

Article

A Hybrid Approach for Photovoltaic Maximum Power Tracking under Partial Shading Using Honey Badger and Genetic Algorithms

Zhi-Kai Fan ¹, Annisa Setianingrum ¹, Kuo-Lung Lian ^{1,*} and Suwarno Suwarno ²

¹ Department of Electrical Engineering, National Taiwan University of Science and Technology, No. 43, Section 4, Keelung Rd., Taipei 106, Taiwan; d11107012@gapps.ntust.edu.tw (Z.-K.F.); m11107805@mail.ntust.edu.tw (A.S.)

² Department of Electrical Power Engineering, School of Electrical Engineering and Informatics, Bandung Institute of Technology, Jalan Ganesha No. 10, Bandung 40132, Indonesia; suwarno@stei.itb.ac.id

* Correspondence: ryanlian@gapps.ntust.edu.tw

Abstract: This study presents a new approach for Maximum Power Point Tracking (MPPT) by combining the honey badger algorithm (HBA) with a Genetic Algorithm (GA). The integration aims to optimize photovoltaic (PV) system performance in partial shading conditions (PSCs). Initially, the HBA is utilized to explore extensively and identify potential solutions while avoiding local optima. If necessary, the GA is then employed to escape local optima through selection, crossover, and mutation operations. On average, this proposed method has a 40% improvement in tracking time and 0.77% in efficiency compared with the HBA. In a dynamic case, the proposed method achieves a 4.81% improvement compared to HBA.

Keywords: maximum power point tracking; photovoltaic system; honey badger algorithm; genetic algorithm; partial shading condition



Citation: Fan, Z.-K.; Setianingrum, A.; Lian, K.-L.; Suwarno, S. A Hybrid Approach for Photovoltaic Maximum Power Tracking under Partial Shading Using Honey Badger and Genetic Algorithms. *Energies* **2024**, *17*, 3935. <https://doi.org/10.3390/en17163935>

Academic Editor: Francesco Nocera

Received: 15 July 2024

Revised: 1 August 2024

Accepted: 6 August 2024

Published: 8 August 2024



Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Renewable energy is now a crucial element in the global initiative to transition towards a sustainable and low-carbon future. With growing concerns about climate change, diminishing fossil fuel reserves, and the need for environmental preservation, renewable energy systems are widely acknowledged for their potential to offer clean and limitless power. Among various renewable technologies, photovoltaic (PV) systems emerge as particularly promising and fast-developing. By directly converting sunlight into electricity, these systems provide a viable solution to numerous energy challenges worldwide.

However, the widespread adoption of solar PV technology also introduces significant safety challenges, particularly in large-scale applications. A critical issue is the increased risk of fire accidents caused by hot spot effects and DC arcs. These risks are exacerbated by factors such as non-uniform shading, irradiance, and temperature variations, which accelerate the aging process of solar panels and create power generation mismatches. In PV modules, series-connected cells are often used, where partial shading from objects like fallen leaves, dust accumulation, and bird droppings can create hot spots due to non-uniform power generation. This effect increases local currents and voltages, causing the module's temperature to rise, which can lead to spontaneous ignition [1].

Given these safety concerns, the role of Maximum Power Point Tracking (MPPT) algorithms becomes crucial. MPPT is a method that ensures PV systems operate at their highest power point, maximizing the power generated by the PV panels. This not only enhances the efficiency of PV systems but also mitigates safety risks by preventing conditions that lead to hot spots. By continuously adjusting the PV system's operating point to align with environmental changes, MPPT algorithms optimize the system's performance, thus reducing the likelihood of power generation mismatches and associated hazards.

Moreover, from an economic perspective, MPPT algorithms significantly increase the viability of PV systems by maximizing the energy output and efficiency. This optimization reduces energy losses and enhances the overall return on investment for PV installations. By ensuring that PV systems consistently operate at their maximum potential, MPPT contributes to the economic feasibility and sustainability of renewable energy projects, addressing safety and performance concerns. The integration of MPPT not only resolves technical challenges but also presents a compelling economic justification for its widespread implementation in PV systems.

Various MPPT algorithms have been developed to ensure precise tracking operations, including Deterministic Approaches (DAs), Artificial Neural Networks (ANNs), Fuzzy Logic (FL) control, and Meta-Heuristic Approaches (MHAs).

Methods such as Perturb and Observe (P&O) [2,3], Incremental Conductance (IC) [4,5], and Golden Section Search (GSS) [6] are part of decentralized algorithms. The implementation of these algorithms is essential for optimizing the performance of PV systems, thereby maximizing their energy generation capabilities.

The utilization of ANN-based MPPT represents a significant advancement in enhancing the efficiency and optimization of PV systems, especially in situations involving multiple peak power points and PSCs [7,8]. ANNs offer excellent tracking performance by effectively handling complex patterns in power–voltage curves. However, they also present several drawbacks. The accuracy of ANNs heavily depends on the quality and volume of training data, which can be challenging to obtain for all possible shading scenarios. Additionally, ANNs require substantial computational resources and time for training, making real-time applications difficult. Adapting ANNs to different PV systems or conditions often necessitates retraining, further increasing complexity and computational burden. These limitations underscore the need for alternative approaches, such as FL methods and MHAs, which can offer reliable tracking with less dependency on extensive data and computational resources [9–12].

Recently, MHAs have been utilized to attain the GMPP [13]. The latest MPPT methods for MHAs include Flying Squirrel Search Optimization (FSSO) [14], Golden Eagle Optimizer (GEO) [15], Most Valuable Player Algorithm (MVPA) [16], Falcon Optimization Algorithm (FOA) [17], etc. Teshome et al. [18] proposed a modified firefly algorithm (FA) to locate the maximum power in P-V curves. The modified FA is intended to address the limitation of the current FA by reducing computation time and improving convergence speed. Millah et al. [19] introduced an enhanced gray wolf optimizer (GWO) algorithm to improve the accuracy and speed of MPPT in PV systems under PSCs. This algorithm enhances the original GWO by incorporating a weighting average, a pouncing behavior inspired by wolf hunting, and a nonlinear convergence factor. Gundogdu et al. [20] proposed an improved GWO method for GMPP in PV systems under PSCs. The improved GWO enhanced tracking efficiency and speed by up to 82% and improved energy harvesting by 2.3% compared to basic GWO. Li et al. [21] enhanced standard PSO by integrating asynchronous learning factors, adaptive inertia weights, and mutation mechanisms. These improvements synchronized learning factors and inertia weights while mutating particle positions to accelerate convergence and improve global optimization capability. Overall, the algorithm significantly boosted efficiency and accuracy. Koh et al. [22] presented a modified PSO algorithm; the algorithm included a reinitialization scheme to track new GMPPs when shading conditions changed abruptly. Mohammed et al. [23] introduced an improved Rat Swarm Optimizer (RSO). The algorithm incorporated an adaptive perturbation step size method for load variations, enhancing its robustness. Sangrody et al. [24] proposed a novel approach to estimate the convex area of the P-V curve using two voltage boundaries to locate the GMPP. Xu et al. [25] proposed an improved Mayfly Algorithm (MFA) that included a shading detection strategy to handle multi-peak and single-peak P-V curves under varying irradiance conditions. The approach integrated an elimination strategy for multi-peak scenarios and a bisection search for single-peak scenarios. Putera et al. [26] introduced a modified Human Psychology Optimization (HPO) algorithm. The

method adjusted the duty cycle of a SEPIC converter to regulate voltage output effectively, ensuring that the PV system consistently achieved the GMPP and optimized power output even under partial shading. Pervez et al. [27] introduced a modified bat algorithm (BA) to address the non-convex nature of PV array power curves due to bypass diodes. Previous algorithms either failed to effectively track the GMPP or were computationally intensive. The algorithm dynamically reduced the search space to avoid exploring low-power regions.

