

Article

# Performance improvement of PV systems during dynamic partial shading conditions using optimization algorithms

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Received: 05 September 2023; Accepted: 29 February 2024; Published: 07 May 2024

**Abstract:** PV power plants encounter varying levels of irradiance, temperature fluctuations, and partial shading because of the differences in sunlight conditions. Partial shading can cause an increase in the power loss, leading to a reduction in efficiency. Maximum Power Point Tracking (MPPT) is of utmost importance in the functioning of photovoltaic (PV) systems for electricity generation because it is indispensable for maximizing power extraction from PV modules, thereby increasing the overall power output. In situations where partial shading is present, the utilization of MPPT algorithms to achieve maximum power output becomes complex because of the existence of multiple distinct peak power points, each having a unique local optimum. To overcome this issue, a method is proposed that uses Darts Game Optimization (DGO), a game-based optimization process, to efficiently determine and extract the maximum power from various local optimal peaks. A population-based optimization method known as the Darts Game Optimization algorithm exists. In this approach, the optimization process begins by creating a population of random players. Then, the algorithm iteratively updates and improves the population to search for the best player or solution. In this study, the DGO algorithm was applied to the MPPT process for voltage optimization in the PV procedure. The DC-DC converter is utilized to capture the maximum available power, and the findings demonstrate that the DGO algorithm efficiently identifies the global maximum, resulting in accelerated convergence, reduced settling time, and minimized power oscillation. Through simulations, the feasibility and effectiveness of the DGO centered MPPT approach was confirmed and compared with MPPT algorithms relying on perturb and observe (P&O) and Particle Swarm Optimization (PSO). The simulation results offer compelling evidence that the DGO algorithm, as proposed in this study, proficiently traces the global maximum, thereby substantiating its practicality and efficiency.

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**How to cite this article:** Soma, Keerthi; Balamurugan, R.; Natarajan, Karuppiah. Performance improvement of PV systems during dynamic partial shading conditions using optimization algorithms. *Transactions on Energy Systems and Engineering Applications*, 5(1): 557, 2024. DOI:10.32397/tesea.vol5.n1.557

## 1. Introduction

The escalating need for energy consumption and the limited availability of fossil fuels such as coal and oil have spurred significant interest in renewable energy sources. These resources offer sustainability, unlimited availability, and are environmentally friendly, making them a popular alternative to traditional energy sources [1–3]. Fuels for energy generation releases carbon and sulfur into the atmosphere, leading to harm to the environment, pollution, and ozone layer depletion. Photovoltaic (PV) systems are developing prevalent in the world. The rising popularity of economically viable PV systems in India, attributed to their low maintenance and absence of carbon and sulfur emissions, is expected to lead to a projected installed capacity of 60GW by the year 2022. The applications of PV systems are wide-ranging, encompassing low-power devices as well as large-scale power plants. However, PV generation systems have two main drawbacks: low conversion efficiency and reliance on atmospheric conditions. There are two modes of PV generation schemes: Stand-alone systems find common application in electric vehicle chargers, electrical pumps, streetlights, and various other similar uses. Meanwhile, grid-connected systems serve different purposes. On the other hand, grid-connected systems offer solutions for micro grids and hybrid power systems. Atmospheric conditions, such as irradiance and temperature, have an impact on the execution of PV systems. Partial shading can change the power output of PV arrays, influencing current, voltage, and power characteristics. The variations are influenced by the panel specifications and the prevailing atmospheric conditions. The IV and PV curves display the behavior of PV systems and highlight a specific point known as the maximum power point. This point helps determine the optimal output voltage needed to achieve the highest power outcome from the PV array.

