and the ANN-predicted power under cloudy sky conditions

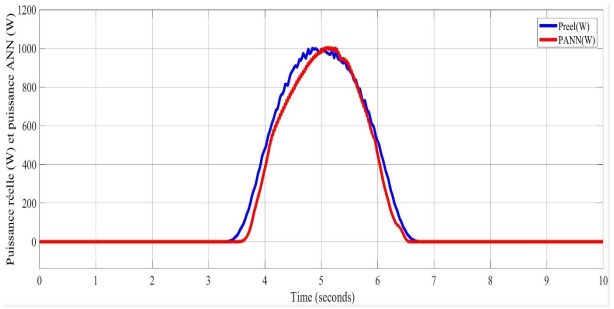

Fig. 12. Comparison between the actual power and the ANN-predicted power under clear sky conditions

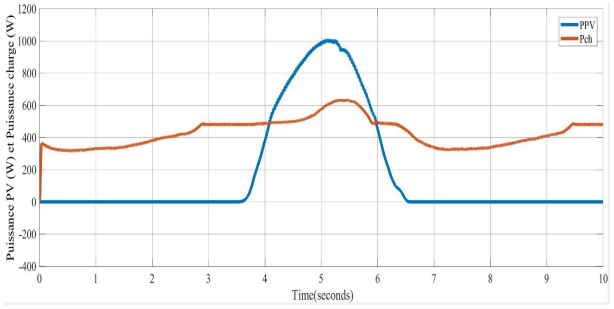

Fig. 13. Comparison between PV power and load power

climatic disturbances. Under favorable weather conditions (Figure 12), both curves are nearly superimposed, indicating that the model prediction closely matches the actual power. This reflects a high level of accuracy and excellent synchronization between the predicted and real values. Overall, the ANN-based MPPT model demonstrates strong adaptability. It ensures accurate tracking of the maximum power point under stable irradiance conditions and stabilizes the power output under rapidly changing weather conditions. This approach guarantees efficient optimization and improves the overall performance of the PV–BESS system under all climatic scenarios. The following curves illustrate the energy dynamics

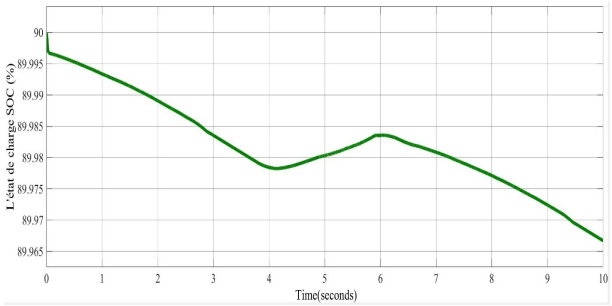

Fig. 14. Battery state of charge (SOC) as a function of time

TABLE V
BATTERY CHARACTERISTICS

Characteristic	Value
Model	BT-12M8.0AC
Nominal Voltage	12 V
Maximum Voltage	13.8 V
Minimum Voltage	10.5 V
Capacity	8 Ah
Energy	96 Wh
Internal Resistance	30 mΩ
SOC Limits	30% – 90%

of the building-integrated PV–BESS system. They highlight the alternation between periods where the photovoltaic power (P_{PV}) is higher or lower than the charging power (P_{ch}). In the PV–BESS system, the battery plays a crucial role in energy regulation by alternating between charging and discharging modes depending on the availability of solar irradiation(Figures 13 and 14). Before 3.5 s and after 6 s, photovoltaic production is low or nearly zero, forcing the battery to discharge in order to support the load and maintain power supply stability. This controlled discharge results in a slight decrease in the state of charge (SOC), confirming that the battery effectively compensates for the power deficit. In contrast, between 3.5 s and 6 s, solar irradiation is high and photovoltaic power reaches a peak close to 1000 W. During this period, the load is directly supplied by the PV source, and the excess energy allows the battery to partially recharge, which is reflected by a slight increase in SOC. Overall, the SOC variation remains limited, indicating a well-balanced energy management strategy between charging and discharging operations. This behavior demonstrates that the ANN-based MPPT system ensures optimal coordination between the PV source and the battery, guaranteeing stable load supply and efficient utilization of the storage system, even under fluctuating solar conditions.

C. Discussion

The obtained results confirm that the integration of Artificial Neural Networks (ANNs) into the energy management of PV–BESS systems represents a robust and high-performance solution. Under favorable conditions, the power predicted by the ANN closely matches the actual power, demonstrating high accuracy and excellent synchronization between predicted and measured values. In contrast, under cloudy conditions, the ANN effectively filters rapid fluctuations caused by variations in solar irradiation, providing a smoother and more stable power profile, which highlights its strong adaptability. Furthermore, the battery acts as an energy buffer by discharging when solar production is insufficient and partially recharging during surplus generation, ensuring continuous power supply and balanced SOC management. Finally, the Levenberg–Marquardt algorithm outperforms gradient descent due to its faster convergence and higher accuracy, which significantly enhances the overall performance of the neural network. Thus, the ANN-based MPPT model ensures robust optimization of maximum power point tracking, improved energy stability, and higher efficiency of the PV–BESS system under all weather conditions.

IV. CONCLUSION AND FUTURE WORK

This study has shown that the integration of Artificial Neural Networks (ANNs) into the energy management of PV–BESS systems constitutes an efficient solution for real-time optimization. The developed model, based on a multilayer feedforward neural network trained using the Levenberg–Marquardt algorithm, achieved remarkable accuracy and fast convergence. The results confirm that the ANN is capable of overcoming the limitations of conventional MPPT methods by reducing oscillations and improving response speed under varying climatic conditions. The proposed approach thus contributes to enhancing energy stability, optimizing self-consumption, and supporting the sustainable energy transition in Senegal. Beyond these results, several future research directions can be considered. Experimental validation on a laboratory test bench would be essential to confirm the model performance under real operating conditions. Extending the system to multi-source configurations by integrating other renewable energy sources such as wind or biomass would broaden its applicability. A multi-objective optimization framework considering battery lifetime, grid stability, and energy cost would enable a more comprehensive and sustainable energy management strategy. Finally, advanced deep learning approaches such as Long Short-Term Memory (LSTM) networks and reinforcement learning techniques could further improve energy forecasting and adaptive microgrid control.

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