Another MPPT technique is a hybrid method that combines two or more algorithms. Lian et al. [28] introduced a hybrid method that combined the P&O method with PSO to efficiently track the GMPP. The study confirmed that the method outperformed the PSO method alone by reducing the search space and improving convergence time. Nugraha et al. [29] combined the cuckoo search (CS) algorithm with the GSS method. The CS algorithm was initially used to identify the region containing the GMPP, followed by the application of the GSS to precisely determine the exact location of the GMPP within that region. Liao et al. [30] introduced an improved BA for MPPT in PV systems, specifically addressing the challenges of PSCs. The paper demonstrated that this combined approach outperformed the standard BA and even surpassed other advanced MPPT algorithms in terms of both speed and accuracy. Motamarri et al. [31] proposed a novel JAYA algorithm enhanced by a Lévy flight to find the GMPP under PSCs in PV systems. The algorithm improved tracking efficiency and reduced convergence time compared to conventional methods like JAYA and PSO. Figueiredo et al. [32] proposed a hybrid MPPT technique using PSO and P&O methods. It aimed to optimize energy extraction by efficiently tracking the GMPP despite varying environmental conditions. Simulation results showed the hybrid method achieved 50% faster tracking than standard PSO and improved energy extraction by 0.3% compared to the P&O-PSO hybrid approach. Lyden et al. [33] proposed a hybrid MPPT method combining SA with P&O. SA located the region of the GMPP, while P&O fine-tuned the search to find the exact GMPP with a small step size. In this paper, a novel sentry particle approach detects environmental changes triggering a new global search. The proposed method is a hybrid of the honey badger algorithm (HBA) and a genetic algorithm (GA). The proposed method aims to enhance the speed of convergence and decrease the tracking time. The paper is structured as follows: Section 2 provides an in-depth explanation of HBA, GA, as well as details on the development of the proposed method. Section 3 covers the performance of experiment. Lastly, Section 4 contains the conclusions of this paper.

2. Related Work

2.1. Honey Badger Algorithm

Honey badgers have two ways of searching for food: sniffing out and digging, or following a honeyguide bird. The initial method is known as “digging mode”, while the second is known as “honey mode”. During digging mode, the honey badger depends on its keen sense of smell to estimate the whereabouts of its prey. Once the location is determined, it meticulously chooses the best spot for digging and capturing its target. Conversely, in honey mode, the honey badger leverages signals from the honeyguide bird to efficiently locate beehives [34].

The population of honey badgers can be written as:

$$X = [x_1 \ x_2 \ x_3 \ \dots \ x_n]$$

Updating the search badger’s location involves two main phases: digging mode and honey mode. Before delving into modifying the position descriptors of the honey badger during these stages, certain factors need to be taken into account, such as prey attraction and density factors, in order to define these descriptors. Prey attraction is influenced by both the concentration of prey and their proximity to the i_{th} honey badger. L_i represents the scent intensity of a particular type of prey; a higher value indicates that the i_{th} honey badger

can locate and move towards this specific type of prey more effectively. This relationship can be expressed mathematically as:

$$L_i = r_2 \times \frac{S}{4\pi d_i^2} \quad (1)$$

$$S = (x_i - x_{i+1})^2 \quad (2)$$

$$d_i = x_{prey} - x_i \quad (3)$$

The source intensity is represented by S , while the distance between each honey badger and the target location (i.e., the prey) is denoted by the variable d_i . Furthermore, the position of the prey, which is viewed as the location of an optimal individual within this algorithm, is indicated by x_{prey} .

Based on (2) it is clear that as a honey badger approaches its prey, a stronger attraction (odor) is created. This condition is illustrated in Figure 1. The density factor is gradually reduced over the course of the iterations, enabling a smooth shift from the exploration of the search space to the exploitation of the most promising areas. This adjustment of the density factor after each iteration serves to decrease the level of randomness in the algorithm, as shown in the following mathematical expression:

$$\alpha = C_0 \times \exp\left(\frac{t}{t_{max}}\right) \quad (4)$$

where C_0 is a constant with a minimum value of 1, but it is set to 2 by default. The variable t represents the current iteration number, while t_{max} indicates the maximum allowed iterations.

The process of updating the badger's location involves two phases. The first phase is known as digging mode. The movement of a honey badger follows the pattern of a cardioid, which is a heart-shaped curve as shown in Figure 2. While in motion, the trajectory of the honey badger forms a continuous loop that resembles the shape of a cardioid. The mathematical expression for the digging mode is defined in (5).

$$x_{new} = x_{prey} + F \times \beta \times I \times x_{prey} + F \times r_3 \times \alpha \times d_i \times |\cos(2\pi r_4) \times [1 - \cos(2\pi r_5)]| \quad (5)$$

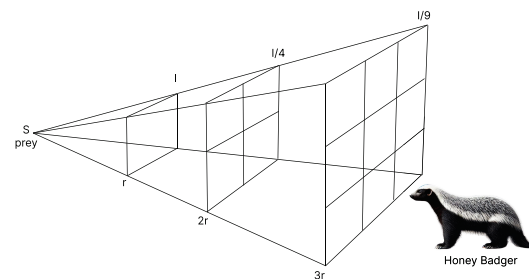


Figure 1. Inverse square law.

The location of the optimal global position is denoted by x_{prey} . The parameter β represents the foraging capability of honey badgers and is assumed to be greater than or equal to 1. d_i represents the distance between the prey and the i_{th} honey badger. Additionally, r_3 , r_4 , and r_5 are random numbers within the range of 0 to 1. Furthermore, F indicates the search direction of the searching agent according to (6):

$$F = \begin{cases} 1 & r_6 \leq 0.5 \\ -1 & \text{else} \end{cases} \quad (6)$$

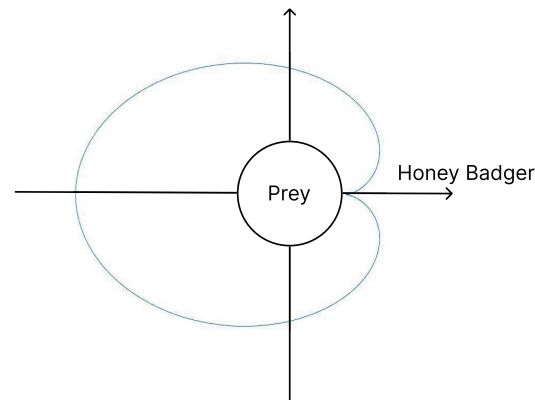


Figure 2. Cardioid shape curve.

The second stage to update the badger's location is the honey phase, with the honeyguide as birds naturally having a mutually beneficial relationship with honey badgers. The honeyguide frequently searches for hives in different locations and when it discovers the hive's whereabouts, it emits a sharp call to signal its finding. The update expression for the honey stage is given by:

$$x_{new} = x_{prey} + F \times r_7 \times \alpha \times d_i \quad (7)$$

where x_{new} represents the honey badger's recent position, where x_{prey} is the prey's whereabouts. F and α are factors used to modify the honey badger's search in the vicinity of the x_{prey} coordinates.

2.2. Genetic Algorithm

A GA is a powerful search algorithm that mimics natural selection, making it a meta-heuristic process. The concept is rooted in the notion that the most well-suited individuals of a population have a higher chance of survival and procreation, thereby passing on their characteristics to future generations. A GA utilizes this evolutionary principle to explore a vast solution space in order to discover optimal or nearly optimal solutions for complex problems. The algorithm utilizes key characteristics of the evolutionary system, including the chromosome population, chromosome selection based on fitness, generation of new offspring via crossover, and random mutation of the new generation. The GA was proposed by Holland in 1992 [35]. The operators used in GAs are as follows:

1. Selection (reproduction): the process of choosing individuals from a population to create offspring for the next generation.
2. Crossover (recombination): in this step, the genetic information from two parent solutions is combined to produce new offspring solutions. Commonly used crossover techniques include single-point crossover, two-point crossover, uniform crossover, and arithmetic crossover. For this study, the uniform crossover method was employed, wherein the genetic material from each gene in the parent solutions is swapped with a specified probability, resulting in a high degree of mixing between the parent solutions [36].

$$\begin{aligned} offspring_1 &= parent_1 \cdot (1 - \gamma) + \gamma \cdot parent_2 \\ offspring_2 &= parent_1 \cdot \gamma + (1 - \gamma) \cdot parent_2 \end{aligned} \quad (8)$$

where $\gamma = 1.5 \times rand$.

3. Mutation introduces random variations into the population of solutions, helping to maintain genetic diversity and allowing the algorithm to explore new areas of the search space. This process is crucial for preventing the algorithm from converging pre-

maturely to local optima, thereby facilitating the identification of the global optimum solution. For each individual, there is a 1% probability of mutation occurring [37].

$$offspring = LB + rand \times (UB - LB) \quad (9)$$

where LB is the lower bound, UB is the upper bound, and $rand$ is a random number between 0 to 1.

2.3. Parameter Setup

For the HBA, it is essential to establish several parameters right from the beginning. Two of these crucial parameters are β and C . Below is a table of results for determining β and C . Through extensive simulations, Table 1 indicates that the value $\beta = 6$ and $C = 2$ yielded the highest accuracy of 99.998% with a tracking time of 5.28 s. These specific values for β and C were utilized in subsequent experiments to attain more precise results in this research. For the GA, the crossover probability was 1 and the mutation probability was 0.01.

