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Article

Hybrid Artificial Bee Colony and incremental conductance—Algorithm for enhanced MPPT in photovoltaic systems

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Abstract: The growing global demand for electricity necessitates efficient renewable energy solutions, with photovoltaic (PV) systems emerging as a prominent candidate. This study presents a novel hybrid Maximum Power Point Tracking (MPPT) algorithm that integrates the Artificial Bee Colony (ABC) optimization method with the Incremental Conductance (IC) technique, ensuring 100% accurate identification of the Global Maximum Power Point (GMPP) under partial shading conditions. Unlike standalone MPPT methods, the proposed approach leverages the exploratory capabilities of ABC for global search while utilizing IC for fast and precise tracking, achieving a convergence time of 0.37 s and minimal power oscillations of 2.7%. Experimental validation demonstrates the algorithm's superior performance, attaining 100% efficiency, significantly outperforming standalone IC (74%) and ABC (99.5%) methods. The hybrid ABC-IC algorithm consistently tracks the GMPP, delivering 60 W under optimal irradiation (1000 W/m^2) and surpassing conventional techniques such as P&O, FA, and PSO in terms of convergence speed, robustness, and adaptability to dynamic shading conditions. This innovative integration of bio-inspired and deterministic MPPT strategies offers a highly efficient and reliable solution for maximizing PV energy harvesting in real-world environments.

Keywords: photovoltaic systems; maximum power point tracking; Artificial Bee Colony algorithm; incremental conductance; hybrid optimization techniques; hybrid MPPT algorithms

1. Introduction

The notable rise in global electricity consumption has driven extensive research and practical applications in energy generation, with a focus on reducing environmental impact and pollutant emissions. Renewable energy sources have emerged as a sustainable solution, with solar energy standing out due to its abundance and wide availability across the Earth's surface. Solar energy has proven to be particularly viable for electricity generation in distributed systems connected to the electricity distribution network [1].

The contribution of photovoltaic (PV) systems to energy generation continues to grow, supported by advancements in academic and industrial research. The design, dimensioning, and specification of PV system components are critical and often evaluated based on financial viability [2]. Economic analyses of PV systems are closely tied to projected energy generation, which is influenced by factors such as geographic location and panel technology. Performance models are commonly employed to estimate power generation, accounting for key components such as panels, power electronics converters (DC-DC, inverters, charge controllers, and protection systems).

Maximum Power Point Tracking (MPPT) is a critical component in photovoltaic (PV) systems, ensuring optimal energy extraction under varying environmental conditions such as solar irradiance and temperature. Perturbative strategies, such as the Incremental Conductance (IC) method and the Perturb and Observe (P&O) method, are widely used for MPPT due to their simplicity and effectiveness. However, these methods face several limitations that hinder their performance:

- Step size dependency: The increment step size in perturbative methods presents a trade-off between response time and power oscillations. Small step sizes result in slow convergence, while large step sizes cause oscillations around the Maximum Power Point (MPP), reducing system efficiency [3–7].
- Oscillations: Both transient and steady-state operations are plagued by oscillations around the MPP, leading to energy losses.
- Partial shading challenges: Under partial shading conditions (PSC), PV panels exhibit multiple power peaks due to the integration of bypass diodes. These include several Local Maximum Power Points (LMPPs) and a single Global Maximum Power Point (GMPP). Conventional methods like P&O and IC often fail to distinguish between LMPPs and GMPPs, resulting in suboptimal energy extraction [8–10].

To address these limitations, optimization methods for GMPP tracking have been developed, broadly categorized into Soft Computing (SC) methods and Segmental Search methods. SC methods, particularly bio-inspired metaheuristics, have gained prominence due to their flexibility and ability to handle complex, non-linear optimization problems under partial shading conditions [11,12]. These methods are computationally intensive but offer superior performance in tracking the GMPP compared to conventional techniques.

Conventional MPPT techniques are further constrained by their step-size dependency, which impacts tracking efficiency and dynamic response. As a result, various advanced algorithms have been proposed to enhance MPP tracking and mitigate power losses caused by shading. An effective MPPT technique should meet the following criteria:

- Stability: The system must provide a reliable response to accurately detect energy changes and avoid instability caused by incorrect parameter settings.
- Fast dynamic response: MPPT algorithms should adapt quickly to changes in irradiance and temperature to minimize energy losses during rapid environmental fluctuations.
- Small steady-state error: Once the MPP is reached, the system should maintain operation at this point with minimal error to optimize energy conversion efficiency.
- Disturbance robustness: The control system must handle disturbances such as input noise, measurement errors, or parameter variations without compromising stability.
- Efficiency across power ranges: MPPT techniques should perform effectively under varying irradiance and temperature conditions to ensure optimal energy generation throughout the day [13–27].

MPPT techniques can be classified into four main categories [13–35]:

1) Model-based techniques: These rely on mathematical models or databases of panel characteristics under varying conditions. While useful, they may not fully adapt to real-world environmental changes.
2) Heuristic techniques: These use online search algorithms to locate the MPP without requiring prior knowledge of panel characteristics.
3) Training-based techniques: These approaches utilize advanced digital processors or microcontrollers to implement algorithms, often incorporating artificial intelligence. Although fast and effective, they involve higher implementation costs.
4) Hybrid techniques: These combine elements of different MPPT techniques, blending heuristic methods with model-based approaches for enhanced performance.

Among heuristic methods, the Artificial Bee Colony (ABC) algorithm stands out as a bio-inspired technique that simulates the foraging behavior of bees. It effectively tracks the GMPP under partial shading conditions by leveraging the coordinated efforts of employed, onlooker, and scout bees. Employed bees explore known food sources, onlooker bees evaluate and select promising solutions based on shared information, and scout bees introduce randomness by searching for new potential solutions, preventing premature convergence to local optima. This dynamic exploration-exploitation balance makes the ABC algorithm highly efficient in navigating complex and multi-peaked power landscapes, ensuring reliable and accurate tracking of the GMPP in photovoltaic (PV) systems. Additionally, its ability to adapt to changing environmental conditions enhances its robustness, making it a powerful tool for optimizing energy extraction in real-world solar power applications [16–20]. Other bio-inspired algorithms, such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Grey Wolf Optimizer (GWO), have also demonstrated significant potential in improving MPPT performance under complex conditions [21–23].

Machine Learning (ML) in MPPT: Recent advancements in machine learning have introduced a paradigm shift in MPPT techniques. ML-based approaches, such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Reinforcement Learning (RL), have shown remarkable potential in addressing the limitations of traditional methods. These techniques leverage historical and real-time data to predict the MPP with high accuracy, even under partial shading and rapidly changing environmental conditions. For instance, ANN-based MPPT systems can learn the non-linear characteristics of PV panels and adapt to dynamic conditions without requiring explicit mathematical models. Similarly, RL-based methods optimize the MPPT process by continuously learning from the system's performance, enabling robust and adaptive control. The integration of ML in MPPT not only improves tracking efficiency but also reduces oscillations and steady-state errors, making it a promising solution for modern PV systems [24–31].

Recent advancements in MPPT algorithms have focused on hybrid approaches that combine the strengths of multiple techniques. For example, hybrid algorithms like PSO-GWO, PSO-GA and GA-FLC integrate the global search capabilities of metaheuristics with the adaptability of fuzzy logic control, offering improved performance under partial shading and dynamic environmental conditions [33–35].

Additionally, emerging algorithms such as Harris Hawks Optimization (HHO) and Equilibrium Optimizer (EO) have shown promise in addressing the limitations of traditional methods, particularly in terms of computational efficiency and robustness [36–39].

This study presents a novel hybrid Maximum Power Point Tracking (MPPT) algorithm, MPPT-ABC-IC, which combines the Artificial Bee Colony (ABC) optimization technique with the Incremental Conductance (IC) method to overcome the limitations of conventional MPPT approaches, particularly under partial shading conditions (PSC). By leveraging the global search capabilities of ABC to locate the Global Maximum Power Point (GMPP) and the precision of IC for dynamic tracking, the proposed algorithm ensures 100% efficiency in GMPP tracking, even in complex shading scenarios. The study evaluates the MPPT-ABC-IC algorithm within a PV system comprising a DC-DC boost converter and a single-phase DC-AC full-bridge inverter, enabling a comprehensive performance assessment across different system stages. The boost converter optimizes PV voltage, while the inverter supports grid integration, ensuring practical applicability. Comparative analysis against traditional MPPT-IC and standalone MPPT-ABC methods highlights the superior efficiency and adaptability of the proposed approach. This research provides a significant advancement in MPPT technology, offering a robust solution for maximizing energy harvesting in real-world PV systems under varying environmental conditions.

