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Revolutionizing Photovoltaic Systems: An Innovative Approach to Maximum Power Point Tracking Using Enhanced Dandelion Optimizer in Partial Shading Conditions

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Abstract: Partial shading (PS) is a prevalent phenomenon that often affects photovoltaic (PV) installations, leads to the appearance of numerous peaks in the power-voltage characteristics of PV cells, caused by the uneven distribution of solar irradiance on the PV module surface, known as global and local maximum power point (GMPP and LMPP). In this paper, a new technique for achieving GMPP based on the dandelion optimizer (DO) algorithm is proposed, inspired by the movement of dandelion seeds in the wind. The proposed technique aimed to enhance the efficiency of power generation in PV systems, particularly under PS conditions. However, the DO-based MPPT is compared with other advanced maximum power point tracker (MPPT) algorithms, such as Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO), Artificial Bee Colony (ABC), Cuckoo Search Algorithm (CSA), and Bat Algorithm (BA). Simulation results establish the superiority and effectiveness of the used MPPT in terms of tracking efficiency, speed, robustness, and simplicity of implementation. Additionally, these results reveal that the DO algorithm exhibits higher performance, with a root mean square error (RMSE) of 1.09 watts, a convergence time of 2.3 milliseconds, and mean absolute error (MAE) of 0.13 watts.

Keywords: maximum power point tracker (MPPT); photovoltaic; partial shading conditions (PSCs); dandelion optimizer; optimization

Citation: Halassa, E.; Mazouz, L.; Seghiour, A.; Chouder, A.; Silvestre, S. Revolutionizing Photovoltaic Systems: An Innovative Approach to Maximum Power Point Tracking Using Enhanced Dandelion Optimizer in Partial Shading Conditions. *Energies* **2023**, *16*, 3617. https://doi.org/10.3390/en16093617

Academic Editor: Enrique Romero-Cadaval

Received: 24 March 2023
Revised: 11 April 2023
Accepted: 20 April 2023
Published: 22 April 2023

1. Introduction

The growing population has led to a higher demand for electricity, as it has become a crucial aspect of modern life, and a blackout could cause serious disruptions and losses. With the world's economy and social life recovering, especially post-pandemic, increasing electricity generation capacity is imperative to meet these demands. However, traditional electricity generation methods such as using coal, gas, and fossil fuels have a harmful effect on the environment. As per the International Energy Agency (IEA), the global power sector's CO_2 emissions rose to nearly 700 million tons in 2021, surpassing the previous record by over 14 Gt. The United Nations (UN) views electricity generation as a major contributor to global climate change, with fossil fuels still accounting for over 80% of global energy production [1].

The degradation of PV modules can negatively impact MPP tracking, particularly in regions with low humidity. Over time, the performance parameters of PV modules, such as efficiency, current, and series resistance, may change due to degradation, which could necessitate adjustments to MPP tracking algorithms. When a PV module experiences a decline in efficiency, the MPP tracking algorithm might need to be modified to optimize power generation in light of the reduced output power. Similarly, if the series resistance of the PV module increases as a result of degradation, the MPP tracking algorithm might need to account for this change in impedance and be adjusted accordingly to ensure accurate MPP tracking. In general, the degradation of PV modules can affect the precision and efficacy of MPP tracking algorithms. As such, PV system designers and operators should keep this in mind when implementing MPP tracking algorithms in regions with low humidity. Appropriate updates or adjustments may be necessary to ensure optimal power generation from the PV system [2,3].

Solar power is the most widely popular renewable source because it is clean, accessible, and freely available. However, solar PV systems have limitations, with their output dependent on climate conditions and affected by non-linear characteristics of current–voltage and power–voltage [4]. To overcome these limitations, an effective MPPT is required to retrieve the utmost power from PV systems and ensure they operate at optimal levels under different conditions. The MPPT must operate with speed and efficiency to maintain stability in the PV system, particularly through rapidly changing shading situations. In order to maintain a steady output voltage for the photovoltaic (PV) system, a DC–DC converter is necessary to control the maximum power point (MPP) through adjusting its duty cycle [5]. Figure 1 demonstrates the positioning of a boost converter between the PV array and the load within the MPPT, and various algorithms can be utilized to adjust its duty cycle, which form the basis of the MPPT controller and are often implemented using a microcontroller.

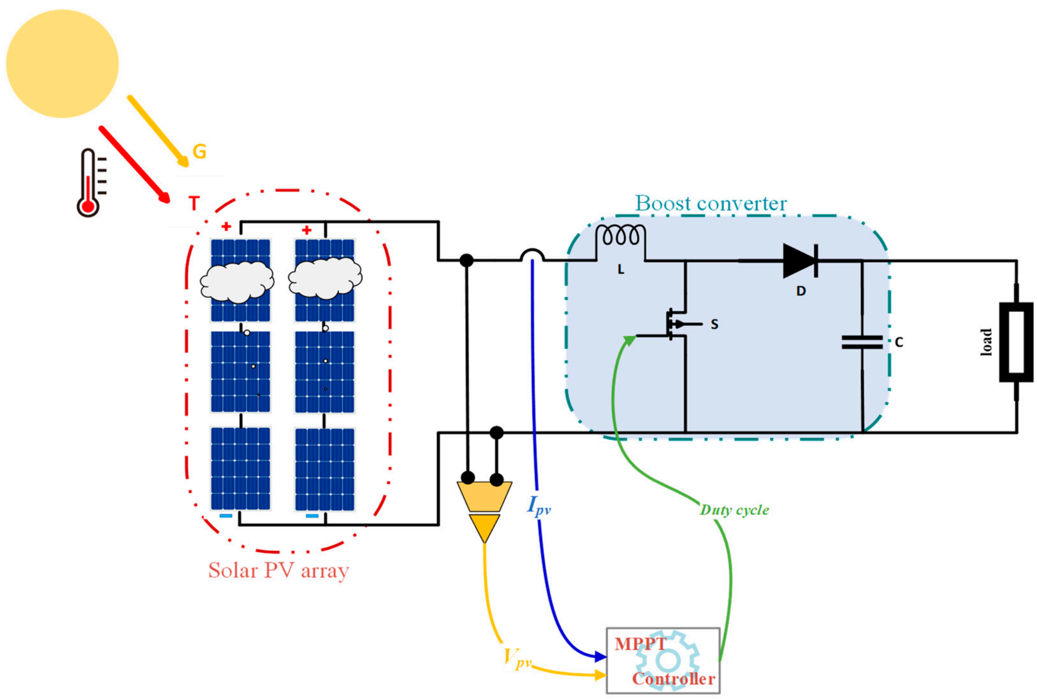


Figure 1. Illustration of PV System with Boost Converter for MPPT.

However, traditional MPPT techniques, such as Perturb and Observe (P&O) and Incremental Conductance (IC), fail to track the GMPP, as they are unable to distinguish between the LMPP and GMPP. This can lead to being stuck at one of the LMPPs and greatly reducing the energy generated by the system. To overcome this problem effectively, various computational intelligence techniques have been suggested by many authors to address these limitations and track the MPP regardless of weather conditions. The optimization algorithms possess several valuable features, including the capability to efficiently solve non-linear optimization problems with low failure rates, fast convergence times, and minimal oscillations, covering a broad range of research [6]. These attributes are highly desirable for researchers who intend to monitor the GMPP across diverse weather conditions. The first feature is crucial in avoiding the algorithm becoming fixed at a local peak, thus minimizing the loss of production power from the PV system. The second attribute ensures stability in the PV system, particularly during online optimization with substantial dynamic changes in PSCs. The last feature ensures the attainment of the GMPP. Metaheuristic techniques constitute a set of algorithms used to address optimization problems. These algorithms are influenced by natural phenomena such as evolution, migration, and swarm behavior and are employed when traditional optimization methods are either infeasible or too slow. With several beneficial characteristics, including the ability to effectively solve non-linear optimization problems with low failure rates, quick convergence times, and minimal oscillation, they have gained popularity among researchers seeking to track the GMPP under any weather conditions. The first advantage of these techniques prevents the algorithm from becoming stuck at a local peak, thereby avoiding significant losses in the output power of the PV system. The second characteristic helps maintain the stability of the PV system during online optimization with changing PSCs.

In the field of MPPT, numerous optimization algorithms have been developed, including HOA [1], PSO [7], GWO [8], ABC [9], Cuckoo Search Optimization (CSO) [10], Group Teaching Optimization (GTO) [11], Harris Hawk Optimization (HHO) [12], Grasshopper Optimization (GHO) [13], Bat Algorithm (BA) [14], Improved Team Game Optimization (TGO) [10], Ant Colony Optimization (ACO) [11], Modified Butterfly Optimization (MBO) [15], Henry Gas Solubility Optimization (HGSO) [16], and Pattern Search (PS) [17]. Most of these algorithms are based on updating the position of the agent based on its location, making them less susceptible to high oscillation and weak convergence [1,18]. However, the main difference between these algorithms lies in the use of various strategies in the initial and final steps of optimization to enhance exploration and exploitation, respectively [6]. The PSO algorithm is based on the social behavior of bird flocks and fish schools. It utilizes a group of particles that navigate the search space to find the optimal solution. Each particle's movement, consisting of its position and speed, is impacted by its personal best solution, and the best solution found by the entire swarm [19]. The PSO algorithm targets the solution space, where each location signifies a particular level of problem-solving potential [20]. To determine the best solution, it guides particles throughout the solution space, with each particle relying on its understanding of nearby particles [21]. The particle position is defined by the duty cycle value of the DC–DC converter, with the generated power serving as the fitness value evaluation function.