Table 1. HBA tracking results with various β and C values.

Parameter		Scenario 1 C = 0.5	Scenario 2 C = 1.0	Scenario 3 C = 1.5	Scenario 4 C = 2.0	Scenario 5 C = 2.5
$\beta = 4.000$	Accuracy	99.996 ± 0.019	99.993 ± 0.038	99.997 ± 0.013	99.990 ± 0.038	99.959 ± 0.338
	Time	4.28 ± 0.742	5.08 ± 0.622	5.28 ± 0.487	5.98 ± 0.001	5.78 ± 0.137
$\beta = 4.500$	Accuracy	99.991 ± 0.048	99.995 ± 0.025	99.987 ± 0.063	99.989 ± 0.045	99.968 ± 0.085
	Time	4.58 ± 0.447	5.08 ± 0.274	4.88 ± 0.542	5.48 ± 0.354	5.88 ± 0.112
$\beta = 4.625$	Accuracy	99.996 ± 0.019	99.984 ± 0.106	99.997 ± 0.019	99.929 ± 0.652	99.995 ± 0.015
	Time	4.28 ± 0.576	5.08 ± 0.671	4.98 ± 0.707	5.78 ± 0.224	5.68 ± 0.335
$\beta = 4.750$	Accuracy	99.986 ± 0.056	99.911 ± 0.417	99.967 ± 0.128	99.956 ± 0.435	99.946 ± 0.425
	Time	4.18 ± 0.720	4.68 ± 0.698	4.58 ± 0.671	5.18 ± 0.285	5.68 ± 0.224
$\beta = 4.875$	Accuracy	99.997 ± 0.015	99.955 ± 0.200	99.981 ± 0.070	99.979 ± 0.122	99.871 ± 1.058
	Time	4.48 ± 0.771	3.88 ± 0.647	4.88 ± 0.371	5.78 ± 0.137	5.68 ± 0.335
$\beta = 5.000$	Accuracy	99.994 ± 0.034	99.994 ± 0.035	99.989 ± 0.037	99.997 ± 0.016	99.967 ± 0.175
	Time	3.78 ± 0.487	4.68 ± 0.742	5.98 ± 0.001	5.28 ± 0.548	5.98 ± 0.001
$\beta = 6.000$	Accuracy	99.979 ± 0.123	99.940 ± 0.349	99.973 ± 0.201	99.998 ± 0.027	99.985 ± 0.087
	Time	3.58 ± 0.716	4.38 ± 0.542	5.58 ± 0.274	5.28 ± 0.335	5.88 ± 0.112

2.4. Proposed Method

The proposed method is to combine the HBA with the GA. Figure 3 shows the flowchart of the proposed method. Initially, the HBA is used for extensive initial exploration to find a potential solution. The algorithm uses (10) and (11). If $|A| > 1$, the GA is invoked to help escape local optima by employing selection, crossover, and mutation operations. The GA then operates to locate the GMPP.

$$a = 2 - t \left(\frac{2}{t_{max}} \right) \quad (10)$$

where a decreases linearly from 2 to 0.

$$A = 2a \cdot r_1 - a \quad (11)$$

where r_1 is a random number with interval 0 and 1.

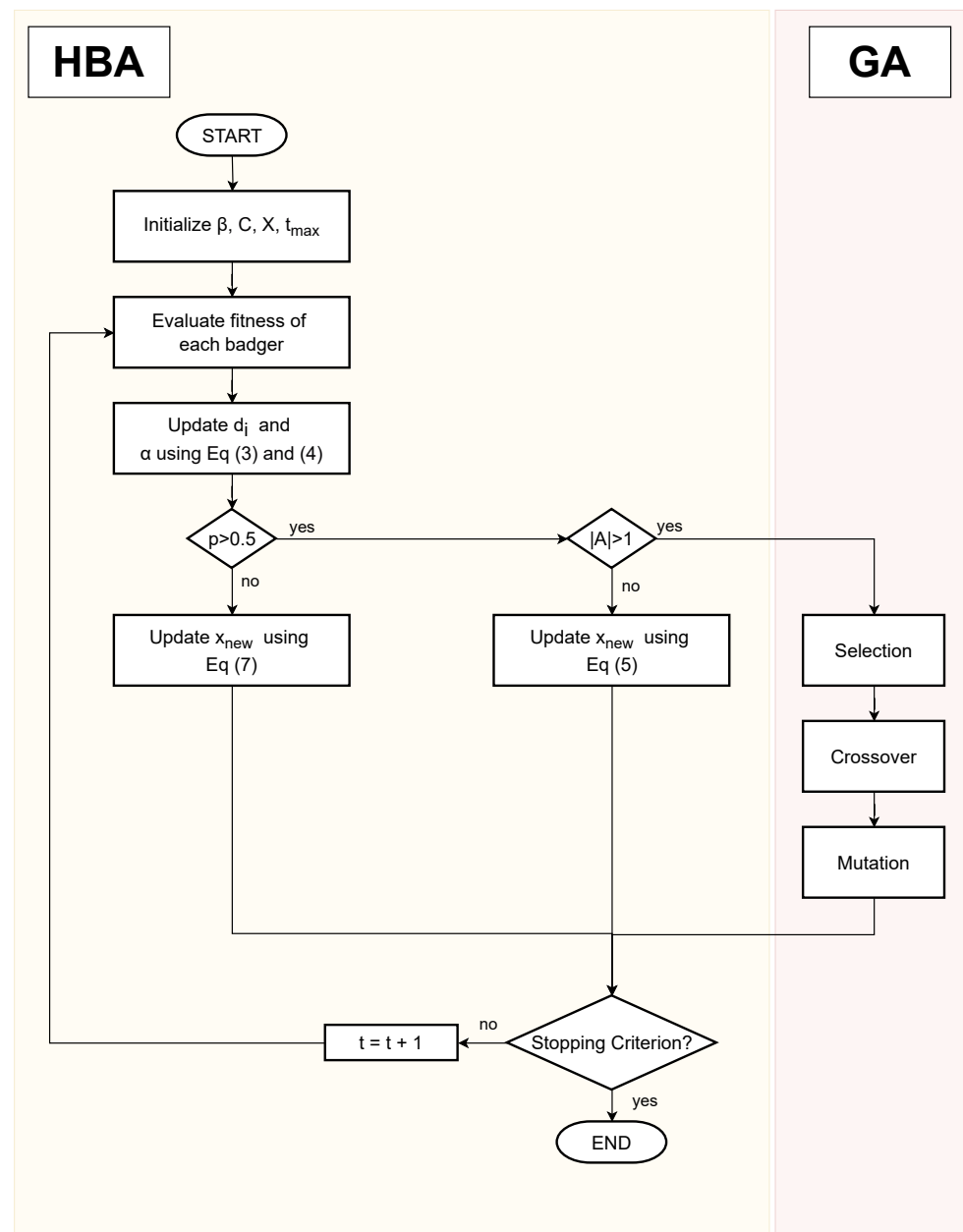


Figure 3. Flowchart of the proposed method.

3. Experimental Setup and Results

In this section, we conducted experiments on twelve P-V curves under static conditions and four cases under dynamic conditions to assess the accuracy and tracking time of the proposed method compared with a range of algorithms, including HBA, GA, slap swarm algorithm (SSA), PSO, sine cosine algorithm (SCA), and SA. In the static cases, where there were no continuously changing P-V curves, we analyzed twelve static P-V curves with varying values. For the dynamic conditions, we used P-V curves that changed continuously in four cases, allowing us to test the algorithms' capabilities under more challenging scenarios. From these experiments, we compared the tracking accuracy and tracking time for each algorithm. The experimental schematic is depicted in Figure 4, and the PV experiment setup is shown in Figure 5. This experiment utilizes the TerraSAS PV emulator (AMETEK ETS600X8C-PVF), capable of replicating different PV panel models under a range of conditions, including partial shading scenarios. The digital signal processor from Texas Instruments (TMS320F28035) is used to implement the MPPT control technique.

Multiple sets of inductors, diodes, and power switches are employed in the interleaved DC-DC boost converter to achieve increased efficiency compared to conventional DC-DC boost converters.