2. Operation of photovoltaic systems

The equivalent circuit of a photovoltaic (PV) cell is depicted in **Figure 1**, illustrating the passive elements comprising a PV panel cell, along with their respective voltages and currents. The photocurrent of the PV panel is denoted as I_{ph}, with an anti-parallel diode D_1, series resistance R_s, and parallel resistance R_p. The current and voltage at the PV panel terminals are represented by I_{pv} and V_{po}, respectively [34].

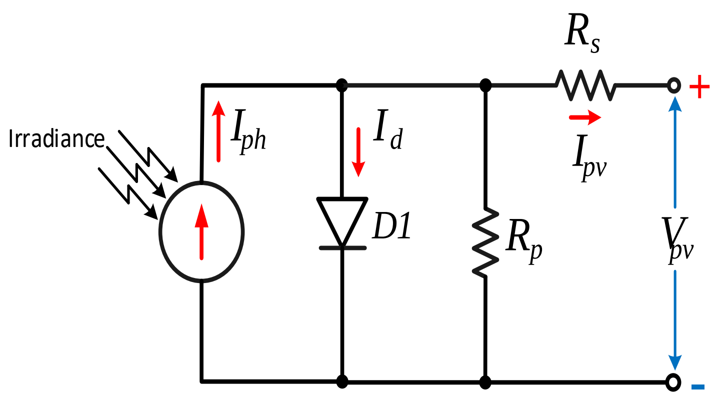


Figure 1. Equivalent circuit of a photovoltaic cell.

The current of the PV panel is expressed in Equation (1), where the panel current accounts for the contributions of all the cells, excluding losses due to shading. These losses are influenced by irradiance variations and are described by Equation (2) and conductivity losses, as indicated in the second term of Equation (1) [40].

$$I_{pv} = n_p I_{pv} - n_p I_o \left\{ exp\left(\frac{n_p V_{pv} + n_s I_{pv} R_s}{n_p I_{pv} \, A V_t} \right) \right\} - \frac{V_{pv} \frac{n_s}{n_p} I_{pv} R_s}{R_p \frac{n_s}{n_p}} \tag{1}$$

where

- n_p and n_s: Number of cells connected in parallel and series;
- I_{ph}: Photocurrent;
- I_o: Diode saturation current;
- V_{pv} and I_{pv}: Voltage and current at the photovoltaic panel terminals;
- V_t: Diode terminal voltage;
- R_p and R_s: Parallel and series resistors of the PV panel;
- A: Diode Quality Factor.

Equation (1) quantifies the contributions of each current component to I_{pv}. The first term represents the contribution of the chain, considering the cell association. The second term accounts for current loss through the anti-parallel diode, and the final term captures current dissipation in the parallel resistor R_p. The behavior of I_{ph} is given in Equation (2) [41,42].

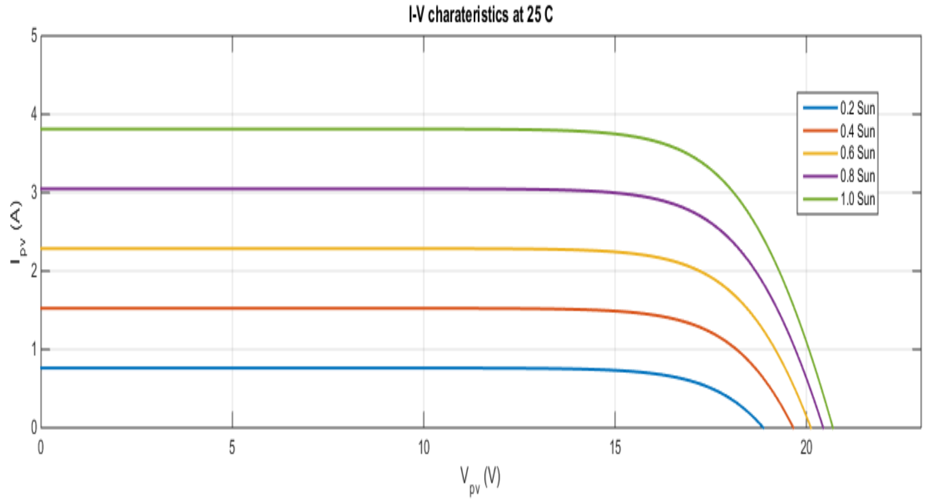
$$I_{ph} = I_{SC_{STC}} \left\{ \left(\frac{R_s + R_p}{R_p} \right) + K_i \Delta T \right\} \frac{G}{G_{STC}} \tag{2}$$

where:

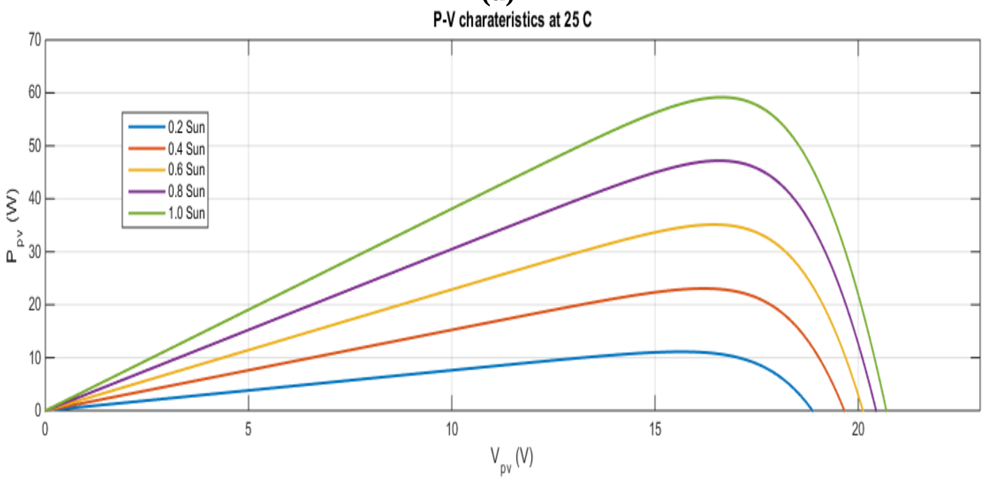
- I_{SCSTC}: PV panel short-circuit current under STC (Standard Test Conditions, 1000 W/m^2 and 25 °C);
- K_i: Short circuit temperature coefficient;
- ΔT: Variation of ambient temperature 2 °C;
- G and G_{STC}: Value of local irradiance and control irradiance (1000 W/m^2), respectively.

From Equation (2), it is evident that I_{ph} is directly proportional to the irradiance incident on the PV cells. An increase in I_{pu} is directly linked to an increase in irradiance, offset by losses in the diode and conductance [43].

Figure 2 illustrates the I-V and P-V characteristic curves of a PV solar module under varying irradiance levels. In **Figure 2**, the short-circuit current I_{sc} is shown to be proportional to irradiance, where a 90% reduction in irradiance (from 1000 W/m^2 to 100 W/m^2) results in a corresponding 90% reduction in I_{sc} [44].



(a)



(b)

Figure 2. (a) I-V curves for different irradiance values; **(b)** P-V curves for different irradiance values.

Figure 3 highlights the P-V curve, showing a unique Maximum Power Point (MPP) where the product of voltage and current is maximized. At this point, the slope of the tangent to the curve equals zero. The MPP is further defined by PMPP, IMPP. VMPP, where IMPP and VMPP represent the current and voltage at the MPP, respectively [45].