The ABC algorithm is a metaheuristic optimization method inspired by the foraging behavior of honeybee swarms [22]. This algorithm integrates local search techniques performed by employed bees with global search techniques carried out by onlookers and scouts to strike a balance between exploration and exploitation. The GWO algorithm is based on the hunting behavior of a grey wolf pack. The pack consists of Alpha, Beta, Delta, and Omega wolves with a strict hierarchical structure. Alpha wolves are the leaders, Beta wolves provide support, Delta wolves follow instructions, and Omega wolves occupy the lowest rank and may be used as scapegoats [23]. The MPPT-based GWO approach optimizes the power output of photovoltaic systems by combining the strengths of the GWO algorithm and the MPPT technique. MPPT-based PSO is a popular optimization method in photovoltaic systems. Despite its widespread use, it is not without limitations. One of its major drawbacks is the slow convergence time, which can occur when particles move at a low speed, leading to longer optimization times and reduced efficiency of the system. Another issue is the tendency for the algorithm to diverge when particles move too quickly, resulting in suboptimal solutions [15]. A significant issue with the ABC algorithm is its failure to distinguish between uniform and partial shading conditions, as the same termination criteria are used for both. Consequently, uniform shading conditions may lead to a slower convergence time, as the controller must undergo repeated iterations to establish the steady-state duty cycle, just as in complex partial shading conditions [15]. In one study, a proposed enhanced CS algorithm is recommended as the MPPT approach for PV systems under dynamic partial shading. The research found that the improved CS strategy outperforms other swarm optimization techniques, addressing the problem of local peaks and improving the performance of the CS algorithm. Otherwise, the paper [10] mentions that optimization techniques, in general, can suffer from long convergence times. The authors of [14] propose using bat-based optimization techniques for MPPTs in PV systems and compare the performance of these techniques, including Bat-P&O, Bat-Beta, and Bat-IC, to traditional algorithms. The paper also suggests combining bat-based algorithms with traditional algorithms to reduce power oscillations and improve system performance.

The latter metaheuristic optimization algorithms have been widely used due to their ability to handle complex and non-linear systems. The dandelion algorithm is an innovative optimization method inspired by the sowing behavior of dandelions. Specifically, it incorporates self-learning capability and dynamic radius adjustment to efficiently explore the solution space and optimize extreme learning machines (ELM). Notably, the algorithm has exhibited superior performance compared to other optimization algorithms in terms of convergence speed and accuracy [24]. Further, in one study, the DA is applied to optimize extreme learning machines (ELM) for biomedical classification problems, resulting in significant enhancements in classification accuracy. Moreover, the study delves into exploring different fusion methods to generate fusion classifiers with superior accuracy and stability [25]. The authors in [26] postulate using DO to identify the Proton Exchange Membrane Fuel Cells (PEMFC) model parameters with precision, overcoming the pitfalls of metaheuristic algorithms. The study appraises the DO approach under steady-state and dynamic conditions and gauges its efficacy against other techniques, evincing a promising yield and superior performance. To improve the DO algorithm's exploration ability and prevent it from falling into local optima, ref. [27] proposes a novel competition mechanism that incorporates historical information feedback. The fitness value of each dandelion in the next generation is compared with the current best dandelion, and the weaker dandelion is replaced by a new offspring. This approach improves the offspring generation process by utilizing an estimation-of-distribution algorithm to exploit historical information. Three historical information models are designed: the best, worst, and hybrid historical information feedback models. The authors in [28] have presented a novel approach, the dandelion code, as an alternative to the widely used Pruumlfer code for finding optimal spanning trees. While the Pruumlfer code has been criticized for its low locality, the dandelion code exhibits higher efficiency and greater locality. Although direct encoding and NetKeys currently outperform the dandelion code in test problems, the proposed method is still a strong alternative, particularly for larger networks.

Reference [29] introduces a new swarm intelligence bioinspired optimization algorithm named DO to tackle continuous optimization problems. The DO algorithm is inspired by the flight patterns of dandelion seeds carried by the wind, which are modeled into three stages: rising, descending, and landing. The DO algorithm employs Brownian motion and a Levy random walk to simulate the flying trajectory of a seed during the descending stage and landing stage. The DO algorithm can be used as an MPPT method in photovoltaic systems. It is capable of effectively balancing the trade-offs between tracking speed, accuracy, and convergence. By simulating the process of dandelion seed long-distance flight relying on wind, the DO algorithm can optimize the efficiency and performance of solar PV systems. In the rising stage, the seeds rise in a spiral manner due to the eddies from above or drift locally in communities according to different weather conditions. In the descending stage, flying seeds steadily descend by constantly adjusting their direction in global space. In the landing stage, seeds land in randomly selected positions so that they grow. The moving trajectory of a seed in the descending stage and landing stage is described by Brownian motion and a Levy random walk.

Although widely used, some optimization algorithms have limitations in tracking MPP for PV systems, as previously mentioned. DO is a promising solution, inspired by the dispersal mechanism of dandelion plants. Its unique features make it a strong candidate for MPPT algorithms in photovoltaic systems. A comprehensive evaluation of

DO's performance is provided in Table 1, in comparison to existing optimization algorithms. This article aims to thoroughly investigate the potential of DO for MPPTs in photovoltaic systems. This paper focuses on the following key contributions:

- This work introduces a novel optimization algorithm referred to as DO, which is designed to determine the GMPP of the Algerian PV system. The DO algorithm employs advanced mathematical techniques to search for and locate the optimal operating point of the system, thereby ensuring the system operates at its highest possible efficiency.
- The paper presents a comprehensive comparison between the newly proposed DO optimization algorithm and five established benchmark optimization algorithms, namely, PSO, ABC, GWO, CSA, and BA, utilizing a simulation model for a photovoltaic (PV) system with maximum power point tracking (MPPT). The comparative analysis evaluates the algorithms' performance based on various performance metrics, including convergence speed, accuracy, and robustness. The results of the analysis demonstrate the superior performance of the DO algorithm over the benchmark algorithms, indicating its potential for effective optimization of PV systems with MPPT.
- A dataset is utilized consisting of records collected over a two-day period of uniform irradiance and complex PS. These databases are employed in a co-simulation paradigm, leveraging MATLAB-PSIM software, to undertake dynamic validation of the proposed approach. Such an approach enables the investigation of the system's behavior over time, considering the impact of changing environmental conditions, and facilitates the assessment of model robustness and accuracy. By integrating the databases with the simulation software, the approach provides a comprehensive platform for testing and validating the proposed methodology, thereby enabling its effective implementation in real-world applications.

Table 1. Comparison study between metaheuristic algorithms' MPPT techniques.

Methods	Reference	Year	Convergence Speed	Tracking Efficiency	Implementation Complexity	Oscillation
GWO	[8]	2016	Low	High	High	Medium
ACO	[30]	2017	Medium	Medium	Medium	Low
PSO	[7]	2018	High	High	High	Low
BA	[31]	2020	Medium	High	High	Medium
GHO	[13]	2020	High	High	High	Low
CS	[10]	2021	Low	Low	Medium	Low
ABC	[9]	2021	High	High	High	Low
DO	Proposed		Very High	Very High	Medium	Very Low

The structure of the rest of this paper is as follows: The modeling of the photovoltaic cell is outlined in Section 2. Section 3 delves into the topic of partial shading's effects and its characteristics. Section 4 provides a thorough explanation of the novel DO algorithm as well as the simulation results. The paper concludes in Section 5.

2. PV System Modelling

2.1. Overview of the PV System

This study examines a 9.54 kW PV system placed at the "Centre de Développement des Energies Renouvelables" (CDER) in Algiers, Algeria. The system comprises 30 photovoltaic modules (Isofoton 106W) arranged in 2 strings of 15 modules each. Both horizontal and plane irradiances are measured using a thermoelectric pyranometer, while the temperature of the PV modules is monitored with a thermocouple (refer to Figure 2). The data acquisition system is used to measure weather conditions such as solar irradiance and temperature, as well as electrical parameters such as voltage, current, and power. The main electrical specifications of the PV modules under Standard Test Conditions (STC) are listed in Table 2. The weather and MPP current and voltage measurements were taken at 1-min intervals.

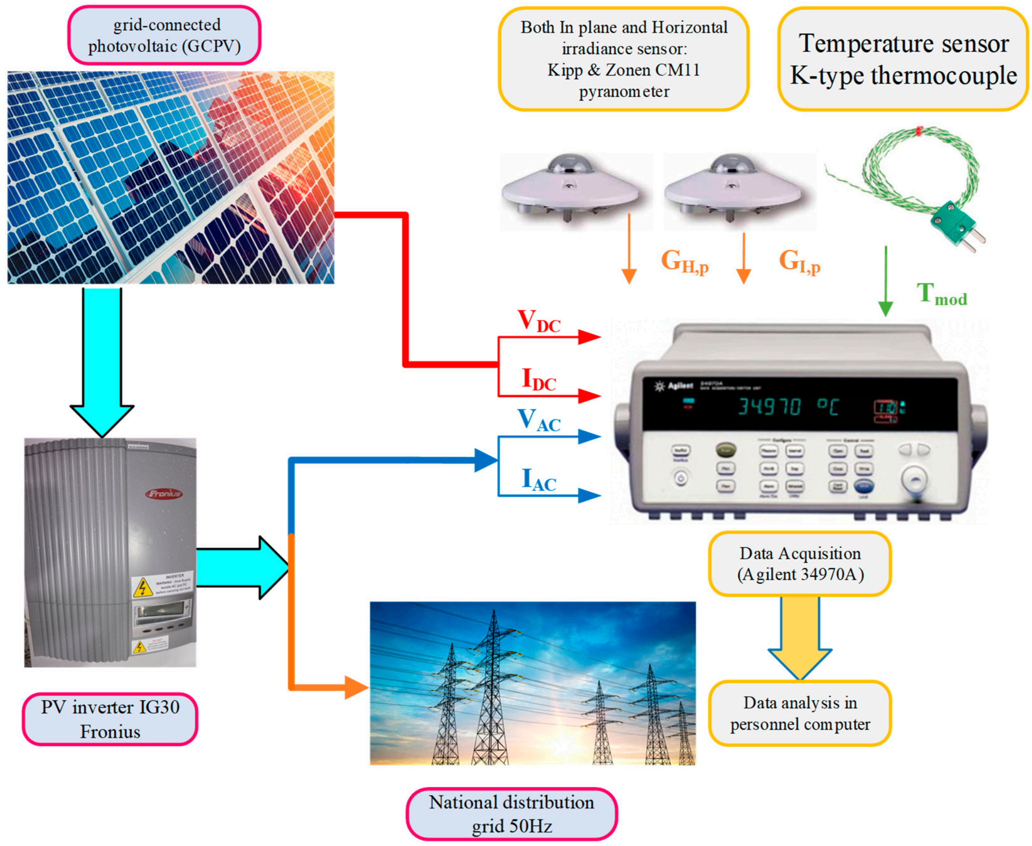


Figure 2. PV study plant and the monitored system.