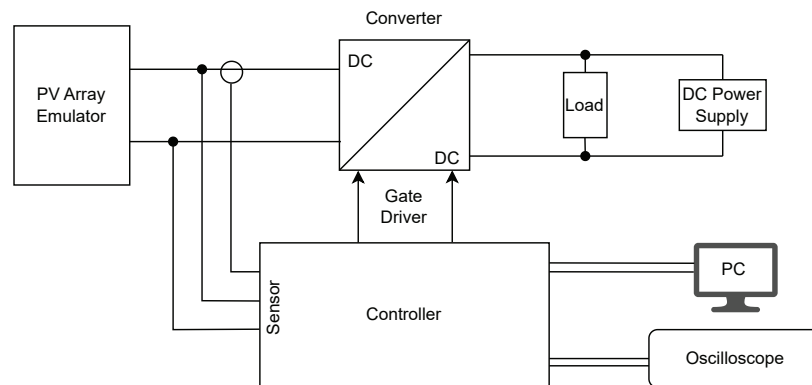


Figure 4. PV system schematic.

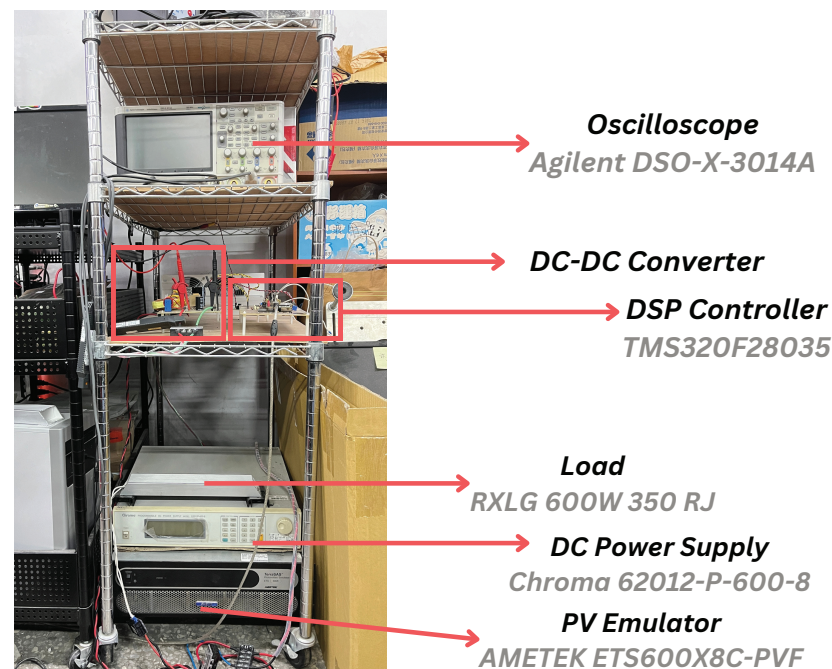


Figure 5. Experiment setup.

In this paper, we chose voltages as positions of the search agents for the voltage control strategy. For the initial conditions, after the algorithm's start, the initial values of the five search agents were set to be 90%, 75%, 60%, 45%, and 30% of the open-circuit voltage (V_{oc}). This was not only applied in the HBA, but also in the GA, SSA, PSO, SCA, SA, and the proposed method. The objective was the maximization of the power. The function was given by:

$$f_{obj} = \text{MAX}(P_{PV}) \quad (12)$$

where $P_{PV} = V_{PV} \times I_{PV}$.

Two constraints defined the variable bounds for $V_{PV,n}$ and $I_{PV,n}$ through

$$0 \leq V_{PV,n} \leq V_{oc} \quad (13)$$

$$0 \leq I_{PV,n} \leq I_{sc} \quad (14)$$

The convergence condition was defined as follows:

$$|P_{PV,best} - P_{PV,n}| \leq \varepsilon, \quad n \in N \quad (15)$$

where ε is the tolerance value, N is the total number of search agents, and we set the number to be five. $P_{PV,best}$ is the best maximum power so far, which is chosen from the best performance element of $P_{PV,n}$. $P_{PV,n}$ is the memory of the maximum power of each search agent. When the distances between $P_{PV,best}$ and $P_{PV,n}$ are less than ε for five times, the convergence condition is reached. If (15) is still not satisfied, the algorithm keeps updating new data until (15) is satisfied or the maximum number of iterations T is reached.

The algorithm's renew process and memory renew process continue for the next iteration until the convergence condition is satisfied, which is mentioned in (15) or the maximum number of iterations T is reached to stop the renew process, as shown in Figure 3.

3.1. Static Case Result

In the static case, the experiment was conducted using twelve P-V curves (referred to in this paper as PSC 1-12). Table 2 lists the parameters of the solar module that the PV emulator mimics in Figure 6. Table 3 presents the results when using the P&O method for tracking. The results show that only six P-V curves successfully found the GMPP when the initial value was 60% of the open-circuit voltage. This is because P&O tended to get easily trapped in a local maximum rather than finding the GMPP. Therefore, we used six MHA methods to compare with the proposed method. The results can be seen in Table 4 and Figure 7a–d. Table 4 presents a comparative analysis of various optimization algorithms like GA, SA, SSA, SCA, PSO, HBA, and the proposed method based on their accuracy and tracking time. The results show the proposed method outperformed all other algorithms, with an average accuracy of 99.32%. The proposed method performed exceptionally well in all arrays used, delivering a tracking time of just 3.27 s. While the proposed method's tracking time was marginally longer compared to that of the GA, the accuracy enhancement of 1.83% represented a substantial achievement.

Table 2. Parameters of each P-V curve.

PSC	Irradiance (W/m ²)				GMPP
	1	2	3	4	
1	600	600	500	500	239.93 W
2	1000	950	300	250	220.32 W
3	1000	850	800	350	289.48 W
4	1000	1000	700	600	310.01 W
5	1000	950	700	400	265.61 W
6	1000	700	600	400	226.11 W
7	1000	800	800	500	283.39 W
8	600	500	200	200	119.97 W
9	900	900	300	300	204.17 W
10	1000	600	500	400	209.84 W
11	900	800	400	300	189.29 W
12	1000	700	400	400	202.65 W

Table 3. Tracking result of P&O.

PSC	1	2	3	4	5	6
Accuracy	98.62%	56.71% *	96.26%	83.27% *	96.65%	97.23%
Time	1.89 (s)	0.61 (s)	0.45 (s)	0.50 (s)	0.43 (s)	0.35 (s)
PSC	7	8	9	10	11	12
Accuracy	96.15%	92.90% *	77.47% *	89.29% *	83.73% *	96.56%
Time	0.24 (s)	1.61 (s)	2.18 (s)	0.46 (s)	0.88 (s)	2.39 (s)

* P&O gets trapped in a local maximum.