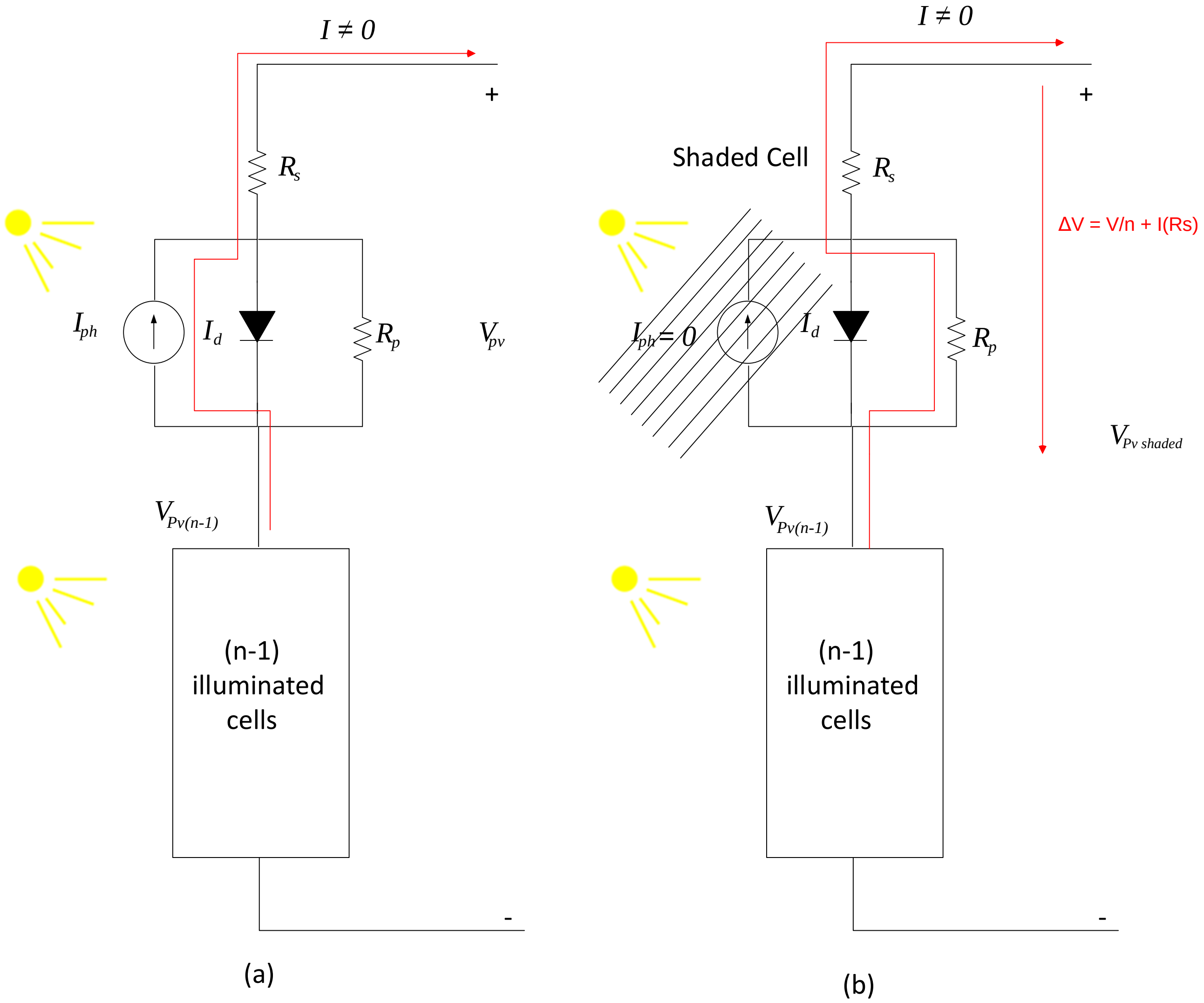


Figure 3. Module with n cells, the first upper one **(a)** illuminated or **(b)** shaded.

3. Partial shading condition—PSC

Partial shading conditions (PSC) can arise in photovoltaic (PV) systems due to various factors such as neighboring buildings, vegetation, or cloud cover. These conditions can significantly impact the power output of PV panels. Without appropriate mitigation measures, even a single shaded cell can reduce the output power of the entire module by as much as 50% [46,47].

To explain the behavior of a photovoltaic module in partial shading, a module composed of n cells connected in series is considered, where I is the current generated by the module and V is the voltage between the terminals. The first cell is highlighted with the representation by the 5-parameter circuit model, and the other $(n-1)$ cells represent a module with current I and output voltage V_{n-1}.

In **Figure 3a**, the module is fully illuminated, allowing current I to flow through all cells. Conversely, in **Figure 3b**, the first cell is shaded, producing no current (I_{sc} = 0 A). The shaded cell forces current through the parallel resistor R_p, causing a voltage drop while maintaining the reverse bias of the anti-parallel diode. Consequently, the shaded cell acts as a load for the remaining cells, potentially creating hotspots due to energy dissipation in R_s and R_p. These hotspots can cause permanent damage to the module [48].

To mitigate the effects of partial shading, bypass diodes are introduced in parallel with Rp. As depicted in **Figure 4**, these diodes remain reverse-biased under illumination, preventing conduction. However, during shading, the bypass diode becomes forward-biased, allowing current to bypass the shaded cell. The voltage drop perceived by the system is limited to the diode's forward voltage, typically ranging from 0.6 V to 0.7 V. Although bypass diodes are usually installed for groups of cells or panels, not individually, their inclusion modifies the characteristic curves of the PV array, resulting in local and global maximum points on the P-V curve [49–51].

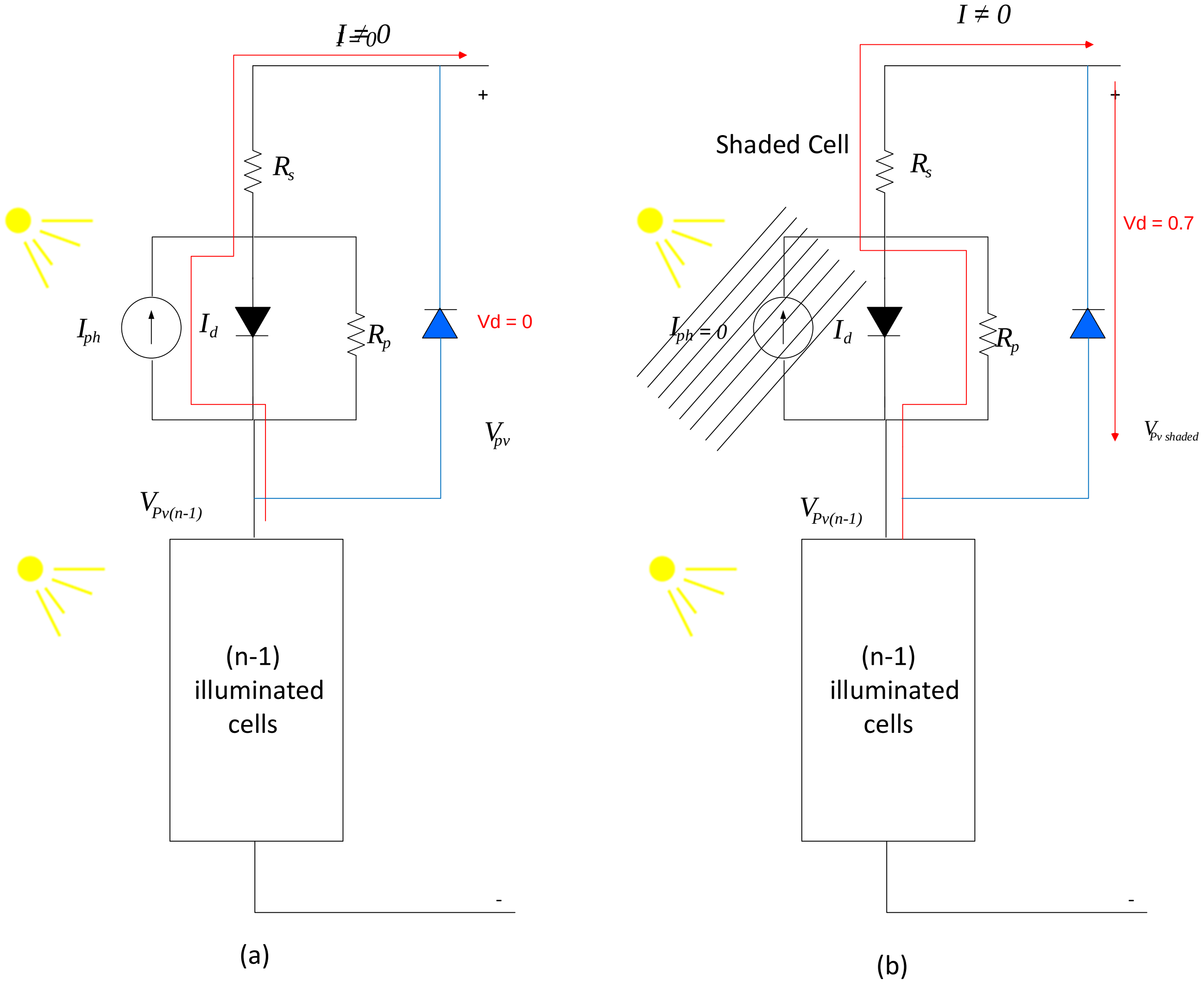


Figure 4. Inclusion of the bypass, the first upper one **(a)** illuminated or **(b)** shaded.

MPPT algorithms are categorized based on environmental conditions: those designed for uniform conditions and those for non-uniform conditions. Under stable and uniform conditions, the PV system exhibits a characteristic P-V curve with a single maximum point, as shown in **Figure 4a** [52]. However, real-world conditions often involve partial shading, uneven panel orientations, and other factors, resulting in non-linear behavior. This is reflected in the presence of multiple maximum points on the I-V and P-V curves, as illustrated in **Figure 4b**. Identifying the correct operating point, especially the global maximum, becomes challenging in such scenarios [53,54].