Table 2. Standard Test Conditions "Isofoton 106-12" parameters.

Parameters	I_{sc} [A]	I_{mpp} [A]	V_{oc} [V]	V_{mpp} [V]	P_{mpp} [W]
Values	6.54	6.4	21.6	17.4	106

2.2. The Modeling of the Photovoltaic Cell

The modeling process requires collecting data to experimentally determine the relationships between the inputs and outputs. The data are then used to develop a mathematical model that describes the cell's behavior. The model's accuracy depends heavily on the quality of the data. Generally, the One-Diode Model (ODM) represents the actual behavior of a PV module (refer to Figure 3). It is presented in an analytical form that establishes a relationship between the PV current (I_{PV}) and PV voltage (V_{PV}) through the following equation [32,33]:

$$I_{PV} = I_{ph} - \overbrace{I_0\left(exp\left(\frac{q(V_{PV} + R_s I_{PV})}{nk_B T_p}\right) - 1\right)}^{I_d} - \overbrace{\frac{V_{PV} + R_s I_{PV}}{R_{sh}}}^{I_{sh}} \quad (1)$$

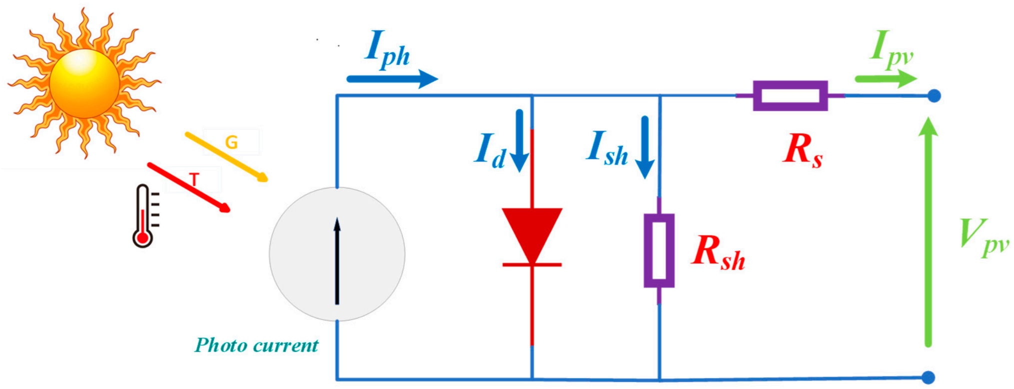


Figure 3. ODM of PV cell.

The optimization algorithm is a powerful tool for extracting the parameters of solar cells. The optimization algorithm works by finding the values of the parameters that minimize the difference between the modeled and experimental data. This is done by adjusting the parameters until the model provides the best fit to the data. There are several optimization algorithms that can be used for parameter extraction in solar cells, which are presented in [26,27]. In this research, the effective parameters of a PV cell are considered to be of great importance. To this end, the effective parameters that were reported in References [25,28] have been selected for use in this study. The reason for this choice is that these parameters have been experimentally validated and found to be highly accurate. The effective parameters of a PV cell play a crucial role in determining its performance, including its power output and conversion efficiency. These parameters describe the internal characteristics of the cell and the way it behaves under different operating conditions. By using accurate and experimentally validated effective parameters, this study aims to ensure that the results obtained are reliable and representative of the actual behavior of the PV cell. The Coyote Optimization Algorithm (COA) identified the best selected parameters, including R_{sh}, R_s, I_{ph}, I_0, and n, which are presented in Table 3 in [32].

Table 3. Isofoton 106W-12V PV module extracted parameters.

Parameter	Estimated Values
I_{ph} [A]	6.44
I_0 [A]	2.5×10^{-5}
N	1.63
R_s [Ω]	0.1403
R_{sh} [Ω]	202.46
RMSE [A]	0.011

3. Partial Shading and Its Effects

The effect of partial shading on the PV module's power–voltage (P–V) curve can be significant. The P–V curve is a graphical representation of the relationship between the module's output power and voltage at different levels of solar irradiance. When the module is not shaded, the P–V curve has a characteristic shape with a single maximum power point (MPP), which represents the optimal operating point of the module.

However, when the module is partially shaded, the P–V curve undergoes changes. The shading can cause multiple MPPs to occur, which can lead to significant power losses. The MPP is no longer a single point but rather a range of points, which makes it challenging to determine the optimal operating point. Additionally, shading can cause some of the shaded cells to become reverse-biased, leading to their degradation and potential hotspots, which can cause permanent damage to the module.

Partial shading in PV systems (see Figure 4) refers to a situation where some portions of a solar panel are obstructed from receiving direct sunlight. This can be caused by a variety of factors, including trees, buildings, or other objects that cast a shadow on the panels. The effects of partial shading can be significant, as it can impact the performance of an entire PV system. When a portion of a panel is shaded, it can diminish the overall power output, as well as the performance of the other panels connected to the same string. The MATLAB-PSIM software was employed in this study to execute multiple shading scenarios, utilizing a reliable model.

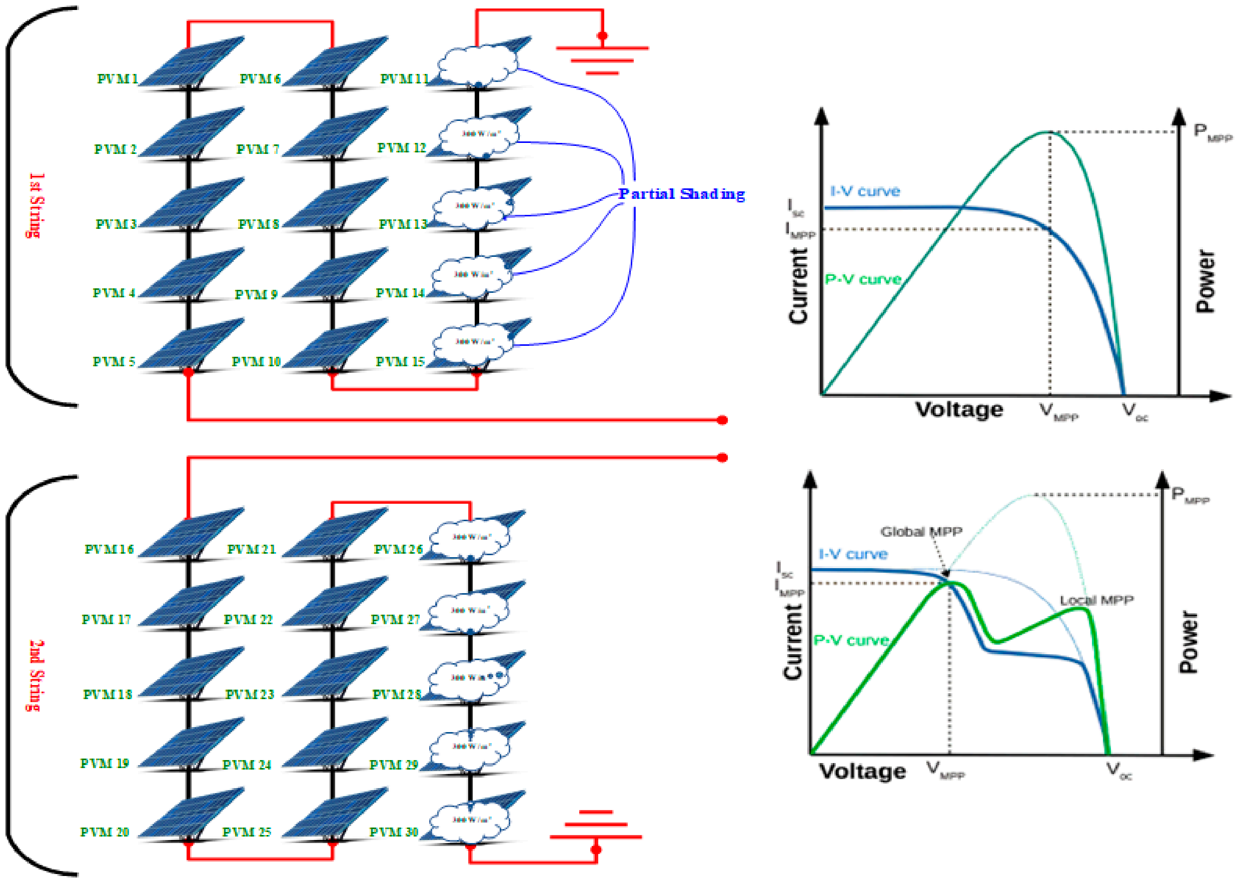


Figure 4. PV study plant under partial shading and its effects on P–V curve.

4. Implementing Dandelion Optimizer Algorithm as MPPT

In 2022, Shijie Zhao introduced a highly effective global optimization algorithm that leverages the mechanism by which dandelion seeds are dispersed over long distances by the wind, as shown in Figure 5, to achieve faster convergence rates on globally smooth problems, surpassing previous methods that only utilized local smoothness of the function. This algorithm demonstrates exceptional results and has been mathematically proven to outperform a pure random search algorithm [29].

The optimization process in dandelion optimization is based on how dandelion seeds spread in the wind, allowing them to colonize new environments and adapt to changing conditions. Similarly, the DO algorithm generates multiple solutions and explores different areas of the solution space using randomness and variability to find the best solution [29].