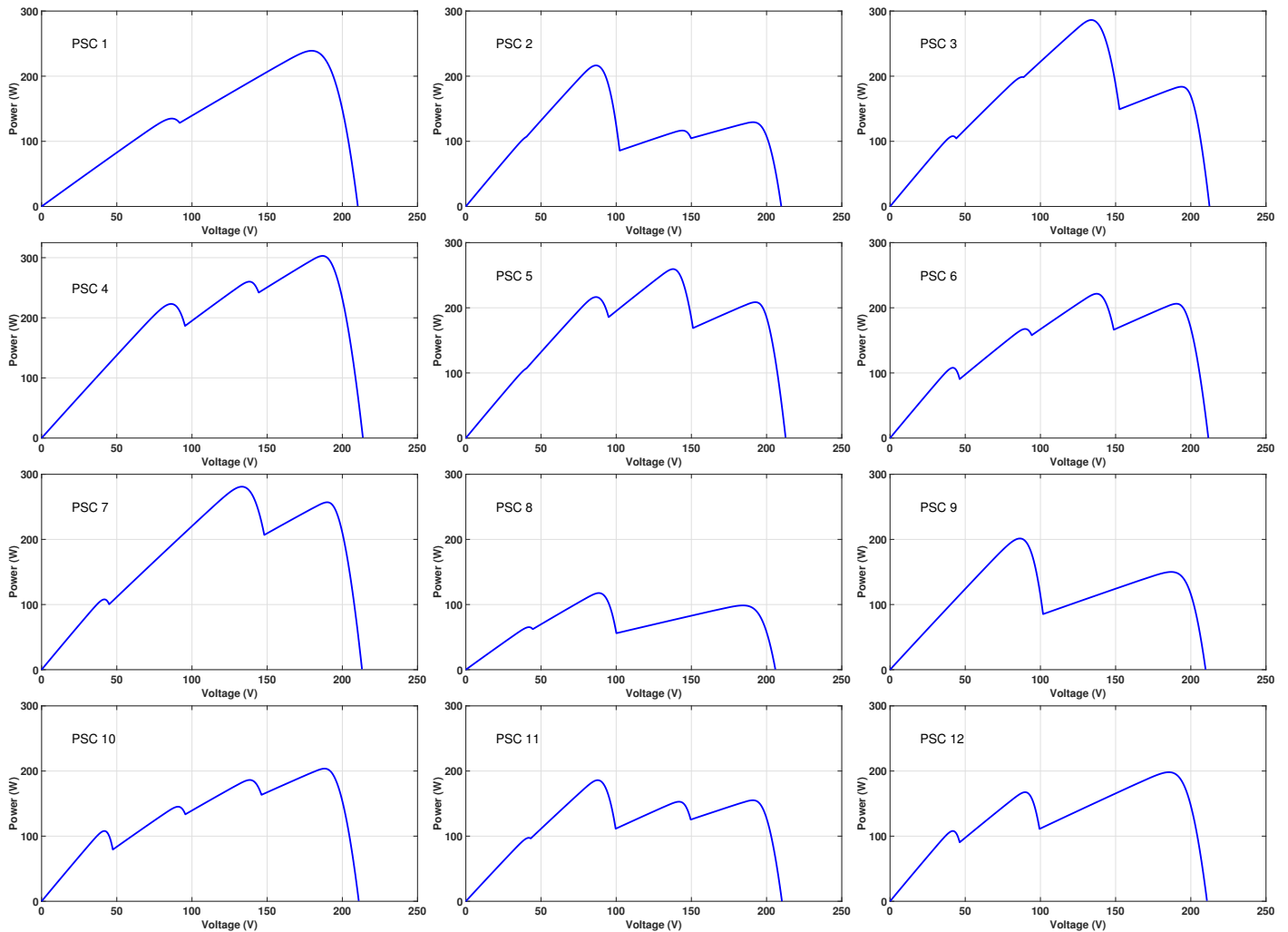


Figure 6. The P-V curve used in the experiment.

Table 4. Tracking accuracy and time result static case.

PSC	GA	SA	SSA	SCA	PSO	HBA	Proposed
Tracking Accuracy (%)							
1	96.59 ± 0.10	97.62 ± 0.12	98.40 ± 0.04	97.68 ± 0.45	99.12 ± 0.13	99.79 ± 0.19	99.81 ± 0.12
2	98.08 ± 0.07	79.45 ± 2.57	99.12 ± 0.20	98.85 ± 0.10	99.35 ± 0.17	99.20 ± 0.15	99.88 ± 0.09
3	97.96 ± 0.26	95.41 ± 0.12	98.55 ± 0.03	98.67 ± 0.03	99.10 ± 0.05	98.95 ± 0.04	99.87 ± 0.13
4	97.18 ± 0.22	97.33 ± 0.27	98.40 ± 0.15	98.38 ± 0.09	99.13 ± 0.35	98.44 ± 0.17	99.61 ± 0.39
5	95.41 ± 0.19	97.50 ± 0.41	98.98 ± 0.03	98.70 ± 0.11	99.11 ± 0.38	99.72 ± 0.30	99.10 ± 0.12
6	98.37 ± 0.25	93.58 ± 1.88	97.02 ± 0.09	97.79 ± 0.19	99.20 ± 0.09	99.30 ± 0.14	99.77 ± 0.27
7	99.23 ± 0.17	95.68 ± 3.37	99.50 ± 0.49	99.54 ± 0.30	98.95 ± 0.67	98.38 ± 0.07	99.28 ± 0.17
8	97.24 ± 0.17	56.51 ± 0.12	99.56 ± 0.64	98.29 ± 0.08	99.61 ± 0.12	96.91 ± 0.17	97.59 ± 0.18
9	98.01 ± 0.04	57.98 ± 0.14	99.80 ± 0.12	98.96 ± 0.09	97.85 ± 0.06	97.57 ± 0.03	98.43 ± 0.07
10	96.97 ± 0.28	98.05 ± 0.35	99.76 ± 0.15	93.04 ± 0.51	98.75 ± 0.36	98.37 ± 0.32	99.12 ± 0.47
11	98.10 ± 0.32	98.47 ± 0.17	99.61 ± 0.12	99.76 ± 0.02	98.24 ± 0.10	97.72 ± 0.36	99.84 ± 0.14
12	96.70 ± 0.16	98.02 ± 0.35	99.65 ± 0.28	99.14 ± 0.10	98.15 ± 0.10	98.24 ± 0.07	99.54 ± 0.07
Average	97.49 ± 0.19	88.80 ± 0.82	99.03 ± 0.19	98.24 ± 0.17	98.71 ± 0.21	98.55 ± 0.17	99.32 ± 0.19

Table 4. Cont.

PSC	GA	SA	SSA	SCA	PSO	HBA	Proposed
Tracking Time (s)							
1	2.02 ± 0.005	4.82 ± 0.012	6.02 ± 0.009	5.86 ± 0.067	3.98 ± 0.071	3.02 ± 0.005	3.50 ± 0.017
2	2.52 ± 0.008	4.41 ± 0.559	5.51 ± 0.017	6.04 ± 0.009	5.84 ± 0.012	5.91 ± 0.017	3.03 ± 0.005
3	2.94 ± 0.041	4.81 ± 0.008	6.01 ± 0.009	6.01 ± 0.005	5.83 ± 0.118	5.91 ± 0.005	3.04 ± 0.008
4	2.52 ± 0.005	4.03 ± 0.563	6.01 ± 0.005	6.01 ± 0.014	6.02 ± 0.005	5.94 ± 0.025	4.17 ± 0.172
5	2.62 ± 0.076	4.83 ± 0.014	6.00 ± 0.012	6.02 ± 0.017	5.72 ± 0.460	5.94 ± 0.005	3.04 ± 0.012
6	2.06 ± 0.033	4.82 ± 0.009	6.01 ± 0.009	6.01 ± 0.005	5.63 ± 0.017	5.94 ± 0.045	3.04 ± 0.001
7	2.04 ± 0.017	4.82 ± 0.017	6.02 ± 0.008	6.03 ± 0.005	5.88 ± 0.193	5.93 ± 0.021	3.16 ± 0.193
8	2.68 ± 0.017	4.83 ± 0.024	6.02 ± 0.001	6.02 ± 0.021	5.94 ± 0.096	5.96 ± 0.042	3.27 ± 0.204
9	2.51 ± 0.400	3.84 ± 0.014	5.85 ± 0.212	6.02 ± 0.012	4.78 ± 0.208	5.97 ± 0.051	3.02 ± 0.001
10	2.82 ± 0.012	4.41 ± 0.536	6.02 ± 0.009	6.01 ± 0.009	5.91 ± 0.038	5.78 ± 0.193	3.91 ± 0.005
11	2.61 ± 0.008	4.81 ± 0.012	5.35 ± 0.224	6.01 ± 0.001	6.03 ± 0.009	5.92 ± 0.021	3.03 ± 0.016
12	2.54 ± 0.024	3.63 ± 0.137	6.00 ± 0.005	6.02 ± 0.008	3.52 ± 0.008	3.98 ± 1.348	3.02 ± 0.001
Average	2.49 ± 0.054	4.50 ± 0.159	5.90 ± 0.043	6.00 ± 0.014	5.42 ± 0.103	5.52 ± 0.148	3.27 ± 0.053