Under partial shading, the point of maximum power is classified as the Global Maximum Power Point (GMPP), while all other peaks are considered Local Maximum Power Points (LMPPs). **Figure 5** demonstrates these characteristics, highlighting the increased complexity in identifying the GMPP for optimal system performance.

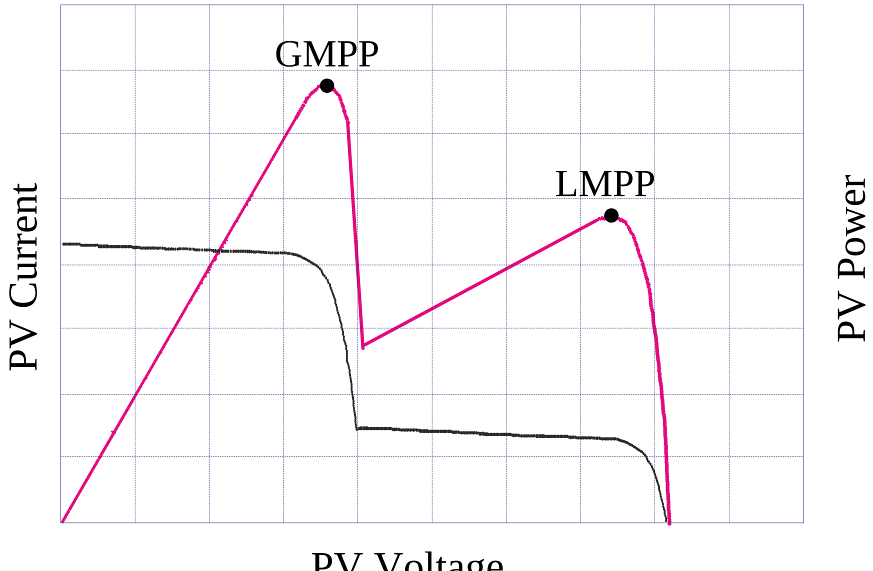


Figure 5. PV V-I and V-P characteristics under partial shading.

4. MPPT using ABC and ABC-IC

Despite advances in MPPT algorithms for identifying global maxima, there are still gaps that need further study, such as, for example, their inability to identify the GMPP in 100% of cases. In this sense, the present work proposes the combined use of GMPPT algorithms, such as ABC, and MPPT, such as the Incremental Conductance algorithm (IC), with the aim of ensuring the identification of the GMPP in 100% of cases [55–59].

4.1. The Artificial Bee Colony (ABC)

The Artificial Bee Colony Optimization Algorithm (ABC) is an algorithm designed by Karaboga based on the intelligent foraging behavior of bee colonies. ABC is a collective intelligence optimization algorithm inspired by the process of finding food for bees. The colony of bees is divided into three categories: Employed bees, onlookers, and scouts. According to the role of the bees, the place where the most food (nectar) exists (food source), that is, the global optimum is searched. Half of the colony consists of hired bees and the other half is made up of watch bees, and each food source can only have one hired bee. The simplified optimization process of ABC is as follows [60].

Step 1: Create solution vectors x_i considering the number of food sources (N) and the number of variables (D). Initial solution vectors are generated by Equation (3).

$$x_{ij} = x_{j,min} + \text{rand}[0,1]\left(x_{j,max} - x_{j,min}\right) \tag{3}$$

At this time, x_{ij} is the location of the initial food source, $i \in \{1,2,\cdots,N\}$, $j \in \{1,2,\cdots,D\}$, $\text{rand}[a,b]$ is a random number between a and b, $x_{j,\max}$ and $x_{j,min}$ are the maximum and minimum values of each variable.

Step 2: Evaluate the suitability (f_i) of each food item using Equation (4).

$$f_i = \begin{Bmatrix} 1/(1 + f(x_i)) \text{ if } f(x_i) \geq 0 \\ 1 + [f(x_i)] \text{ if } f(x_i) < 0 \end{Bmatrix} \tag{4}$$

Here, $f(x_i)$ is the value of the objective function for each food source x_i.

Step 3: Based on Equation (5), search for a new location for food sources and move the wages.

$$v_{ij} = x_{ij} + \text{rand}[-1,1]_{ij}\left(s_{ij} - x_{kj}\right) \tag{5}$$

where v_{ij} is the location of the new food source, $j \in \{1,2,\cdots,D\}$, $k \in \{1,2,\cdots,N\}$.

If the newly created vector v_i has a better value of f_i than the existing candidate solution x_i, v_i is replaced with the candidate solution instead of x_i.

Step 4: Observer bees select each food source based on the roulette wheel method, and the probability value depends on f_i as shown in Equation (6).

$$p_i = fi\frac{1}{\sum_{i=1}^{N} f_i}$$

$$v_{ij} = x_{ij} + \text{rand}[-1,1]_{ij}\left(s_{ij} - x_{kj}\right)v \text{ for rand } [0,1] < p_i \tag{6}$$

here, p_i is the probability value of the i-th food source. When the observer selects the i-th food by Equation (6), the new food location is searched again based on the location of the food.

Step 5: f_i remembers the best food source to be exhausted.

Step 6: When the value of the objective function does not improve as much as the limit of the number of iterations (cycle) for a certain food source, the hired bee in the food source is changed to a scout bee to search for a new food source, and this process the expression for is the same as Equation (7).

$$x_{ij} = x_{j,min} + \text{rand}[0,1]\left(x_{j,max} - x_{j,min}\right) \tag{7}$$

Step 7: Return to step 3 and repeat the optimization process until the convergence condition is satisfied.

Figure 6 shows the ABC MPPT algorithm.

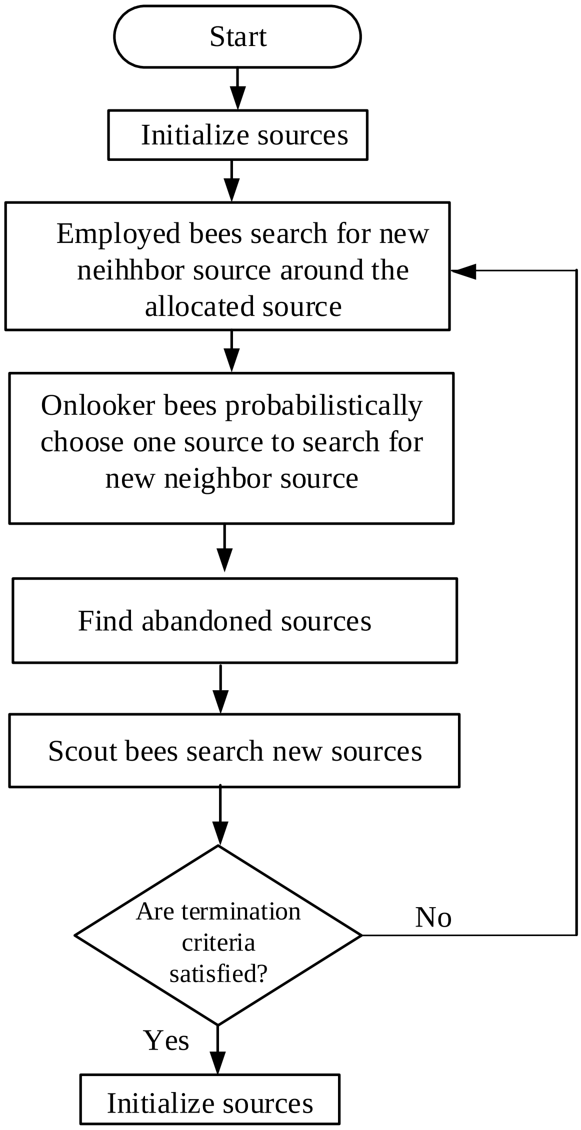


Figure 6. Flowchart of the ABC technique.

4.2. Proposed hybrid ABC-IC algorithm

The ABC-IC hybrid algorithm integrates the Artificial Bee Colony (ABC) algorithm with the Incremental Conductance (IC) method to achieve an efficient and adaptive Maximum Power Point Tracking (MPPT) strategy. The ABC algorithm is responsible for identifying the Global Maximum Power Point (GMPP) by exploring multiple peaks in the P-V curve, particularly under partial shading conditions (PSC). Once the GMPP is located, the IC algorithm takes over to maintain operation at the optimal point by making fine adjustments in response to dynamic changes in irradiance and load. This transition occurs both at the beginning of the operation and whenever a significant change in shading conditions is detected. The combination of these algorithms does not significantly increase computational complexity, as ABC is only activated when searching for the GMPP, while IC continuously ensures local tracking with minimal computational overhead. This balance allows for an efficient trade-off between performance and complexity, ensuring robust MPPT performance without excessive computational burden.