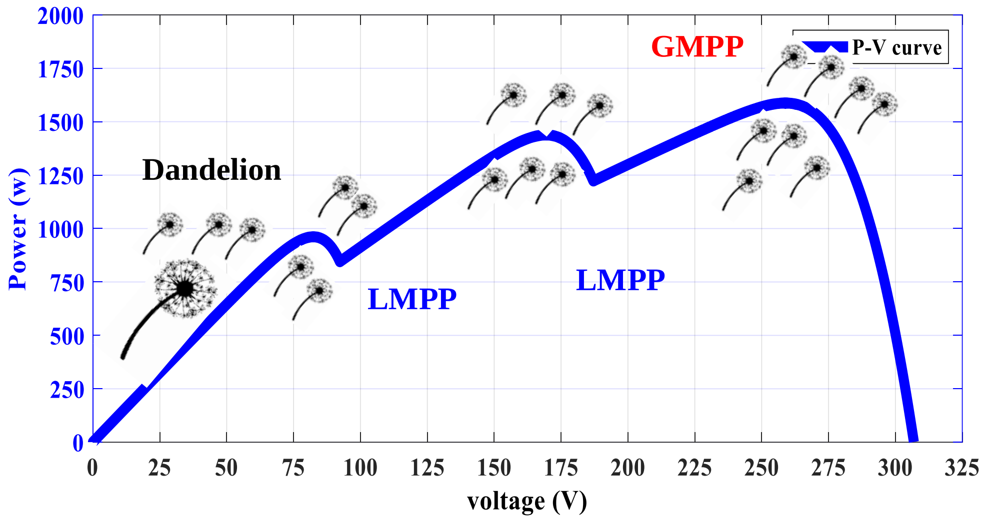


Figure 5. Wind-borne dandelion flowers searching for GMPP.

4.1. Mathematical Model

The DO algorithm repeats the wind and reproduction operators until an ending criterion is met, such as a desired level of fitness or a maximum number of iterations. The algorithm selects the top solution found during the optimization process as the final solution. This subsection specifically discusses the mathematical formulas for DO.

4.1.1. Initialization

Like other nature-inspired metaheuristic algorithms, DO implements population evolution and iterative optimization based on population initialization, i.e., seed generation. In the proposed MPPT-based DO, the algorithm generates multiple solutions that are duty cycles of boost converter (D), which represent potential solutions to our optimization problem, and the population is represented as

$$\text{population} = \begin{bmatrix} D_1 \\ \vdots \\ \vdots \\ D_{pop} \end{bmatrix} \quad (2)$$

where pop represents the population size.

Every potential solution is generated at random between the upper bound (UB) and lower bound (LB), and the expression of the *i*th individual D_i is

$$D_i = \text{rand} \times (UB - LB) + L \quad (3)$$

where rand stands for a random number between 0 and 1, and i is an integer between 1 and pop.

During the initialization stage, DO identifies the participant with the best fitness value as the initial elite, which is considered the most suitable starting point for the dandelion seed to grow and flourish. The mathematical expression of the initial elite (D_{elite}) is then defined as where the function find() refers to two equal-valued indexes.

$$\begin{gathered} f_{best} = \min(fD_i) \\ D_{elite} = D(\text{find}(f_{best} = f(D_i))) \end{gathered} \quad (4)$$

4.1.2. Rising Stage

Dandelion seeds must reach a certain height during the rising stage before they can float away from their parent. Dandelion seeds rise to different heights depending on wind speed, air humidity, and other factors. The weather is divided into two categories in this case.

Case 1: On a clear day, wind speeds can be assumed to have a lognormal distribution. The Y-axis is where random numbers are more distributed in this distribution, increasing the likelihood that dandelion seeds will travel to distant regions, with the goal of exploring new regions of the search space and discovering new potential solutions that are better than the current best solution. The higher the wind, the higher the dandelion flies and the farther the seeds spread. The vortexes above the dandelion seeds are constantly adjusted by the wind speed to cause them to rise in a spiral form. In this case, the corresponding mathematical expression is

$$D_{t+1} = D_t + \alpha \times \upsilon_x \times \upsilon_y \times \ln Y \times (D_s - D_t) \tag{5}$$

where

$$\begin{aligned} \upsilon_x &= r \times \cos\theta \\ \upsilon_y &= r \times \sin\theta \end{aligned} \tag{6}$$

θ is a random number between $[-\pi, \pi]$ and $r = \frac{1}{e^\theta}$.

The position of the dandelion seed during iteration t is represented by D_t; however, D_s is the randomly chosen position in the search space during iteration t. The expression for the randomly generated position is given by Equation (7).

$$D_s = \text{rand}(1,1) \times (UB - LB) + LB \tag{7}$$

$\ln Y$ signifies a lognormal distribution subject to $\mu = 0$ and $\delta^2 = 1$, and its mathematical formula is

$$\ln Y = \begin{cases} \frac{1}{y\sqrt{2\pi}} \exp\left[-\frac{1}{2\delta^2}(\ln y)^2\right] & y \geq 0 \\ 0 & y < 0 \end{cases} \tag{8}$$

y symbolizes the standard normal distribution $N(0, 1)$ in Equation (8). α is an adaptive parameter used to adjust the search step length, and the mathematical expression is

$$\alpha = \text{rand}() \times (\frac{1}{T^2}t^2 - \frac{2}{T}t + 1) \tag{9}$$

Case 2: When it is raining, dandelion seeds are unable to be carried away by the wind due to factors such as air resistance and humidity. This leads to the seeds staying in their local area, which can be represented mathematically by the equation

$$D_{t+1} = D_t \times k \tag{10}$$

where k is used to organize a dandelion's local search domain, which is determined using Equation (11).

$$qd = \frac{1}{T^2 - 2T + 1}t^2 - \frac{2}{T^2 - 2T + 1}t + 1 + \frac{1}{T^2 - 2T + 1} \tag{11}$$

$$k = 1 - \text{rand}() \times qd$$

At the conclusion of each iteration, the value of the parameter k gradually moves closer to 1, ensuring that the population ultimately reaches the optimal search agent. To sum up, the mathematical representation of dandelion seeds in the rising stage is given by the expression

$$D_{t+1} = \begin{cases} D_t + \alpha \times \upsilon_x \times \upsilon_y \times \ln Y \times (D_s - D_t) & \text{randn} < 1.5 \\ D_t \times k & \text{else} \end{cases} \quad (12)$$

where the random number generated by the function randn() follows the normal distribution.

4.1.3. Descending Stage

During this phase, the DO algorithm places a strong emphasis on exploration. The motion of dandelion seeds is modeled in DO using Brownian motion, which simulates their descent after rising to a certain height. This motion allows individuals to easily explore a wider range of search communities during the iteration process, as Brownian motion follows a normal distribution at each step. To reflect the stability of dandelion descent, the DO algorithm utilizes the average position information after the rising stage, which helps guide the overall population towards more promising communities. The mathematical representation for this process is

$$D_{t+1} = D_t - \alpha \times \beta_t \times (D_{mean\_t} - \alpha \times \beta_t \times D_t) \quad (13)$$

where β_t is a random number drawn from the normal distribution and denotes Brownian motion.

The mathematical expression of D_{mean_t}, which stands for the population's average position in the ith iteration, is

$$D_{mean\_t} = \frac{1}{pop} \sum_{i=1}^{pop} D_i \quad (14)$$

4.1.4. Landing Stage

During the exploitation phase of the DO algorithm, the dandelion seed selects its landing spot based on the results of the first two stages. As the iteration process continues, the algorithm aims to reach the global optimal solution. This process is represented by Equation (12).

$$D_{t+1} = D_{elite} + levy(\lambda) \times \alpha \times (D_{elite} - D_t \times \delta) \quad (15)$$

where D_{elite} denotes the dandelion seed's optimal position in the ith iteration. levy(λ) denotes the Levy flight function and is calculated using Equation (16), and σ is a linear increasing function between [0, 2] and is calculated by Equation (17).

$$levy(\lambda) = s \times \frac{\omega \times \sigma}{|t|^{\frac{1}{\beta}}} \quad (16)$$

$$\delta = \frac{2t}{T} \quad (17)$$

A random number between [0, 2] called β is used in Equation (16). In this study, β = 1.5, ω, and t are random numbers between [0, 1], while s is a fixed constant of 0.01. The mathematical expression of σ is

$$\sigma = \left(\frac{\Gamma(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}} \right) \quad (18)$$

A detailed description of the MPPT-based DO is shown in the flowchart Figure 6.

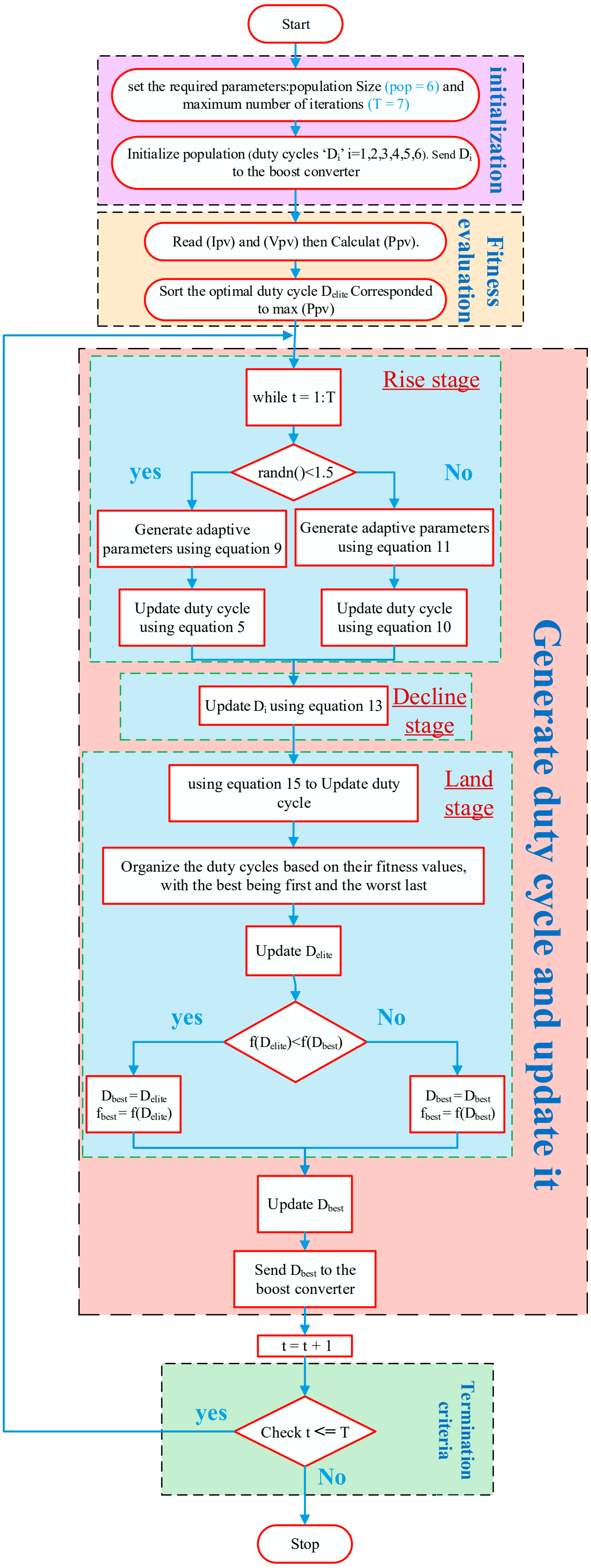


Figure 6. Flowchart of the MPPT-based DO.