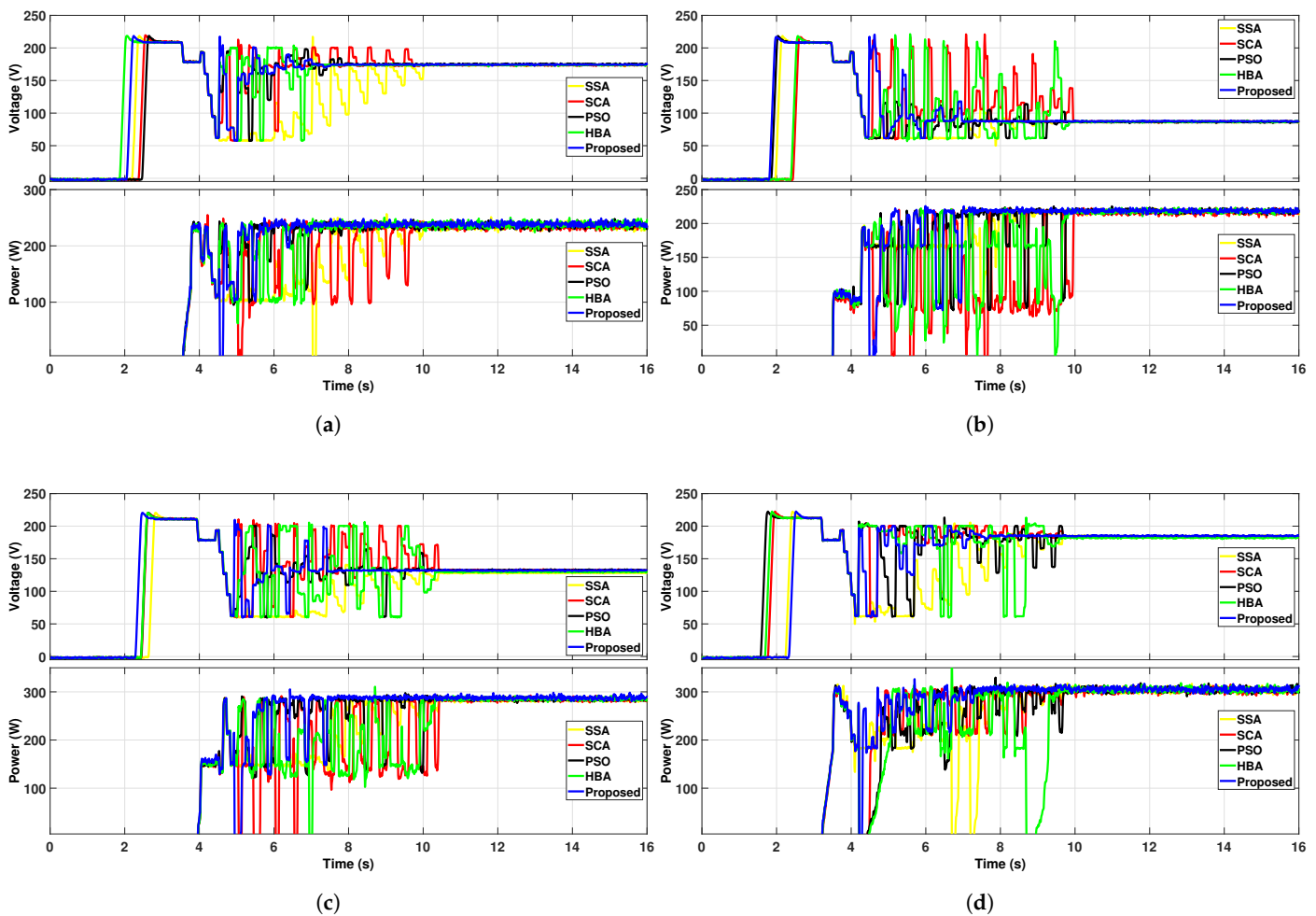


Figure 7. Voltage and power tracking waveforms of SSA, SCA, PSO, HBA, and the proposed method for (a) PSC 1; (b) PSC 2; (c) PSC 3; (d) PSC 4.

3.2. Dynamic Case Result

To evaluate the dynamic tracking abilities of these systems, a PV emulator was utilized to continuously generate P-V curves. This enabled the observation and analysis of power variations resulted from changes in irradiance or temperature. Equation (16) was used to detect if the GMPP had been changed:

$$\left| \frac{P_{PV} - P_{PV,last}}{P_{PV,last}} \right| \geq \Delta P_{PV}, \quad (16)$$

where $P_{PV,last}$ is the power of the previous detection, and ΔP_{PV} was set to 6% of the maximum power.

The efficiency of dynamic tracking was defined as follows:

$$\eta_d = \frac{\sum_i V_{PV,i} \cdot I_{PV,i} \cdot \Delta T_i}{\sum_j GMPP_j \cdot \Delta T_j}, \quad (17)$$

where ΔT_i represents the duration during which $V_{PV,i}$ and $I_{PV,i}$ are tested, and ΔT_j is the time frame when the $GMPP_j$ is provided.

The experiment for the dynamic case consisted of four cases. The results are shown in Table 5 and Figure 8a–d. The dynamic case is described as follows:

1. First case: The results for dynamic case 1 are displayed in Figure 8a. In this scenario, the MPPT algorithms were tested using three P-V curves: PSC 5 transitioning to PSC 9 and then back to PSC 1. The proposed method achieved an accuracy of 94.52%, while PSO achieved 96.88%, SSA reached 88.81%, HBA obtained 94.88%, and SCA concluded with an accuracy of 94.01%.
2. Second case: In this case, the MPPT algorithms were tested on PSC 6 then moved to PSC 2 and back to PSC 10. In Figure 8b are the waveforms for the voltage and power for PSO, SCA, SSA, HBA, and the proposed method. The proposed method demonstrated the highest accuracy among all other algorithms, reaching 97.14%. The PSO algorithm scored 93.6%, the SCA algorithm scored 93.6%, the HBA algorithm scored 90.07%, and the SSA algorithm scored 85.43%.
3. Third case: The performance of MPPT algorithms was tested by applying three P-V curves that transitioned from PSC 3 to PSC 7 to PSC 11. The power and voltage waveforms results are shown in Figure 8c. During this test, the proposed method achieved the best result with an accuracy of 94.8%, while other methods such as PSO achieved an accuracy of 93.88%, HBA achieved 87.71%, SCA achieved 87.19%, and SSA achieved 90.68%.
4. Fourth case: The results for case 4 are shown in Figure 8d. The MPPT algorithms were tested from PSC 8 to PSC 12 to PSC 4. The proposed algorithm attained the highest accuracy of 97.82%. Other algorithms such as PSO attained 97.37%, SCA attained 93.11%, HBA attained 92.38%, and SSA attained 89.33%.

Table 5. Tracking accuracy result dynamic case.

Case	PSC	SSA	SCA	PSO	HBA	Proposed
Tracking Accuracy (%)						
1	5-9-1	88.81 ± 0.04	94.01 ± 0.76	96.88 ± 0.15	94.88 ± 0.45	94.52 ± 0.17
2	6-2-10	85.43 ± 0.13	93.30 ± 0.25	93.60 ± 0.99	90.07 ± 0.51	97.14 ± 0.34
3	3-7-11	90.68 ± 0.01	87.19 ± 0.19	93.88 ± 0.01	87.71 ± 0.16	94.80 ± 0.13
4	8-12-4	89.33 ± 0.43	93.11 ± 0.51	97.38 ± 0.02	92.38 ± 0.37	97.82 ± 0.57
Average		88.56 ± 0.15	91.90 ± 0.43	95.44 ± 0.29	91.26 ± 0.37	96.07 ± 0.31