4.3. Power structure connected to the electric grid

Figure 7 shows the complete scheme of the single-phase grid-connected PV system adopted in this work. The 60 W_p PV panel is connected by the boost converter, which is connected to the grid by a single-phase full-wave DC-AC inverter. The PV system was implemented in simulation software. The implemented experimental set is based on the digital signal processor (DSP), where all the MPPT, PLL, grid-side control, and all controllers are embedded [61,62].

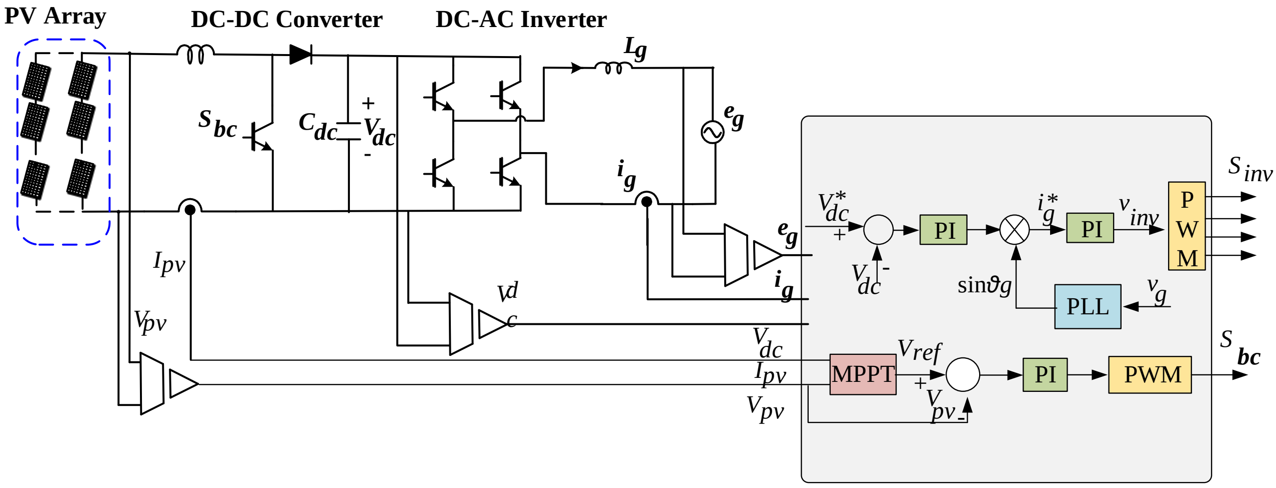


Figure 7. Complete scheme of the distributed generation system connected to the single-phase power grid.

In **Figure 7**, the general PV system is composed of a photovoltaic arrangement in series with a static boost converter formed by an IGBT switch, an inductor L, a diode and an associated capacitor. Connected to the IGBT transistor gate is the MPPT strategy controller, which has voltage and current V_{pv} and I_{pv} as input data, respectively, and the duty cycle of the converter as output. and given by a digital signal resulting from PWM modulation (Pulse Width Modulation), dictating the switching interval of the converter. Therefore, the time intervals during which the changeover switch remains open and closed will dictate the transformation ratio between the input voltage and the output voltage and, consequently, the output power of the PV system. With the converter duly characterized and operating according to the desired design data, it is necessary to analyze which meta-heuristic allows the converter to operate in GMPPT for different shading conditions.

5. Results and discussion

This section evaluates the effectiveness and performance of the PV system shown in **Figure 7** under static and dynamic conditions. The experimental verification subjected the PV modules to three levels of solar irradiation, simulating partial shading conditions:

- Profile 1: The PV modules were exposed to 550 W/m^2 of solar irradiation.
- Profile 2: From 2 to 7 s, the upper part of the PV modules received 750 W/m^2 of solar irradiation.
- Profile 3: From 7 to 10 s, the irradiation on the upper part of the PV modules increased to 1000 W/m^2.

The experimental results show that the maximum power level was achieved in Profile 3, where the Global Maximum Power Point (GMPP) was located at 60 W. Under Profile 1 and Profile 2, the maximum power was limited to 36 W. Notably, the Local Maximum Power Point (LMPP) remained constant at approximately 23 W across all profiles, as the solar irradiation on the lower PV modules remained unchanged.

Figure 8 demonstrates that the MPPT-IC algorithm was constrained to the LMPP in all three shading profiles. This highlights the algorithm's limited ability to adapt under partial shading conditions, resulting in suboptimal performance.

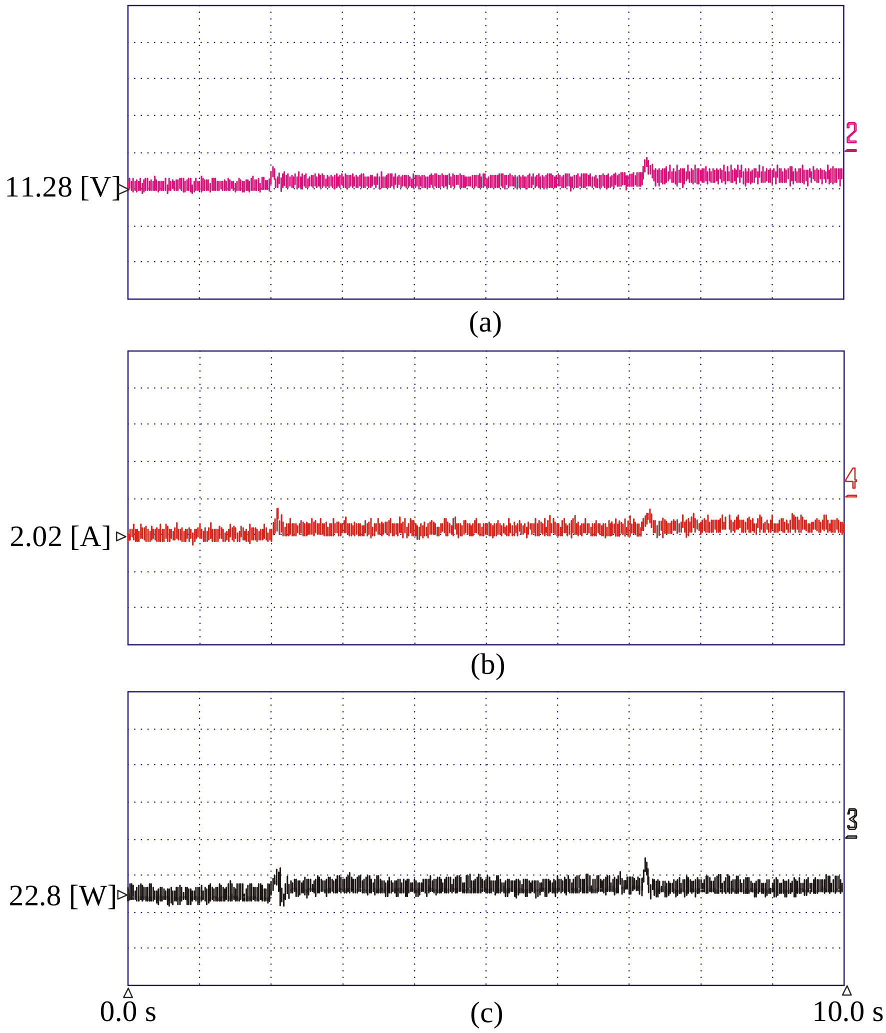


Figure 8. Simulation results under conditions of partial shading for the IC algorithm. **(a)** MPP Voltage Variations at Different Irradiation Levels; **(b)** MPP Current Variations at Different Irradiation Levels; **(c)** MPP Power Variations at Different Irradiation Levels.

By contrast, the proposed MPPT-ABC algorithm exhibited robust performance in tracking the GMPP. **Figure 9** shows that the ABC algorithm maintained the reference duty ratio effectively, even with GMPP variations. This stability negated the need for the algorithm to restart random searches, ensuring the GMPP was accurately tracked throughout Profile 1.

Figure 10 provides further evidence of the superior performance of the MPPT-ABC-IC algorithm. It adapted effectively to gradual changes in solar irradiation, achieving efficiency levels above 99% across all partial shading profiles. This highlights its suitability for real-world conditions requiring dynamic adaptability and robust power tracking.