4.2. Simulation Results

4.2.1. Ability to Track GMPP

Extensive simulation studies have been conducted to evaluate the performance of the proposed MPPT algorithm. The PV system in Figure 4 has been specifically designed for this purpose, consisting of two series-connected PV modules, a DC–DC boost converter, a DC load, and an MPPT controller. The evaluation has been performed using a co-simulation methodology that combines the Matlab/Simulink and PSIM platforms. The co-simulation enables the assessment of the proposed DO-based MPPT algorithm's feasibility and effectiveness, as well as the comparison of its performance against the PSO, GWO, ABC, BA, and CS algorithms, under stable and dynamic climatic conditions. Table 4 presents the parameters for the optimization algorithms utilized in this study.

The MPPT algorithms have been implemented in a Matlab/Simulink environment, as shown in Figure 7, while the PSIM platform has been utilized to implement the DC–DC boost converter and the PV array as illustrated in Figure 8.

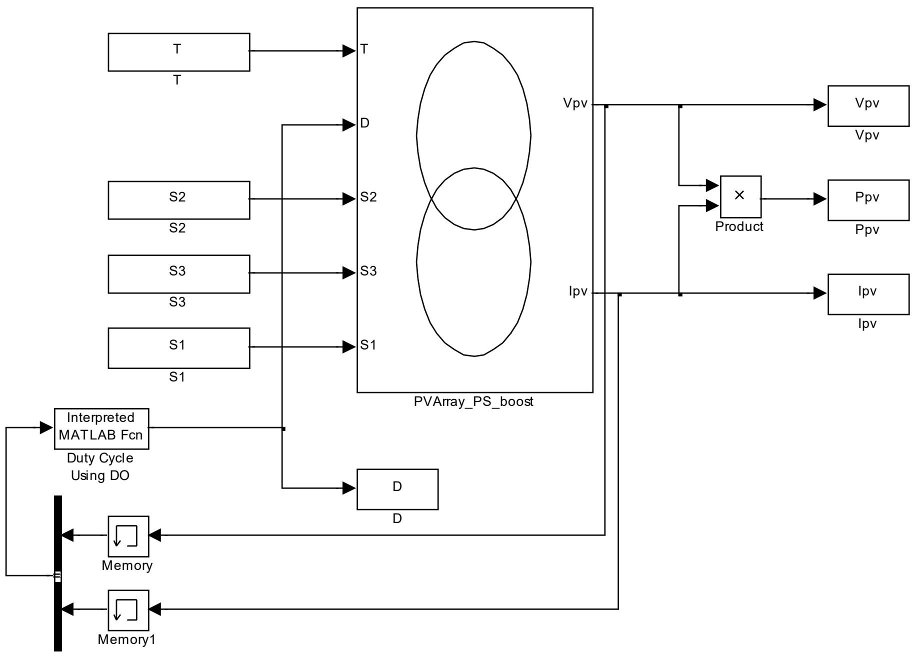


Figure 7. Implemented Matlab/Simulink model for MPPT algorithms.

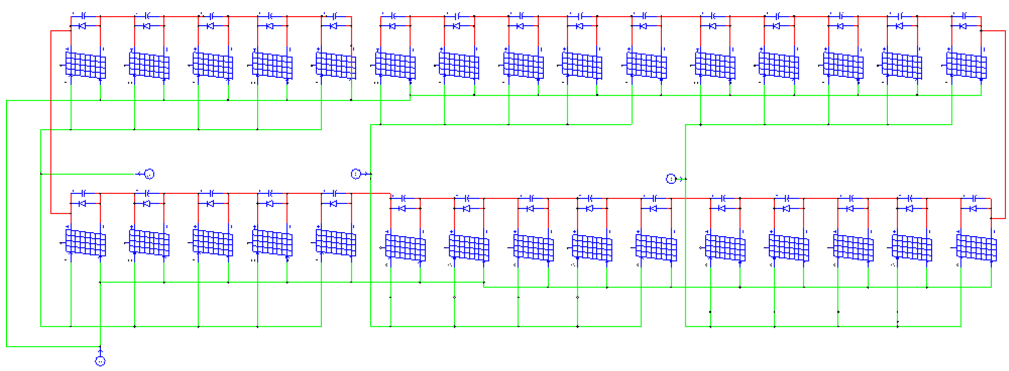


Figure 8. PV array and DC–DC boost converter circuits employed in Psim environment.

Assessing all non-uniform climatic conditions can be challenging, which is why three preselected shading patterns (SPs) have been used to evaluate the performance of the proposed DO-based MPPT algorithm. These shading patterns, designated as SP1, SP2, and SP3 and shown in Figure 9, are used to evaluate the algorithm's ability to track the variant GMPP under static solar insolation. By using these preselected shading patterns, it is possible to evaluate the performance of the algorithm under a range of different conditions, without the need to assess all possible non-uniform climatic conditions, which can be time-consuming and resource-intensive. The following are the three different shade patterns with different irradiance levels, as shown in Figure 9: SP1 involves no shading; SP2 includes partial shading; and SP3 introduces partial shading.

Table 4. Optimization techniques and their control parameters investigated in the study.

Technique	Parameters	Number of the Population	Maximum Number of Iterations
PSO	W = 0.4, c1 = 1.2, c2 = 1.6 and r1, r2 = random [0, 1]	10	17
GWO	r1, r2 = random [0, 1], A = 2 × 0.1 × r1 − 0.1 and C = 2 × r2	6	10
ABC	50% employed bees and 50% onlooker bees	6	10
BA	Fmin = 0, Fmax = 2, A = 0.5, r = 0.5, alpha = 0.9, gamma = 0.9	7	10
CS	k = 0.8 Beta = 1.5	4	10
DO	α and β_t are random numbers $a = \frac{-1}{Max\ iteration^2 - 2 \times Max\ iteration + 1}$ $b = -2 \times a$ $c = 1 - a - b$	4	7

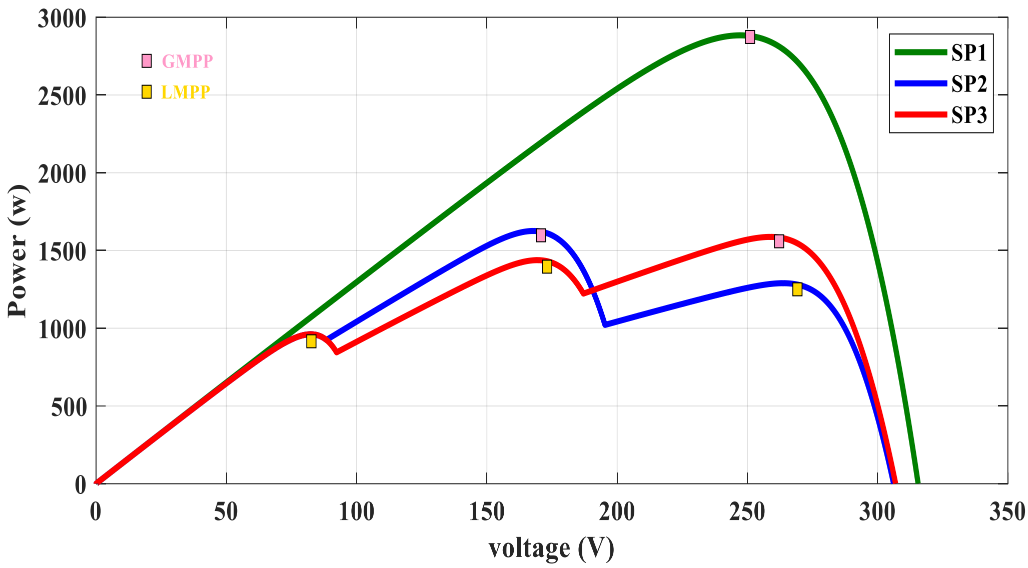
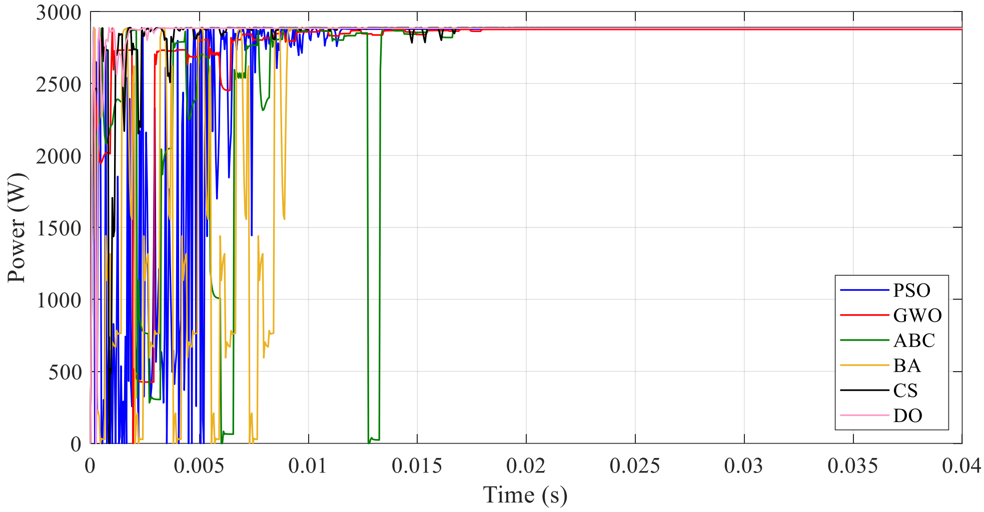
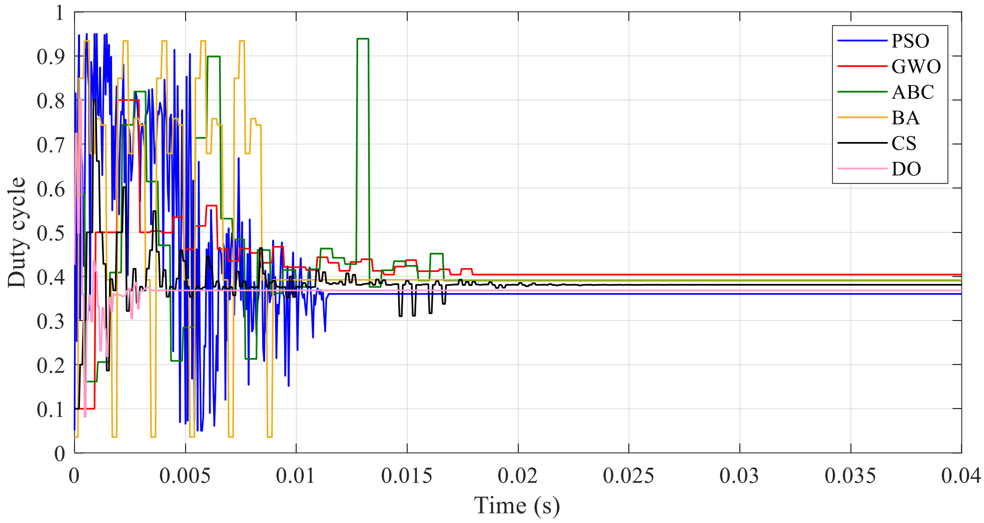