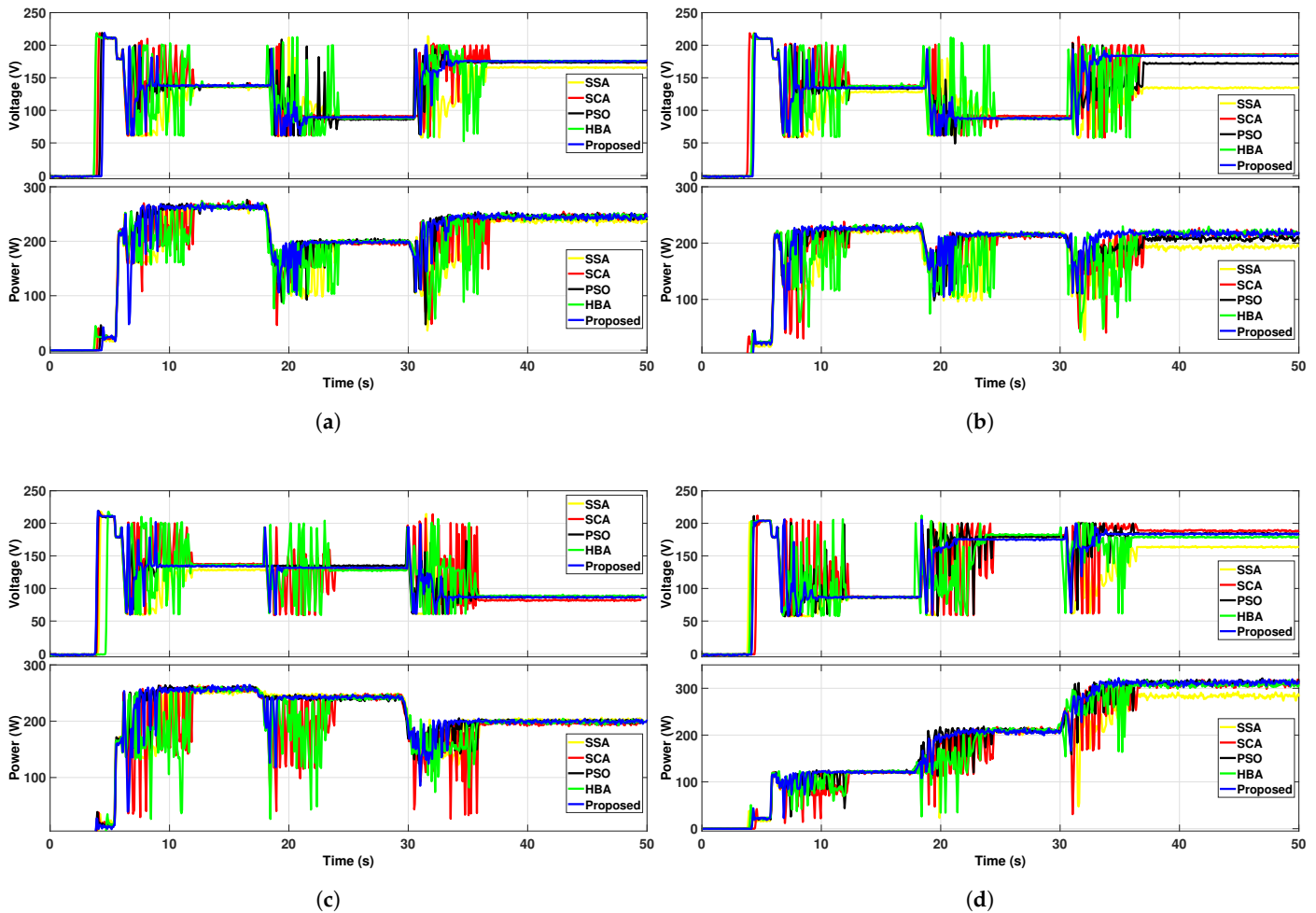


Figure 8. Voltage and power tracking waveforms of SSA, SCA, PSO, HBA, and the proposed method for (a) case 1; (b) case 2; (c) case 3; (d) case 4.

The findings from Sections 3.1 and 3.2 demonstrate that the proposed method generally outperforms algorithms such as PSO, SCA, and SSA for several key reasons:

1. **Enhanced exploration and exploitation:** The proposed method capitalizes on the strengths of the HBA by effectively balancing exploration and exploitation. During the “digging phase”, the algorithm explores the solution space broadly, allowing it to investigate various potential areas thoroughly. In the “honey phase”, the algorithm focuses on exploiting promising regions identified during the digging phase, refining the search and homing in on the most optimal solutions. This dual-phase strategy ensures that the algorithm does not prematurely converge to suboptimal solutions and instead explores a wide range of possibilities before intensifying its focus on the most promising areas.
2. **Integration of GA for accelerated convergence:** By integrating the GA into the HBA, the proposed method significantly enhances the convergence speed during the “digging phase”. In GA, the reproduction process involves both crossover and selection mechanisms that operate based on the fitness of new individuals. Crossover combines information from two parent solutions to produce offspring, introducing new genetic material and promoting diversity in the solution pool. Selection ensures that the fittest individuals have a higher chance of passing on their genes to the next generation. This combination results in a more efficient search process, as it allows the algorithm to maintain diversity while also homing in on high-quality solutions.
3. **Avoidance of local optima and increased accuracy:** Incorporating the GA’s mutation mechanism during the exploration phase allows the proposed method to avoid getting

trapped in local optima. The mutation introduces random changes to individual solutions, providing the algorithm with the ability to escape local optima by exploring new areas of the solution space. This mechanism increases the robustness of the search process and helps maintain genetic diversity, which is crucial for finding global optima.

4. Conclusions

This paper employed a GA to enhance the HBA for MPPT in PV systems. The addition of the mutation mechanism to the HBA increased the probability of escaping from LMPPs. Furthermore, the incorporation of crossover and selection mechanisms reduced the tracking time, making the process more efficient. The proposed method outperformed other algorithms such as SSA, SCA, PSO, and HBA. When compared with the HBA, the proposed method achieved a 40% improvement in tracking time and 0.77% in accuracy. When compared to a GA, the proposed method achieved a 1.83% improvement in accuracy. In the dynamic case, the proposed method achieved 4.81%, 0.63%, 4.17%, and 7.51% of improvement compared to HBA, PSO, SCA, and SSA, respectively. Since an ANN is also a very powerful method for MPPT, comparing the ANN with MHA methods in a detailed manner is a valuable direction for future study.

Author Contributions: The study was conducted successfully with the involvement of all the authors. K.-L.L. provided the primary research concept, case studies, and experimental setup design. Z.-K.F. contributed to the execution of simulations and experiments and the analysis of the resulting data. A.S. took part in the implementation of the experiment and simulations. S.S. provided advice and feedback regarding this work. K.-L.L., Z.-K.F., A.S. and S.S. were mainly involved in preparing the manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported in part by the National Science and Technology Council, Taiwan, under Grant NSTC 113-2221-E-011-081, and in part by the Taiwan Building Technology Center from the Featured Areas Research Center Program within the framework of the Higher Education Sprout Project by the Ministry of Education in Taiwan.

Data Availability Statement: Data are contained within the article.

Acknowledgments: The author would like to sincerely thank the editor and anonymous reviewers for their valuable comments and suggestions, improving the quality of the article.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Wu, Z.; Hu, Y.; Wen, J.X.; Zhou, F.; Ye, X. A Review for Solar Panel Fire Accident Prevention in Large-Scale PV Applications. *IEEE Access* **2020**, *8*, 132466–132480. [\[CrossRef\]](#)
2. Raiker, G.A.; Loganathan, U.; Reddy B.S. Current Control of Boost Converter for PV Interface With Momentum-Based Perturb and Observe MPPT. *IEEE Trans. Ind. Appl.* **2021**, *57*, 4071–4079. [\[CrossRef\]](#)
3. Jabbar, R.I.; Mekhilef, S.; Mubin, M.; Mohammed, K.K. A Modified Perturb and Observe MPPT for a Fast and Accurate Tracking of MPP Under Varying Weather Conditions. *IEEE Access* **2023**, *11*, 76166–76176. [\[CrossRef\]](#)
4. Nezam, A.M.; Mahmood, M.K.; Karim, S.M.; Addawe, A. Evaluation of Incremental Conductance MPPT Algorithm Under Varying Conditions. In Proceedings of the 2024 21st International Multi-Conference on Systems, Signals & Devices (SSD), Virtual, 22–25 April 2024; pp. 98–103. [\[CrossRef\]](#)
5. Gupta, A.K.; Pachauri, R.K.; Maity, T.; Chauhan, Y.K.; Mahela, O.P.; Khan, B.; Gupta, P.K. Effect of Various Incremental Conductance MPPT Methods on the Charging of Battery Load Feed by Solar Panel. *IEEE Access* **2021**, *9*, 90977–90988. [\[CrossRef\]](#)
6. Afzal, I.; Zhang, C.; Wang, J. Maximum Power Point Tracking Utilizing Golden Section Optimization for Photovoltaic Systems. In Proceedings of the 2021 IEEE 2nd China International Youth Conference on Electrical Engineering (CIYCEE), Chengdu, China, 15–17 December 2021; pp. 1–6. [\[CrossRef\]](#)
7. Ye, S.P.; Liu, Y.H.; Pai, H.Y.; Sangwongwanich, A.; Blaabjerg, F. A Novel ANN-Based GMPPT Method for PV Systems Under Complex Partial Shading Conditions. *IEEE Trans. Sustain. Energy* **2024**, *15*, 328–338. [\[CrossRef\]](#)
8. Allahabadi, S.; Iman-Eini, H.; Farhangi, S. Fast Artificial Neural Network Based Method for Estimation of the Global Maximum Power Point in Photovoltaic Systems. *IEEE Trans. Ind. Electron.* **2022**, *69*, 5879–5888. [\[CrossRef\]](#)
9. Alhusseini, H.; Niroomand, M.; Mirzaei Dehkordi, B. A Fuzzy-Based Adaptive P&O MPPT Algorithm for PV Systems With Fast Tracking and Low Oscillations Under Rapidly Irradiance Change Conditions. *IEEE Access* **2024**, *12*, 84374–84386. [\[CrossRef\]](#)