MPPT is a widely used term that refers to the process of optimizing and constantly monitoring a PV system to achieve its highest power output at the specific maximum power point. Several MPPT algorithms, such as Perturb and Observe (P&O) [4], Incremental Conductance (INC) [5], and Hill Climbing (HC) [6], are used and proposed by researchers. These techniques work well when sunlight is evenly distributed on all PV panels. However, in partial shading conditions, where sunlight is not uniform, the IV and PV curves become complex, exhibiting multiple peaks known as local maximum points (LMPP). When dealing with partial shading conditions [7], MPPT algorithms must identify the global maximum power point (GMPP) among multiple local maximum power points. Standard MPPT algorithms like P&O, INC, and Hill Climbing (HC) may face challenges in effectively recognizing the global maximum and may become trapped at a local maximum [8]. For handling partial shading of PV systems conventional MPPT procedures are not satisfactory. Researchers have proposed several optimization techniques that utilize easy processing processes such as fuzzy logic controllers and simulated neural networks. But these artificial intelligence approaches need more calculation time and extensive training and hence require complex hardware execution. Nature-inspired optimization techniques, which combine evolutionary and swarm-based algorithms, are gaining popularity due to their ability to effectively track the global maximum in MPPT applications [9]. To find the global maximum, MPPT applications utilize evolutionary processes like (DE) [10–12] and (GA) [13].

The nature-inspired MPPT techniques like the marine predator algorithm [14–17], and the Mayfly optimization algorithm provides increased efficiency, precision, and quick retort in pursuing the global maximum under partial shading as associated to other algorithms [18]. Nature-inspired optimization methods are popular due to their stochastic search nature and clear concept, making them simple to use [19]. In [20], a new optimization technique, named EPO, was introduced to improve the early duty cycle regulation and the tuning of controller gains in the boost converter. However, the effectiveness of this algorithm largely depends on the population initialization. In a different scenario, the application of the Cuttlefish Algorithm optimizes the parameters of the second-order amplifier, resulting in enhanced PV system performance in partial shading conditions [21]. In [22], the researchers applied a modified

Butterfly-based PSO algorithm to optimize the positioning of DG and DSTATCOM units in unbalanced 25 and IEEE 33 bus radial distribution systems. In the study described in [23], the researchers introduced a new approach for identifying the best locations for distributed generators (DGs) in radial supply networks. Their primary aim was to reduce active power loss and voltage deviation in both the IEEE 33 bus and 69 bus networks.

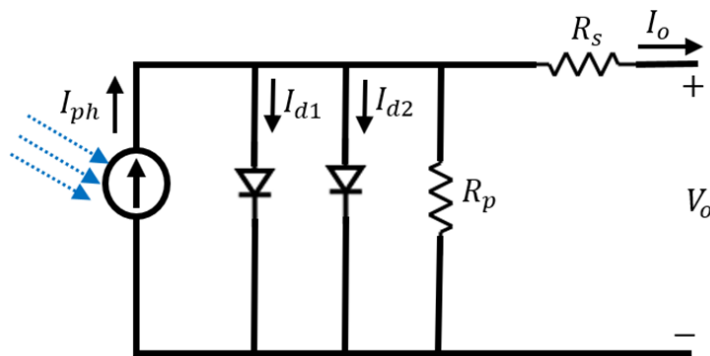
Swarm-based optimization offers the advantage of expediting the search process due to its reliance on swarm populations. However, such algorithms employ a singular strategy for updating the position within the search space. While swarm-based optimization algorithms exhibit superior performance, their execution can be complex and costly. Evaluating the benefits of intelligent algorithms that are compatible with low-cost embedded boards and comparing their efficacy with conventional low-computational cost techniques is crucial for incorporating new control algorithms into commercial devices.

The research aims a novel game-based optimization algorithm to enhance the MPPT technique. The suggested method utilizes the DGO [24], which is primarily employed to analyze the (PV) and (IV) types of PV arrays. Subsequently, the algorithm is utilized to explore the most suitable function sequence for the boost converter. The proposed DGO algorithm offers various benefits such as enhanced tracking ability, increased efficiency, simplicity, and the absence of the need for parameter knowledge. Inspired by the Darts game, the algorithm represents population members as dart players who aim to achieve the highest possible score through Optimization and can be used to improve the throes of a player on the game board. In this study, the effectiveness of the Darts game optimization (DGO) based MPPT process is evaluated and compared to conventional MPPT approaches that use P&O and PSO methods. The presented work is arranged as follows:

Section 2 provides an overview of the system description. In section 3, the paper introduces novel MPPT techniques, which are based on two distinct optimization algorithms: the DGO and the PSO algorithms. Section 4 showcases the simulated outcomes. The paper concludes in Section 5 with a summary of the findings.