Figure 9. Shading patterns.

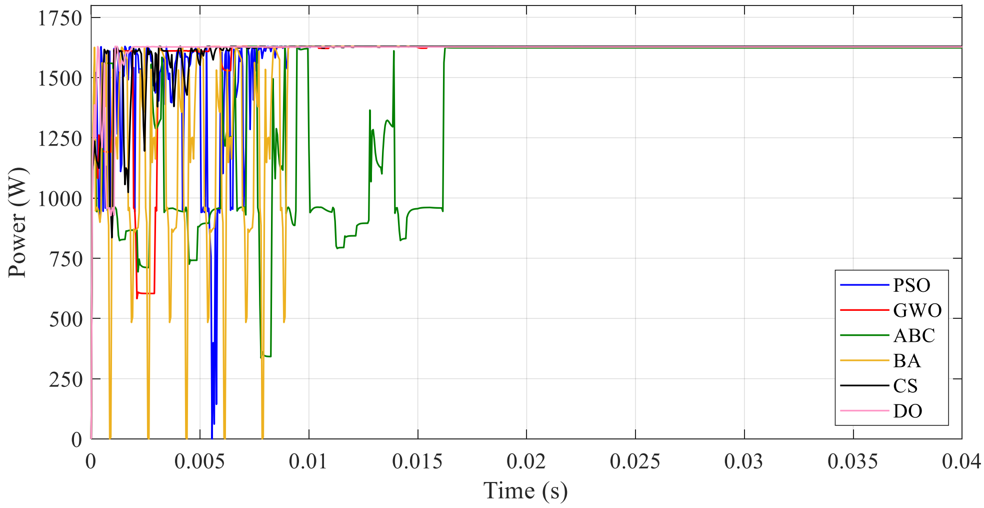
The simulation results present in Figure 10 show that the proposed MPPT algorithm is capable of accurately tracking the GMPP of the PV array under various environmental conditions, and it achieves a fast convergence to the GMPP.



(a)

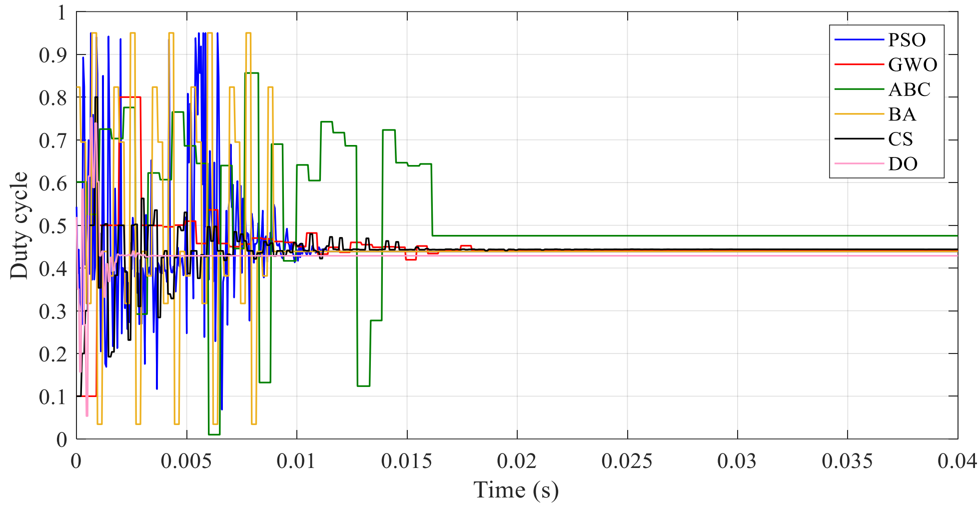


(b)

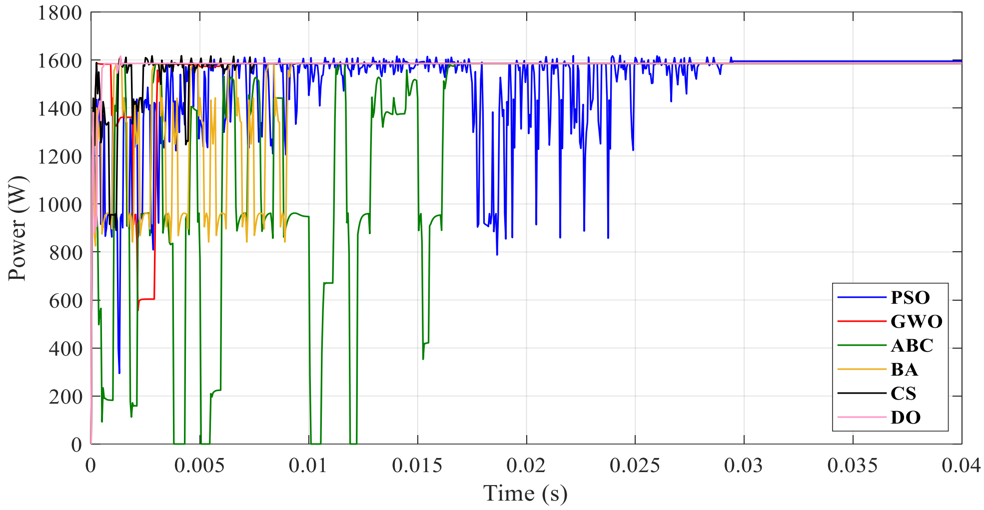


(c)

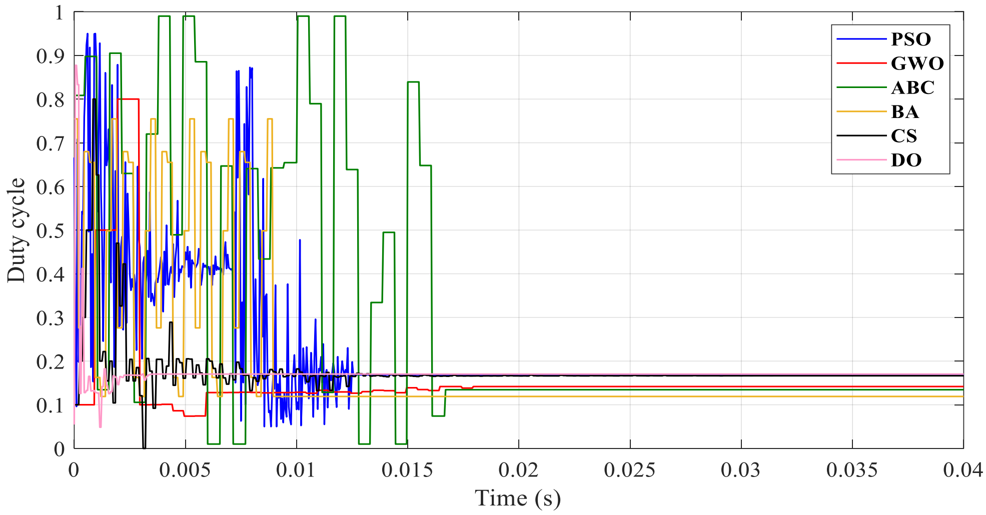
Figure 10. *Cont.*



(d)



(e)

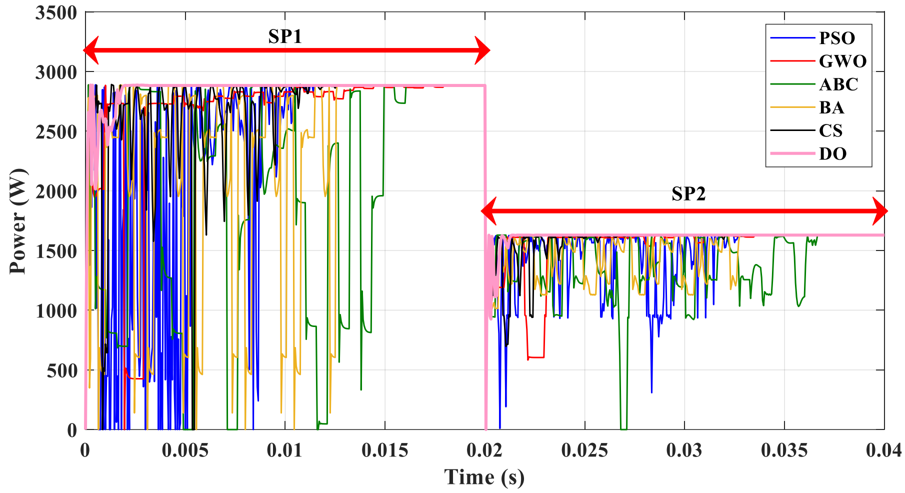


(f)