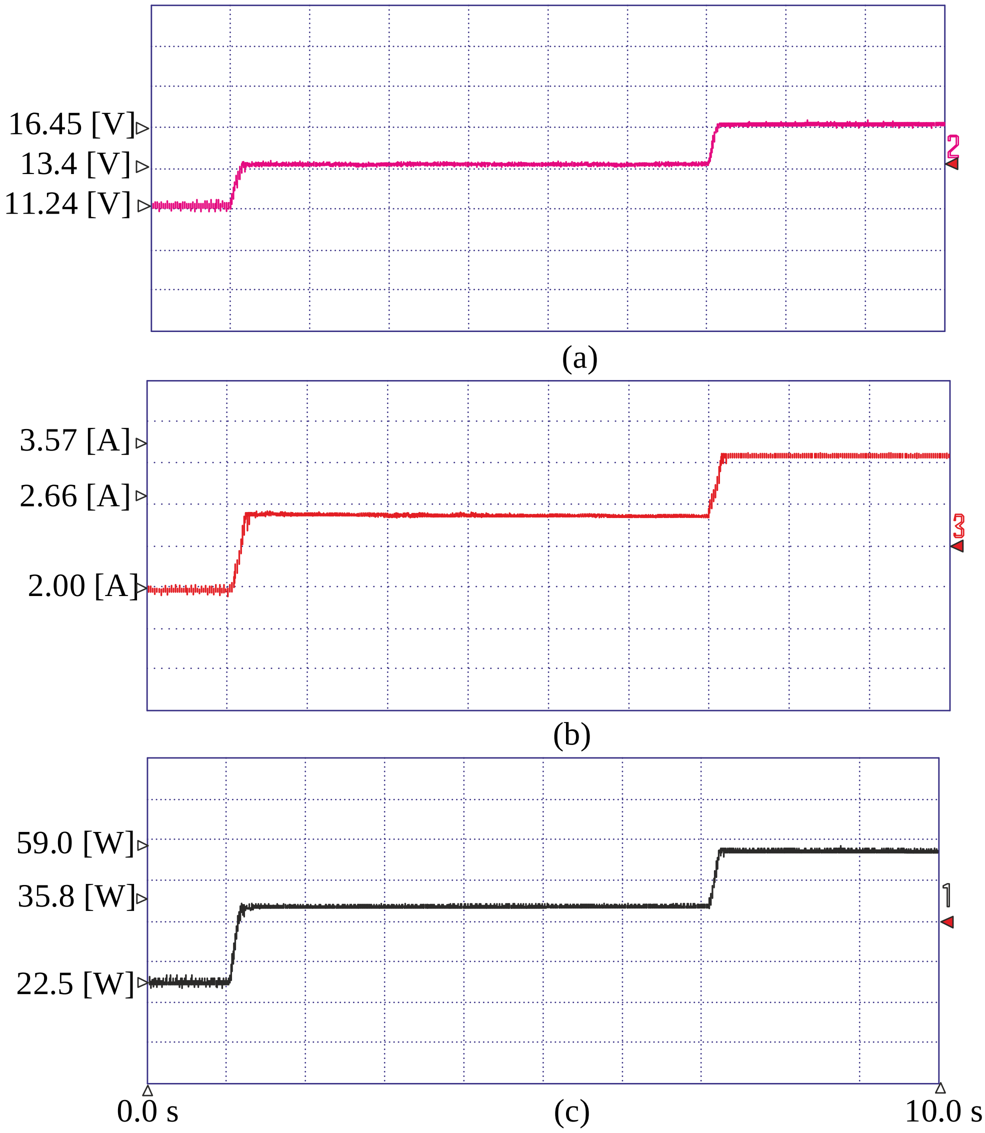


Figure 9. Simulation results under conditions of partial shading for ABC algorithm. **(a)** MPP Voltage Variations at Different Irradiation Levels; **(b)** MPP Current Variations at Different Irradiation Levels; **(c)** MPP Power Variations at Different Irradiation Levels.

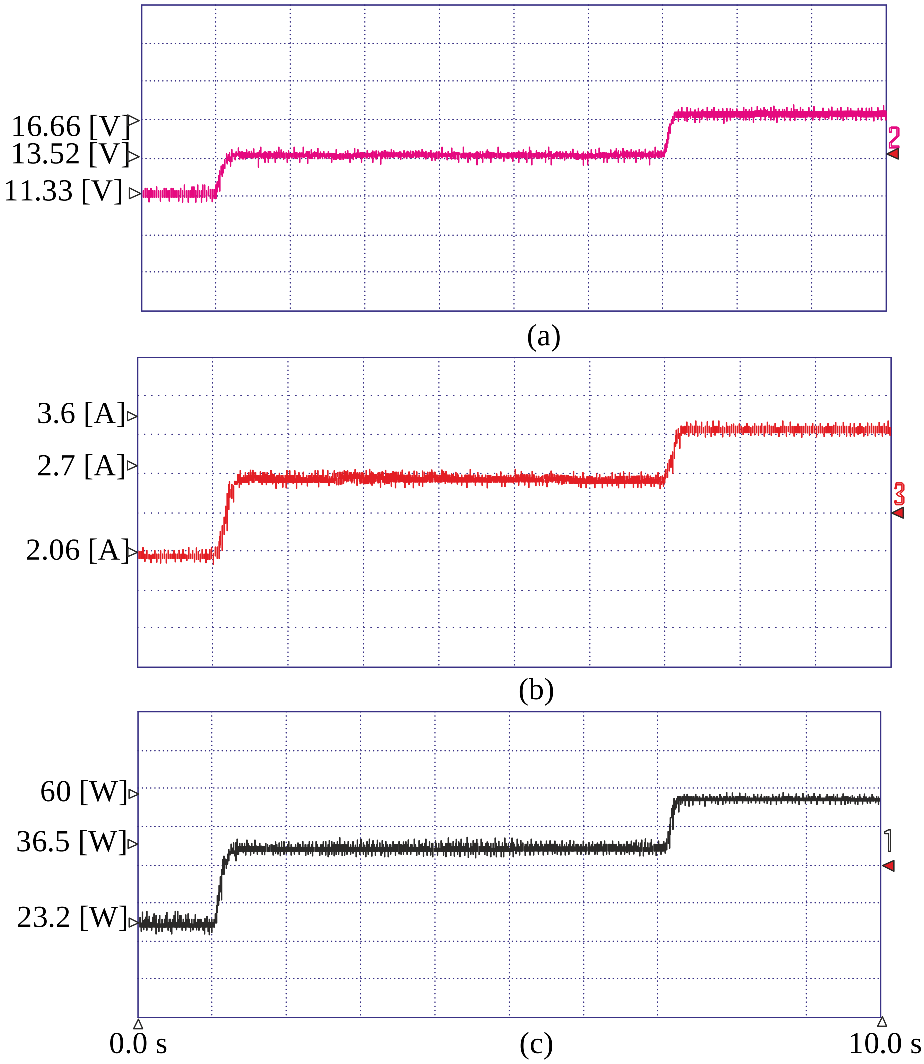


Figure 10. Experimental results under conditions of partial shading for ABC-IC algorithm. **(a)** MPP Voltage Variations at Different Irradiation Levels; **(b)** MPP Current Variations at Different Irradiation Levels; **(c)** MPP Power Variations at Different Irradiation Levels.

Table 1 summarizes the performance of the MPPT-ABC-IC, MPPT-ABC, and MPPT-IC methods in terms of convergence time, power oscillations, extracted power, and efficiency. The proposed MPPT-ABC-IC algorithm achieved a convergence time of 0.37 s, minimal power oscillations of 2.7%, and a perfect efficiency of 100%, outperforming MPPT-ABC and MPPT-IC in all metrics.

Table 1. Summary of ABC-IC, ABC and IC performance comparison.

MPPT Method	**ABC-IC**	**ABC**	**IC**
Convergence time (s)	0.37	0. 5	0.9
Power oscillations (%)	2.7	1.4	8.7
Extracted MPP in [W]	48	47.9	47.8
Efficiency (%)	100%	99.5%	74%

Table 2 highlights the comparison between the proposed ABC-IC method and other state-of-the-art MPPT algorithms under different conditions, including uniform irradiance, partial shading, convergence speed, complexity, and efficiency. The proposed method demonstrates excellent performance across all metrics, achieving perfect efficiency of 100%, fast convergence, and robustness under partial shading.

The results validate the effectiveness of the proposed MPPT-ABC-IC algorithm. Its ability to consistently identify and track the GMPP under partial shading conditions demonstrates superior static and dynamic performance. Furthermore, the comparative analysis in **Tables 1** and **2** reinforces the method's competitiveness, offering high efficiency and reliability for real-world PV systems.

Table 2. Comparison of the proposed ABC-IC method with state-of-the-art MPPT algorithms under varying conditions.