## 2. Modeling of PV Cells

The representation of photovoltaic (PV) systems can be simplified as a DC current source under control, accompanied by an anti-parallel diode. Wherein series and parallel resistances are integrated into the DC current source, PV cells can be studied practically to better comprehend their characteristics and performance under real and dynamic situations. To account for environmental factors' impact on PV cell characteristics, the study employs a 2-diode model [25]. Figure 1 illustrates the circuit setup, the simplified



**Figure 1.** Two Diode Model for PV Cells.

model comprises a controlled current source, along with series and parallel resistances, as well as two anti-parallel diodes.

$$I_o = I_{ph} - I_{d1} - I_{d2} \tag{1}$$

$$I_o = I_{ph} - I_{sat1} \left( e^{\frac{V_o + R_s I_o}{\eta_1 V_T N_s}} - 1 \right) - I_{sat2} \left( e^{\frac{V_o + R_s I_o}{\eta_2 V_T N_s}} - 1 \right) - \frac{V_o + R_s I_o}{R_p} \tag{2}$$

$$V_T = \frac{kT}{q} \tag{3}$$

In the model,  $I_{sat1}$  and  $I_{sat2}$  represent the saturation currents,  $I_{d1}$  and  $I_{d2}$  are the diode currents,  $V_o$  is the output voltage,  $I_o$  is the output current,  $R_s$  is the series resistance,  $R_p$  is the parallel resistance,  $N_s$  is the number of cells in series, and  $k$  and  $q$  are Boltzmann’s constant and electronic charge, respectively, with values of  $k = 1.3806503 \times 10^{-23} \text{ J/K}$  and  $q = 1.602 \times 10^{-16} \text{ C}$ . The output current  $I_o$  can be found by using equations 1 to 3.

Operating the PV generation system at its peak power point is vital for achieving maximum efficiency and optimal performance. This location is influenced by various atmospheric factors, such as irradiation and temperature. It is a widely adopted technique to increase power and voltage levels by connecting PV panels in parallel and series configurations. Then, when shading occurs on some of the panels due to obstructions such as buildings, trees, or clouds, it can lead to non-uniform irradiance levels, resulting in a drop in voltage across the shaded boards. PV panels cause a voltage drop, making them function since a load to the rest of the PV system. Partial shading of PV panels leads to increased discrepancies in both power and voltage, resulting in the occurrence of hotspot effects. A bypass diode across the PV panels reduces these hotspot effects. In Figure 2, the relation between the IV and PV of a PV array are shown for two distinct situations: uniform irradiance and partial shading conditions. For PV methods to harvest the maximum amount of solar energy, they must operate at the global maximum point.