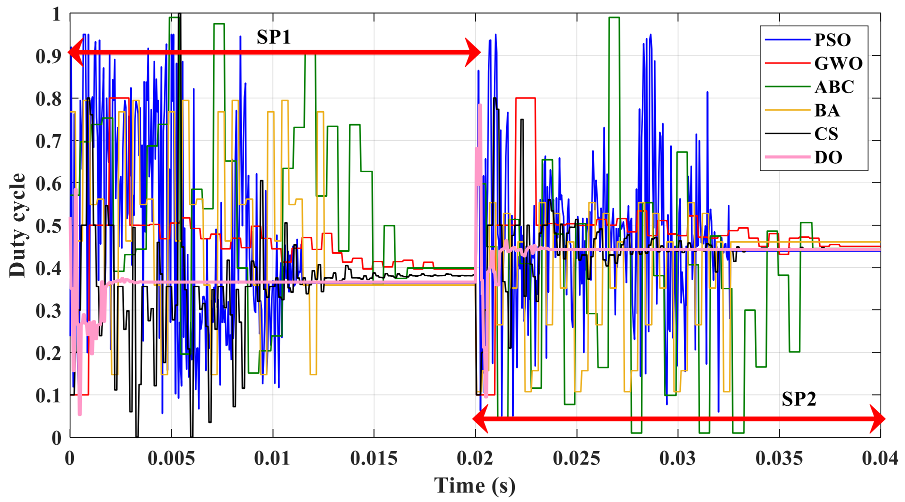
Figure 10. Simulated mean power and duty cycle of PSO, GWO, ABC, BA, CS, and DO for PV string ((**a**,**b**) for SP1, (**c**,**d**) for SP2, (**e**,**f**) for SP3).

4.2.2. Tracking and Comparing Performance

To demonstrate the tracking capability of the proposed DO-based MPPT algorithm under dynamic solar insolation conditions, a transient shading pattern (SP1 to SP3) is generated at t = 0.02 s, where the total simulation time is 0.4 s. The tracking curves obtained by the algorithm are shown in Figure 11. The DO-based MPPT algorithm is able to catch the GMPP of pattern SP1 in less than a 0.005 s, demonstrating its quick response time. When the solar insolation changes to SP3 at 0.02 s, the algorithm restarts the search process based on Equation (12) and is able to successfully track the new GMPP of SP3 in 0.024 s, clearly proving the robustness of the proposed algorithm in handling dynamic partial shading. These results demonstrate the effectiveness of the DO-based MPPT algorithm in tracking the maximum power point under changing solar insolation conditions, which is a critical requirement for achieving high efficiency and performance in PV systems.

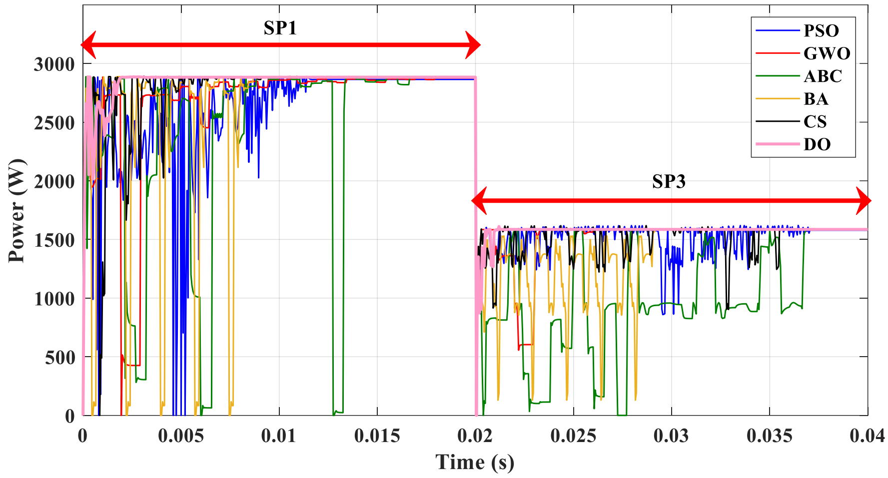


(**a**)

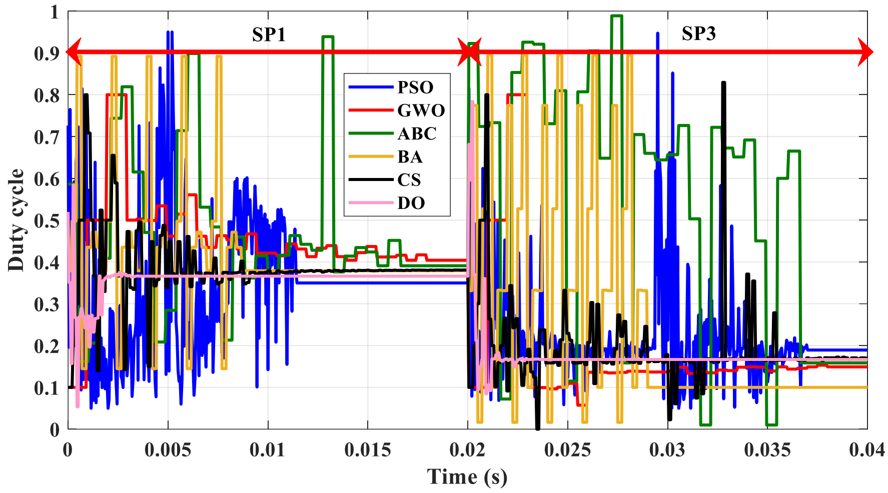


(**b**)

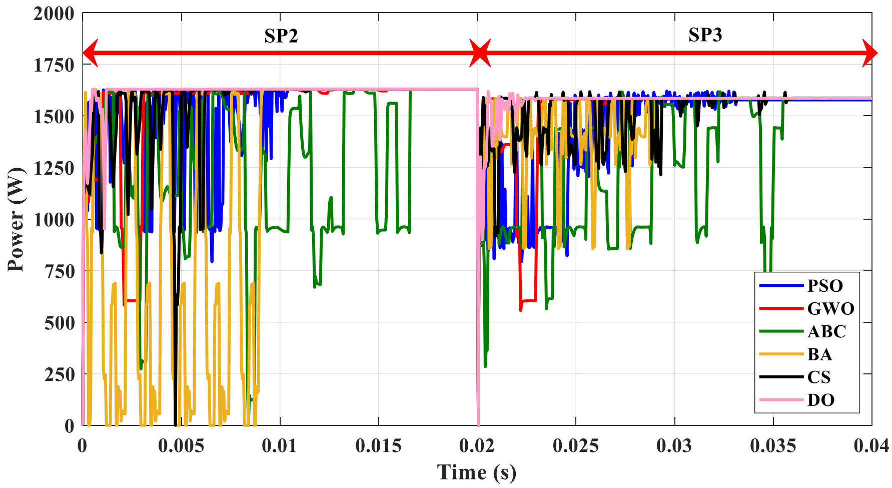
Figure 11. *Cont.*



(**c**)

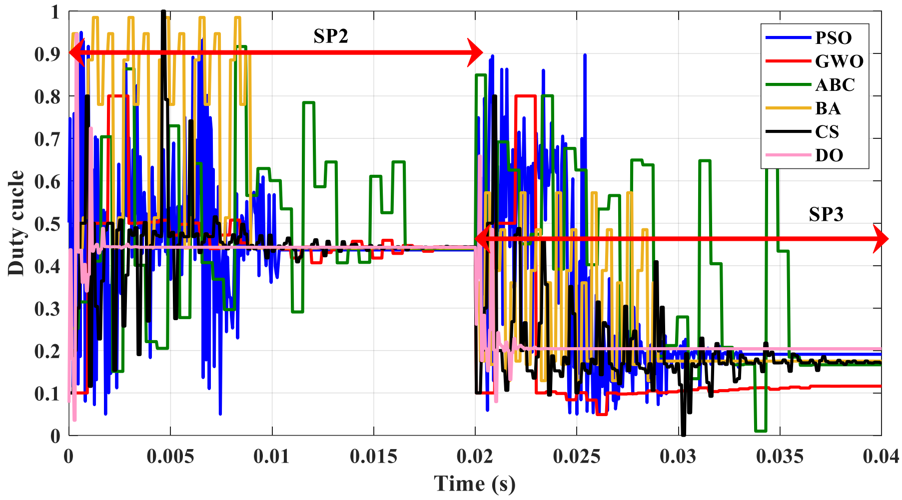


(**d**)



(**e**)

Figure 11. *Cont*.



(**f**)

Figure 11. Tracking curves under shading pattern variation from SP1 to SP2 ((**a**,**b**)), SP1 to SP3 ((**c**,**d**)), and SP2 to SP3 ((**e**,**f**)).

4.2.3. Statistical Analysis

The MPPT techniques presented in Figure 12 were analyzed using three metrics: convergence time, the mean absolute error (MAE) calculated using Equation (19), and the root mean square error (RMSE) calculated using Equation (20).

$$\mathrm{Error}_{\mathrm{MAE}} = \frac{\sum_{i=1}^{n}\left(P_{pve} - P_{pv}\right)}{n} \tag{19}$$

$$\mathrm{Error}_{\mathrm{RMSE}} = \sqrt{\frac{\sum_{i=1}^{n}\left(P_{pve} - P_{pv}\right)^2}{n}}$$

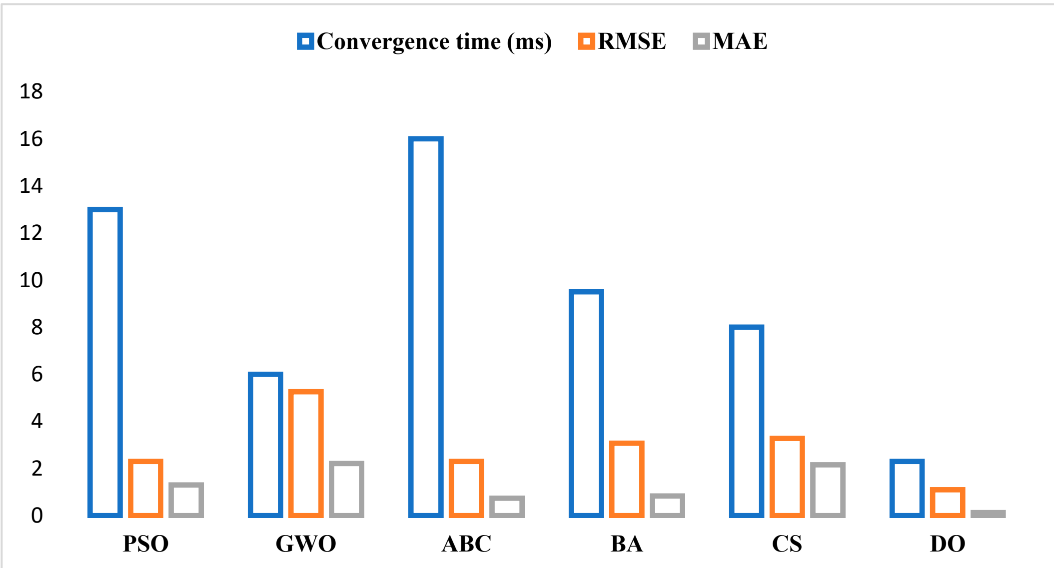


Figure 12. Comparison of RMSE and MAE.