MPPT Method	Uniform Irradiance	Partial Shading	Convergence Speed	Complexity	Efficiency
OFA [61]	Excellent	Excellent	Excellent	High	100%
FA [61]	Good	Moderate	Moderate	Moderate	99.8%
P&O [12]	Good	Poor	Slow	Low	97.55%
IC	Excellent	Moderate	Moderate	Low to Moderate	74%
IC-PI [2]	Excellent	Good	Fast	High	98.5%
CV [6]	Good	Poor	Slow to moderate	Low	93.1%
Beta [2]	Excellent	Excellent	Fast	Moderate	98.5%
P&O-PI [2]	Good	Excellent	Fast	Moderate	98.6%
ABC-P&O [49]	Excellent	Excellent	Fast	High	99.99%
ABC	Excellent	Excellent	Fast	High	99.5%
TSA-PSO [12]	Excellent	Excellent	Fast	High	98.2%
EA-P&O [7]	Excellent	Excellent	Very Fast	High	99%
ACO [16]	Excellent	Excellent	Moderate	High	99.85%
ACO-P&O [16]	Excellent	Excellent	Fast	Moderate to High	99.99%
PC [6]	Moderate	Poor	Slow	High	99.8%
PSO-SVR [48]	Excellent	Excellent	Fast	High	99.8%
DEPSO [52]	Excellent	Excellent	Moderate	High	98%
NA-PSO [53]	Excellent	Excellent	Very Fast	High	98.9%
Vcte [2]	Excellent	Poor	Moderate	Low	89%
IPA/VPA with PSSRA [5]	Excellent	Excellent	Vert Fast	High	98.75%
ARL-NNA [31]	Excellent	Excellent	Very Fast	High	99.9%
GWO_SVM_C [29]	Excellent	Excellent	Very Fast	High	97.28%
ICA–ANN [25]	Excellent	Excellent	Very Fast	High	99.9984%
ANN [24]	Excellent	Excellent	Very Fast	High	98.16%
PSO_ML-FSSO [32]	Excellent	Excellent	Very Fast	High	99.594%
Proposed ABC-IC	Excellent	Excellent	Fast	High	100%

6. Conclusion

This study explored the implementation of MPPT algorithms—specifically the Incremental Conductance (IC), Artificial Bee Colony (ABC), and a novel hybrid ABC-IC approach—in PV systems under partial shading conditions. The conventional IC method, while straightforward, exhibited inherent limitations by tracking only the Local Maximum Power Point (LMPP), achieving 74% efficiency with notable power oscillations of 8.7%. In contrast, the ABC algorithm, grounded in metaheuristic optimization, effectively located the Global Maximum Power Point (GMPP), improving efficiency to 99.5%. The proposed hybrid ABC-IC algorithm combined the strengths of both the heuristic and metaheuristic approaches, achieving 100% efficiency with minimal oscillations (2.7%) and rapid convergence (0.37 s). This hybrid approach consistently tracked the GMPP even under dynamic irradiation changes, demonstrating robust capability in maintaining stable and efficient energy extraction. These results underscore the hybrid algorithm’s superior performance, highlighting its potential as a dependable solution for optimizing PV system output in the face of partial shading and environmental variability.

Despite these significant advancements, challenges remain in the practical implementation of advanced MPPT algorithms in real-time PV systems. Key issues such as computational complexity, parameter tuning, and hardware constraints require further investigation to enhance the feasibility and scalability of these methods in real-world applications. Addressing these challenges will be critical to ensuring that hybrid and metaheuristic algorithms can be deployed cost-effectively and efficiently without compromising performance. Future research should focus on developing hardware-efficient, low-cost solutions capable of maintaining high tracking accuracy while minimizing resource consumption. Such innovations will be pivotal in promoting broader adoption of these advanced MPPT strategies, ultimately contributing to more reliable and efficient utilization of solar energy across diverse and changing environmental conditions.

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References

1. Almutairi A, Abo-Khalil AG, Sayed K, et al. MPPT for a PV Grid-Connected System to Improve Efficiency under Partial Shading Conditions. Sustainability. 2020; 12(24): 10310.
2. de Brito MAG, Galotto L, Sampaio LP, et al. Evaluation of the main MPPT techniques for photovoltaic applications. IEEE Transactions on Industrial Electronics. 2013; 60(3): 1156–1167.
3. Premkumar M, Sumithira TR, Sowmya R. Implementation of Solar PV Based Microconverter with Optimal Mppt Control. J. Electr. Eng. 2108; 18(2): 1–12.
4. Pakkiraiah B, Sukumar GD. Research Survey on Various MPPT Performance Issues to Improve the Solar PV System Efficiency. J. Sol. Energy. 2016; 2016(6): 1–20.

5. Jately V, Bhattacharya S, Azzopardi B, et al. Voltage and Current Reference Based MPPT Under Rapidly Changing Irradiance and Load Resistance. IEEE Trans. Energy Convers. 2021; 36: 2297–2309.
6. Hohm DP, Ropp ME. Comparative study of maximum power point tracking algorithms. Progress in Photovoltaics: Research and Applications. 2003; 11(1): 47–62.
7. Ahmed J, Salam JZ. An enhanced adaptive P&O MPPT for fast and efficient tracking under varying environmental condition. IEEE Transactions on Sustainable Energy. 2018; 9(3): 1487–1496.
8. Elgendy MA, Zahawi B, Atkinson DJ. Assessment of perturb and observe MPPT algorithm implementation techniques for PV pumping applications. IEEE Trans. Sustain. Energy. 2012; 3: 21–33.
9. Masood B, Siddique MS, Asif RM, et al. Maximum power point tracking using hybrid perturb & observe and incremental conductance techniques. In: Proceedings of the 4th International Conference on Engineering Technology and Technopreneuship (ICE2T); 27–29 August 2014; Kuala Lumpur, Malaysia.
10. Safari A, Mekhilef S. Incremental conductance MPPT method for PV systems. In: Proceedings of the 24th Canadian Conference on IEEE; 8–11 May 2011; Niagara Falls, ON, Canada. pp. 345–347.
11. Hussein KH, Muta I, Hoshino T, et al. Maximum Photovoltaic Power Tracking: an Algorithm for Rapidly Changing Atmospheric Conditions. IEE Proceedings-Generation, Transmission and Distribution. 1995; 142(1): 59–64.
12. Sharma A, Sharma A, Jately V, et al. A Novel TSA-PSO Based Hybrid Algorithm for GMPP Tracking under Partial Shading Conditions. Energies. 2022; 15: 3164.
13. Elhaddad, Y. Combined Simulated Annealing and Genetic Algorithm to Solve Optimization Problems. World Academy of Science, Engineering and Technology. 2012; 6: 1047–1049.
14. Long W, Xu S. A novel grey wolf optimizer for global optimization. In: Proceedings of the IEEE Advanced Information Management, Communicates, Electronic and Automation Control Conference (IMCEC); 3–5 October 2016; Xi'an, China. pp. 1266–1270.
15. Mirjalili S, Mohammad S, Lewis A. Grey Wolf Optimizer. Advances in Engineering Software. Elsevier. 2014; 69: 46–61.
16. Sundareswaran K, Vigneshkumar V, Sankar P, et al. Development of an Improved P&O Algorithm Assisted Through a Colony of Foraging Ants for MPPT in PV System. IEEE Transactions on Industrial Informatics. 2016; 12(1). pp. 187–200.
17. Oshaba S, Ali ES, Abd Elazim SM. Artificial bee colony algorithm based maximum power point tracking in photovoltaic system. WSEAS Trans. Power Syst. 2015; 10: 123–134
18. Qi P, Xia H, Cai X, et al. Novel Global MPPT Technique Based on Hybrid Cuckoo Search and Artificial Bee Colony under Partial-Shading Conditions. Electronics. 2024; 13(7): 1337.
19. Kaya CB, Kaya E, Gökkuş G. Training Neuro-Fuzzy by Using Meta-Heuristic Algorithms for MPPT. Computer Systems Science & Engineering. 2023; 45(1).
20. Kishore DK, Mohamed MR, Sudhakar K, et al. Swarm intelligence-based MPPT design for PV systems under diverse partial shading conditions. Energy. 2023; 265: 126366.
21. Silaa MY, Barambones O, Bencherif A, et al. A New MPPT-Based Extended Grey Wolf Optimizer for Stand-Alone PV System: A Performance Evaluation versus Four Smart MPPT Techniques in Diverse Scenarios. Inventions. 2023; 8(6): 142.
22. Ibrahim MH, Ang SP, Dani MN, et al. Optimizing step-size of perturb & observe and incremental conductance MPPT techniques using PSO for grid-tied PV system. IEEE access. 2023; 11: 13079–13090.
23. Naoussi SRD, Saatong KT, Molu RJJ, et al. RETRACTED ARTICLE: Enhancing MPPT performance for partially shaded photovoltaic arrays through backstepping control with Genetic Algorithm-optimized gains. Scientific Reports. 2024; 14(1): 3334.
24. Abouzeid AF, Eleraky H, Kalas A, et al. Experimental validation of a low-cost maximum power point tracking technique based on artificial neural network for photovoltaic systems. Scientific Reports. 2024; 14(1): 18280.
25. Ncir N, El Akchiou N. An advanced intelligent MPPT control strategy based on the imperialist competitive algorithm and artificial neural networks. Evolutionary Intelligence. 2024; 17(3): 1437–1461.
26. Gul S, Malik SM, Sun Y, et al. An artificial neural network based MPPT control of modified flyback converter for PV systems in active buildings. Energy Reports. 2024; 12: 2865–2872.
27. Colbu ŞC, Băncilă DM, Petrescu-Niţă A, et al. A comparative study of support vector machine and risk deterministic approach on a photovoltaic system. UPB Sci. Bull., Series C. 2024; 86(3): 67–80.