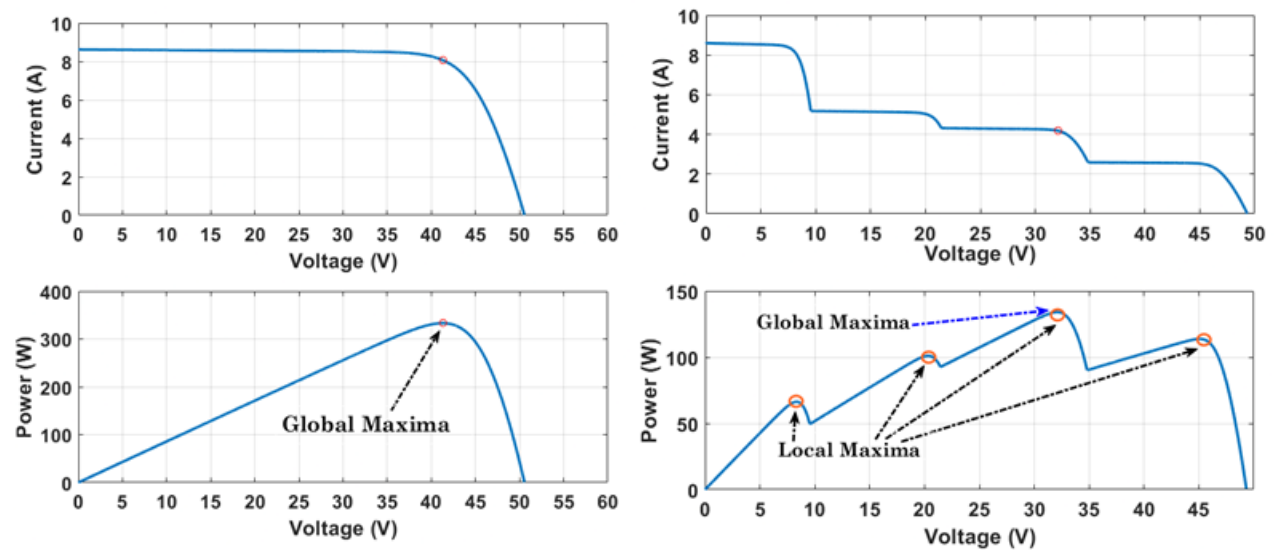
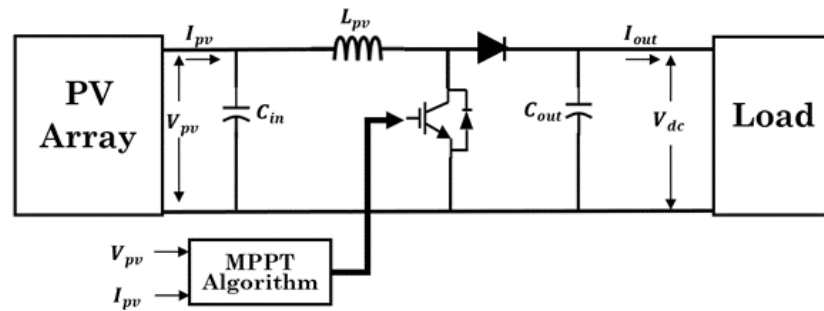


Figure 2. Two Diode Model for PV Cells.



**Figure 3.** Boost Converter with PV array and load.

Towards extract and deliver extreme power, and line among the PV array and load such as a DC-DC boost evangelist can be adopted and utilized. The MPPT controller makes a control signal that modifies the duty cycle within the range of  $[0, 1]$ , which serves as the control variable for MPPT implementation. A diagram of the boost converter with PV and load is pointed in Figure 3. A detailed description and process of the selection of parameters for the boost converter is presented in [26].

### 3. MPPT

The DGO algorithm is chosen as the MPPT technique and is associated with PSO [27], and P&O MPPT [28], to evaluate its performance. Optimizing for the best solution to a problem for any technical discipline amid accessible alternatives is called optimization. The optimization and solution of any problem are contingent upon both the like and uneven restraints of the problem. Before reaching a final decision, it is crucial to verify that the obtained results meet all the constraints. For effective problem optimization, to address the specific needs, it is vital to formulate a suitable mathematical objective function or cost function. When choosing the optimal optimization algorithm, it is important to address challenges like distinguishing between local and global optimal solutions, handling result noise, and fulfilling both equal and unequal constraints. For practical applications, the chosen optimization algorithm should possess properties such as convexity, accurate function calculation, constancy, and nonlinearity. An optimisation problem can be described as,

$$\min_{x \in A} f(x), \text{ subject to } N_i(x) \leq 0, i = 1, 2, \dots, k, \quad (4)$$

where  $k$  is number of constraints,  $A \subseteq \mathbb{R}^n$  is a subsection in an  $n$ -dimensional Euclidean space,  $Y \subseteq \mathbb{R}$  represents a subset of real numbers.