In these equations, P_{pve} represents the expected power, P_{pv} is the power tracked, and n is the number of samples. The study found that MPPTs based on DO have the lowest convergence time compared to the other techniques (the convergence time of shading pattern 3 was used as a reference or sample). On the other hand, the results also show that the DO technique had the lowest RMSE among all the compared techniques, indicating that it tracks the GMPP with higher efficiency and generates negligible oscillations. Additionally, the MAE had a lower magnitude, demonstrating effective GM detection under all operating conditions.

4.2.4. Dynamic Validation

This subsection aims to validate a proposed DO-based MPPT technique using real-world data under varying environmental conditions. To validate its effectiveness, the algorithm was tested on multiple samples during full-day intervals using experimental measurements. In addition, to assess the MPPT algorithm's capability to track the GMPP, actual daily solar irradiation profiles and their corresponding temperatures were utilized to evaluate the algorithm's performance on clear and cloudy days, as presented in Figures 13 and 14.

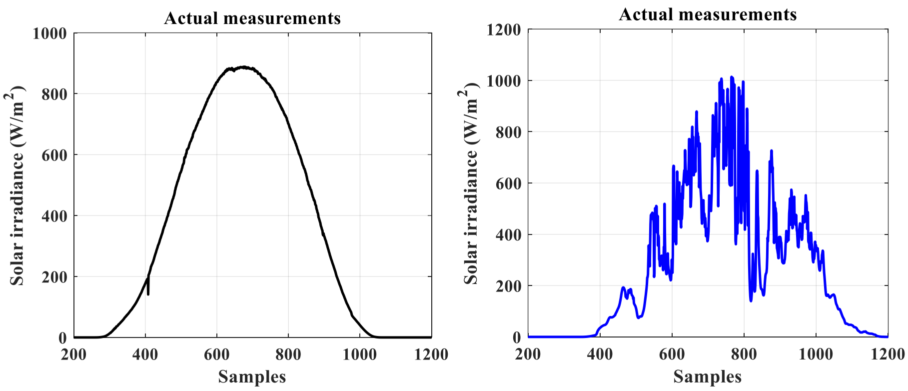


Figure 13. Distinct solar irradiance patterns on clear and shady days based on actual measurements.

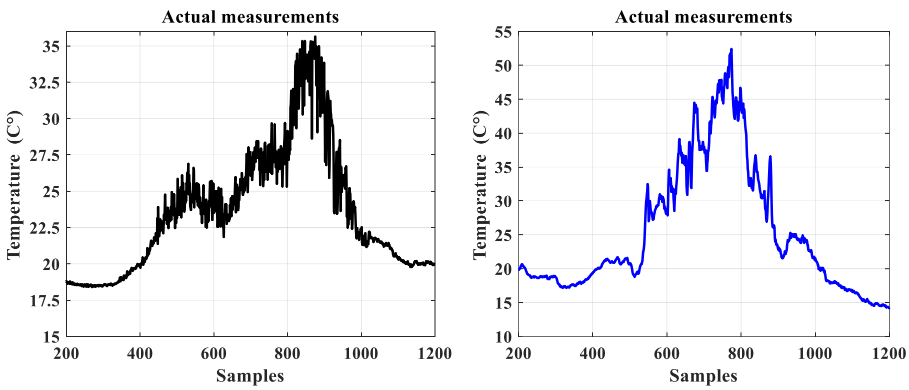


Figure 14. Distinct temperature patterns on clear and shady days based on actual measurements.

The obtained results show that the DO-based MPPT outperformed the other algorithms in terms of convergence speed and achieving maximum power point under varying solar irradiance and temperature conditions. Figures 15 and 16, presenting the results for powers, are provided to support these findings.

According to the findings, among the tested methods, the DO-based MPPT algorithm has demonstrated the most favorable performance with the lowest RMSE and MAE values. This suggests that the DO-based algorithm is capable of achieving more precise and accurate MPP tracking compared to the other methods assessed. Although the other methods performed reasonably well, the results imply that they may not attain the same level of precision as the DO-based algorithm. Consequently, the results indicate that the DO-based MPPT algorithm is the most promising option for accurate MPP tracking in PV.

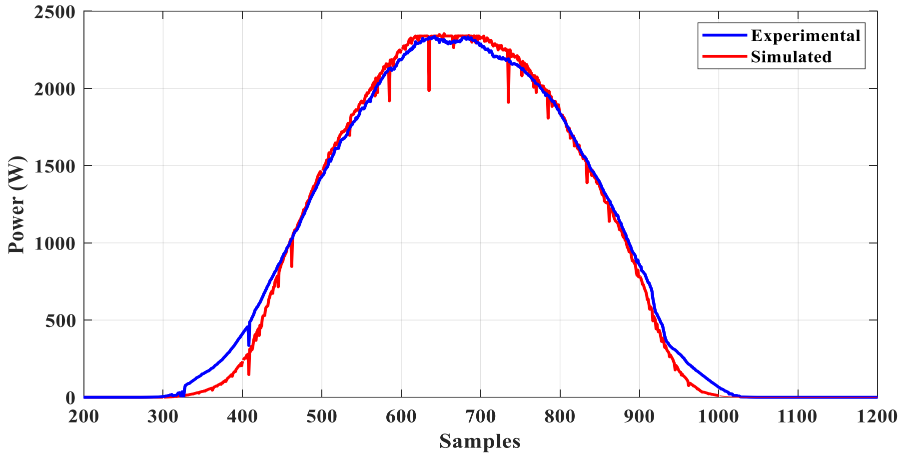


Figure 15. Comparison of experimental and simulated powers at MPP under clear conditions using DO-based MPPT.

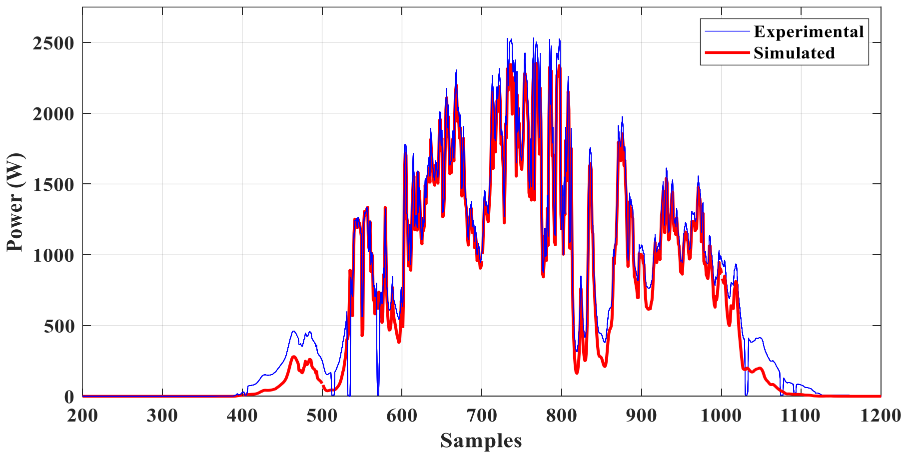


Figure 16. Comparison of experimental and simulated powers at MPP under shading conditions using DO-based MPPT.

5. Conclusions

The utilization of the DO algorithm in MPPT controllers presents a promising approach towards improving the efficiency and performance of solar PV systems. The DO algorithm offers an effective means of balancing the trade-offs between tracking speed, accuracy, and convergence. Through the experiments detailed in this scientific paper, it has been demonstrated that the MPPT-based DO algorithm outperforms other widely used MPPT-based metaheuristic algorithms, including PSO, GWO, ABC, CS, and BA, thereby establishing its superiority. The results show that the proposed MPPT was able to achieve faster tracking speed, higher tracking accuracy, and better stability under changing weather conditions. One of the key advantages of the dandelion optimizer algorithm is its ability to dynamically adjust the search space based on the current operating conditions, which can result in significant improvements in the overall performance of the system. Moreover, the DO algorithm is relatively easy to implement and does not require complex mathematical models or extensive training datasets. Furthermore, the proposed MPPT can provide a cost-effective solution for renewable energy production, which can lead to increased adoption of solar energy systems in both developed and developing countries. The performance of the DO algorithm is sensitive to the initial parameter settings, and different initial parameter values could lead to different results. Careful parameter tuning and optimization would be required to achieve optimal performance. While the DO algorithm is relatively simple compared to other optimization algorithms, it still requires significant computational resources, especially for larger-scale systems. This could limit the practical application of the algorithm in real-world PV systems. Further research and development are needed to optimize the algorithm's performance and address these limitations. This article has presented a newly proposed MPPT algorithm based on DO. Through simulation and experimentation, it has been shown that the DO-based MPPT algorithm outperforms other commonly used MPPT algorithms such as PSO, GWO, ABC, BA, and CS. Additionally, a real-world validation has been conducted to demonstrate the practical applications of the proposed algorithm. In future work, a comparison of the computational complexity and required computational power of the hardware of various MPPT algorithms could be conducted. Overall, the DO-based MPPT algorithm has demonstrated promising results and has the potential to be applied in PVs.

Author Contributions: Methodology, L.M. and A.C.; Validation, L.M.; Formal analysis, A.S.; Investigation, A.S.; Writing—original draft, E.H.; Writing—review & editing, A.C. and S.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy restrictions.

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

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