28. Kumar P, Viswambharan VK, Pillai S. Performance Analysis of Maximum Power Point Tracking of PV Systems using Artificial Neural Networks and Support Vector Machines. In: Proceedings of the 2023 International Conference on Computational Intelligence and Knowledge Economy (ICCIKE); 9–10 March; Dubai, UAE. pp. 511–515.
29. Ahmed QI, Attar H, Amer A, et al. Development of a hybrid support vector machine with grey wolf optimization algorithm for detection of the solar power plants anomalies. Systems. 2023; 11(5): 237.
30. Ghazi GA, Al-Ammar EA, Hasanien HM, et al. Dandelion optimizer-based reinforcement learning techniques for MPPT of grid-connected photovoltaic systems. IEEE Access. 2024; 12: 42932–42948.
31. Leelavathi M, Suresh KV. Enhancing MPPT in partially shaded PV modules: A novel approach using adaptive reinforcement learning with neural network architecture. Bulletin of the Polish Academy of Sciences. Technical Sciences. 2024; 72(4).
32. Kumar D, Chauhan YK, Pandey AS, et al. A novel hybrid MPPT approach for solar PV systems using particle-swarm-optimization-trained machine learning and flying squirrel search optimization. Sustainability. 2023; 15(6): 5575.
33. Bouchakour A, Zarour L, Bessous N, et al. MPPT algorithm based on metaheuristic techniques (PSO & GA) dedicated to improve wind energy water pumping system performance. Scientific Reports. 2024; 14(1): 17891.
34. Sree VS, Ankarao M. Power quality enhancement of solar–wind grid connected system employing genetic-based ANFIS controller. Paladyn J. Behav. Robotics. 2023; 14(1).
35. Ghilani A, Terki A, Alili Z, et al. Experimental Validation of PSO and GWO-Based MPPT for a Single-Stage Three-Phase Grid-Connected PV System Under Partial Shading. Journal Européen des Systèmes Automatisés. 2024; 57(5): 1387.
36. Jia D, Wang D. A Maximum Power Point Tracking (MPPT) Strategy Based on Harris Hawk Optimization (HHO) Algorithm. Actuators. 2024; 13(11): 431.
37. Tao X, Xin J, Zhang S, et al. A Novel Harris-Hawk-Optimization-Based Maximum-Power-Point-Tracking Control Strategy for a Grid-Connected PV Power-Generation System. Energies. 2023; 17(1): 76.
38. Abdelmalek F, Afghoul H, Krim F, et al. Experimental validation of novel hybrid Grey Wolf Equilibrium Optimization for MPPT to improve the efficiency of solar photovoltaic system. Results in Engineering. 2025; 25: 103831.
39. KT S, Venugopal Reddy B. A novel constraint-based improved equilibrium optimization for global peak tracking of photovoltaic system under complex shading conditions. International Journal of Circuit Theory and Applications. 2023; 51(6): 2819–2838.
40. Abo-Khalil AG, Lee DC, Choi JW, et al. Maximum Power Point Tracking Controller Connecting PV System to Grid. Korean Institute of Power Electronics Journal. 2006; 6(3).
41. Syafaruddin, Karatepe E, Hiyama T. Artificial neural network-polar coordinated fuzzy controller based maximum power point tracking control under partially shaded conditions. IET Renewable Power Generation. 2009; 3(2): 239–253.
42. Veerachary M, Senjyu T, Uezato K. Neural-network-based maximum-power-point tracking of coupled-inductor interleaved-boost converter-supplied PV system using fuzzy controller. IEEE Trans. Ind. Electron. 2023; 50(4): 749–758.
43. Eltamaly AM, Al-Saud MS, Abo-Khalil AG, et al. Simulation and Experimental Validation of Fast Adaptive Particle Swarm Optimization Strategy for Photovoltaic Global Peak Tracker under Dynamic Partial Shading. Renewable & Sustainable Energy Reviews. 2020; 124: 109719.
44. Eltamaly AM, Al-Saud MS, Abo-Khalil AG. Performance Improvement of PV Systems' Maximum Power Point Tracker Based on a Scanning PSO Particle Strategy. Sustainability. 2020; 12(3): 1185.
45. Putri RI, Wibowo S, Rifa'i M. Maximum power point tracking for photovoltaic using incremental conductance method. Energy Procedia. 2015; 68: 22–30.
46. Chao RM, Nasirudin A, Wang IK, Chen PL. Multicore PSO operation for maximum power point tracking of a distributed photovoltaic system under partially shading condition. Int. J. Photoenergy. 2016; 2016: 9754514.
47. Eltamaly AM, Al-Saud MS, Abo-Khalil AG. Photovoltaic maximum power point tracking under dynamic partial shading changes by novel adaptive particle swarm optimization strategy. Transactions of the Institute of Measurement and Control. 2019.
48. Abo-Khalil AG. Maximum Power Point Tracking for a PV System Using Tuned Support Vector Regression by Particle Swarm Optimization. Journal of Engineering Research. 2020; 8(4): 139–152.
49. Pilakkat D, Kanthalakshmi S. An improved P&O algorithm integrated with artificial bee colony for photovoltaic systems under partial shading conditions. Sol. Energy. 2019; 178: 37–47.

50. Eltamaly M, Al-Saud MS, AboKhalil AG. A Novel Bat Algorithm Strategy for Maximum Power Point Tracker of Photovoltaic Energy Systems Under Dynamic Partial Shading. IEEE Access. 2020; 8: 10048–1006.
51. Harrag A, Messalti S. Variable step size modified P&O MPPT algorithm using GA-based hybrid offline/online PIDcontroller. Renewable and Sustainable Energy Reviews. 2015; 49: 1247–60.
52. Seyedmahmoudian M, Rahmani R, Mekhilef S, et al. Simulation and hardware implementation of new maximum power point tracking technique for partially shaded PV system using hybrid DEPSO method. IEEE Transactions on Sustainable Energy. 2015; 6: 850–862.
53. Eltamaly AlM, Farh HMH, Abokhalil AG. A novel PSO strategy for improving dynamic change partial shading photovoltaic maximum power point tracker. Energy Sources, Part A: Recovery, Utilization, and Environmental Effects. 2020; 46(4): 1–15.
54. Farh HMH, Othman MF, Eltamaly AM, et al. Maximum power extraction from a partially shaded PV system using an interleaved boost converter. Energies. 2018; 11(10): 2543.
55. Harrag A, Messalti S. Variable step size modified P&O MPPT algorithm using GA-based hybrid offline/online PID controller. Renewable and Sustainable Energy Reviews. 2015; 49: 1247–1260.
56. Abo-Khalil AG, Yu GY. Current Estimation-based Maximum Power Point Tracker of Grid Connected PV. In: Proceedings of the IEEE 10th International Conference on Power Electronics and Drive Systems (PEDS); 22–25 April 2013; Kitakyushu, Japan.
57. Yang XS. Chaos-enhanced firefly algorithm with automatic parameter tuning. International Journal of Swarm Intelligence Research. 2011; 2(4) 1–11.
58. Yang XS. A new metaheuristic bat-inspired algorithm. In: Cruz C, González JR, Gonzalez JR. (editors). Nature Inspired Cooperative Strategies for Optimization (NICSO 2010). Springer; 2010. Volume 284. pp. 65–74.
59. Yang XS. Firefly algorithm, stochastic test functions and design optimization. International Journal of Bio-Inspired Computation. 2010; 2(2): 78–84.
60. Bilal B. Implementation of artificial bee colony algorithm on maximum power point tracking for PV modules. In: Proceedings of the 8th International Symposium on Advanced Topics in Electrical Engineering (ATEE); 23–25 May 2013; Bucharest, Romania.
61. Abo-Khalil AG, Alharbi W, Al-Qawasmi AR, et al. Maximum Power Point Tracking of PV Systems under Partial Shading Conditions Based on Opposition-Based Learning Firefly Algorithm. Sustainability. 2021; 13(5): 2656.
62. Abo-Khalil AG, El-Sharkawy II, Radwan AM, et al. Influence of a Hybrid MPPT Technique, SA-P&O, on PV System Performance under Partial Shading Conditions. Energies. 2023; 16(2): 577.