10. Dehghani, M.; Taghipour, M.; Gharehpetian, G.B.; Abedi, M. Optimized Fuzzy Controller for MPPT of Grid-connected PV Systems in Rapidly Changing Atmospheric Conditions. *J. Mod. Power Syst. Clean Energy* **2021**, *9*, 376–383. [\[CrossRef\]](#)
11. Xia, K.; Li, Y.; Zhu, B. Improved Photovoltaic MPPT Algorithm Based on Ant Colony Optimization and Fuzzy Logic Under Conditions of Partial Shading. *IEEE Access* **2024**, *12*, 44817–44825. [\[CrossRef\]](#)
12. Jalali Zand, S.; Mobayen, S.; Gul, H.Z.; Molashahi, H.; Nasiri, M.; Fekih, A. Optimized Fuzzy Controller Based on Cuckoo Optimization Algorithm for Maximum Power-Point Tracking of Photovoltaic Systems. *IEEE Access* **2022**, *10*, 71699–71716. [\[CrossRef\]](#)
13. Shehu, M.M.; Dong, M.; Hu, J. Optimization of Particle Swarm based MPPT under Partial Shading Conditions in Photovoltaic Systems. In Proceedings of the 2021 IEEE 16th Conference on Industrial Electronics and Applications (ICIEA), Chengdu, China, 1–4 August 2021; pp. 267–272. [\[CrossRef\]](#)
14. Singh, N.; Gupta, K.K.; Jain, S.K.; Dewangan, N.K.; Bhatnagar, P. A Flying Squirrel Search Optimization for MPPT Under Partial Shaded Photovoltaic System. *IEEE J. Emerg. Sel. Top. Power Electron.* **2021**, *9*, 4963–4978. [\[CrossRef\]](#)
15. Khan, Z.A.; Akhter, S.F.; Islam, S.; Abid, F. A Golden Eagle Optimization Based MPPT Control For Partial Shading Conditions. In Proceedings of the 2022 IEEE International Conference on Power Electronics, Smart Grid, and Renewable Energy (PESGRE), Trivandrum, India, 2–5 January 2022; pp. 1–6. [\[CrossRef\]](#)
16. Pervez, I.; Shams, I.; Mekhilef, S.; Sarwar, A.; Tariq, M.; Alamri, B. Most Valuable Player Algorithm based Maximum Power Point Tracking for a Partially Shaded PV Generation System. *IEEE Trans. Sustain. Energy* **2021**, *12*, 1876–1890. [\[CrossRef\]](#)
17. Alshareef, M.J. An Effective Falcon Optimization Algorithm Based MPPT Under Partial Shaded Photovoltaic Systems. *IEEE Access* **2022**, *10*, 131345–131360. [\[CrossRef\]](#)
18. Teshome, D.F.; Lee, C.H.; Lin, Y.W.; Lian, K.L. A Modified Firefly Algorithm for Photovoltaic Maximum Power Point Tracking Control Under Partial Shading. *IEEE J. Emerg. Sel. Top. Power Electron.* **2017**, *5*, 661–671. [\[CrossRef\]](#)
19. Millah, I.S.; Chang, P.C.; Teshome, D.F.; Subroto, R.K.; Lian, K.L.; Lin, J.F. An Enhanced Grey Wolf Optimization Algorithm for Photovoltaic Maximum Power Point Tracking Control Under Partial Shading Conditions. *IEEE Open J. Ind. Electron. Soc.* **2022**, *3*, 392–408. [\[CrossRef\]](#)
20. Gundogdu, H.; Demirci, A.; Tercan, S.M.; Cali, U. A Novel Improved Grey Wolf Algorithm Based Global Maximum Power Point Tracker Method Considering Partial Shading. *IEEE Access* **2024**, *12*, 6148–6159. [\[CrossRef\]](#)
21. Li, X.; Youzhuo, Z.; Wei, H.; Shuyi, Z.; Wenqiang, Z.; Haobin, C. Control Strategy for Photovoltaic Array MPPT Based on an Improved Particle Swarm Optimization Algorithm. In Proceedings of the 2024 9th Asia Conference on Power and Electrical Engineering (ACPEE), Shanghai, China, 11–13 April 2024; pp. 2348–2352. [\[CrossRef\]](#)
22. Koh, J.S.; Tan, R.H.G.; Lim, W.H.; Tan, N.M.L. A Modified Particle Swarm Optimization for Efficient Maximum Power Point Tracking Under Partial Shading Condition. *IEEE Trans. Sustain. Energy* **2023**, *14*, 1822–1834. [\[CrossRef\]](#)
23. Mohammed, K.K.; Mekhilef, S.; Buyamin, S. Improved Rat Swarm Optimizer Algorithm-Based MPPT Under Partially Shaded Conditions and Load Variation for PV Systems. *IEEE Trans. Sustain. Energy* **2023**, *14*, 1385–1396. [\[CrossRef\]](#)
24. Sangrody, R.; Taheri, S.; Cretu, A.M.; Pouresmaeil, E. An Improved PSO-Based MPPT Technique Using Stability and Steady State Analyses Under Partial Shading Conditions. *IEEE Trans. Sustain. Energy* **2024**, *15*, 136–145. [\[CrossRef\]](#)
25. Xu, H.; Zhao, M.; Xue, F.; Zhang, X.; Sun, L. An Improved Mayfly Algorithm with Shading Detection for MPPT of Photovoltaic Systems. *IEEE Access* **2023**, *11*, 110827–110836. [\[CrossRef\]](#)
26. Putera, R.D.S.; Efendi, M.Z.; Qudsi, O.A. MPPT Algorithm Based on Modified Human Psychology Optimization for PV System in Partial Shading Conditions. In Proceedings of the 2023 International Electronics Symposium (IES), Denpasar, Indonesia, 8–10 August 2023; pp. 44–51. [\[CrossRef\]](#)
27. Pervez, I.; Antoniadis, C.; Ghazzai, H.; Massoud, Y. A Modified Bat Algorithm with Reduced Search Space Exploration for MPPT under Dynamic Partial Shading Conditions. In Proceedings of the 2023 IEEE International Symposium on Circuits and Systems (ISCAS), Monterey, CA, USA, 21–28 May 2023; pp. 1–5. [\[CrossRef\]](#)
28. Lian, K.L.; Jhang, J.H.; Tian, I.S. A Maximum Power Point Tracking Method Based on Perturb-and-Observe Combined With Particle Swarm Optimization. *IEEE J. Photovoltaics* **2014**, *4*, 626–633. [\[CrossRef\]](#)
29. Nugraha, D.A.; Lian, K.L.; Suwarno. A Novel MPPT Method Based on Cuckoo Search Algorithm and Golden Section Search Algorithm for Partially Shaded PV System. *Can. J. Electr. Comput. Eng.* **2019**, *42*, 173–182. [\[CrossRef\]](#)
30. Liao, C.Y.; Subroto, R.K.; Millah, I.S.; Lian, K.L.; Huang, W.T. An Improved Bat Algorithm for More Efficient and Faster Maximum Power Point Tracking for a Photovoltaic System Under Partial Shading Conditions. *IEEE Access* **2020**, *8*, 96378–96390. [\[CrossRef\]](#)
31. Motamarri, R.; Bhokya, N. JAYA Algorithm Based on Lévy Flight for Global MPPT Under Partial Shading in Photovoltaic System. *IEEE J. Emerg. Sel. Top. Power Electron.* **2021**, *9*, 4979–4991. [\[CrossRef\]](#)
32. Figueiredo, S.; Nayana Alencar Leão e Silva Aquino, R. Hybrid MPPT Technique PSO-P&O Applied to Photovoltaic Systems Under Uniform and Partial Shading Conditions. *IEEE Lat. Am. Trans.* **2021**, *19*, 1610–1617. [\[CrossRef\]](#)
33. Lyden, S.; Galligan, H.; Haque, M.E. A Hybrid Simulated Annealing and Perturb and Observe Maximum Power Point Tracking Method. *IEEE Syst. J.* **2021**, *15*, 4325–4333. [\[CrossRef\]](#)
34. Hashim, F.A.; Houssein, E.H.; Hussain, K.; Mabrouk, M.S.; Al-Atabany, W. Honey Badger Algorithm: New metaheuristic algorithm for solving optimization problems. *Math. Comput. Simul.* **2022**, *192*, 84–110. : 10.1016/j.matcom.2021.08.013 [\[CrossRef\]](#)
35. Goldberg, D. *Genetic Algorithms in Search, Optimization, and Machine Learning*; Addison Wesley series in artificial intelligence; Addison-Wesley: Boston, MA, USA, 1989.

36. Daraban, S.; Petreus, D.; Morel, C. A novel global MPPT based on genetic algorithms for photovoltaic systems under the influence of partial shading. In Proceedings of the IECON 2013-39th Annual Conference of the IEEE Industrial Electronics Society, Vienna, Austria, 10–13 November 2013; pp. 1490–1495. [[CrossRef](#)]
37. Kumar, P.; Jain, G.; Palwalia, D.K. Genetic algorithm based maximum power tracking in solar power generation. In Proceedings of the 2015 International Conference on Power and Advanced Control Engineering (ICPACE), Bengaluru, India, 12–14 August 2015; pp. 1–6. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.