#### 3.1. Darts Game Optimizer

In the game of darts, players employ small, sharp-pointed missiles known as darts, aiming them at a circular target called a dartboard. Participants can earn points based on where their darts hit the dartboard, with different areas offering varying points. Hitting areas with the highest points allows players to accumulate more scores. Within the dartboard, there are 82 distinct areas, each corresponding to its respective points. The dartboard is composed of 6 circles, with the regions between them referred to as the circular wire.

The inside bull's eye, located inside the first circular wire, is worth 50 points, while the area between the first and the outward bull's eye, referred to as the second circular wire, holds a value of 25 points. Beyond this wire, each circular wire is subdivided into 20 distinct regions. In terms of points, the third and fifth circular wires have identical values for their respective areas. The fourth circular wire, called the triple ring, provides triple points, whereas the outermost circular wire, known as the double ring, grants double

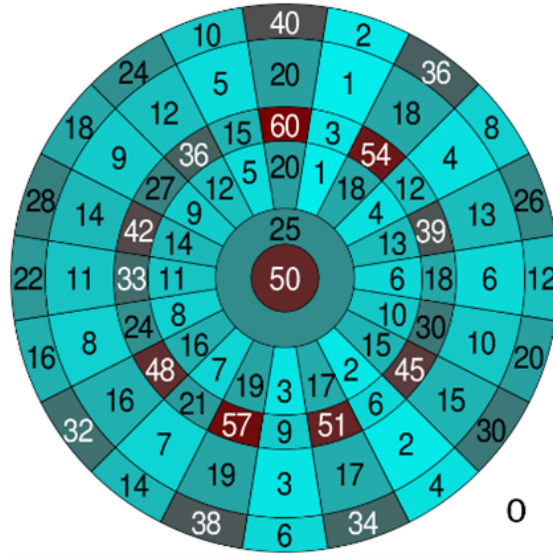


Figure 4. Dart Board.

points. Missing the target and scoring zero points occurs when the dart hits outside the outer circular wire. In Figure 4, the dartboard is depicted, showcasing its 82 areas and their corresponding points. The research implements the optimization strategy, originally employed to achieve peak scores in the dart game, as an MPPT technique for the PV generation process.

The DGO is an optimization algorithm based on a population approach. It begins with a random population of players and iteratively updates them to find the best player through search processes. In this method, a matrix is employed to depict individual players and their respective solutions to the difficulty. All row in the matrix corresponds to a performer, while every row represents the attributes specific to the player. The mathematical depiction of the matrix is as follows:

$$P = \begin{bmatrix} P_1 \\ \vdots \\ P_i \\ \vdots \\ P_n \end{bmatrix} = \begin{bmatrix} p_1^1 & \dots & p_1^j & \dots & p_1^m \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ p_i^1 & \dots & p_i^j & \dots & p_i^m \\ \vdots & \dots & \vdots & \ddots & \vdots \\ p_n^1 & \dots & p_n^j & \dots & p_n^m \end{bmatrix}, \quad (5)$$

where  $P$  signifies the performers,  $n$  represents the total number of players, and  $m$  denotes the size of the problem. And  $p_i^j$  denotes the  $j$ th characteristic of the  $i$ th player.

Let  $F_{fitness}$  is the fitness function to be reduced, then,

$$F_{best} = \min(F_{fitness})_{n \times 1}, \quad (6)$$

$$P_{best} = P(\text{location of } \min(F_{fitness}), 1 : m), \quad (7)$$

$$F_{worst} = \max(F_{fitness})_{n \times 1}, \quad (8)$$

$$P_{worst} = P(\text{location of } \max(F_{fitness}), 1 : m), \quad (9)$$

$$F^{norm} = \frac{F_{fitness} - F_{worst}}{\sum_{k=1}^n ((F_{fitness})_k - F_{worst})}, \quad (10)$$



$$\rho_i = \frac{F_i^{\text{norm}}}{\max(F^{\text{norm}})} . \quad (11)$$

In the context of fitness functions, the following terms are:  $F_{\text{best}}$ : The best fitness value achieved.

$P_{\text{best}}$ : The participant associated by the best fitness value.

$F_{\text{worst}}$ : The extreme value of the fitness function observed.

$P_{\text{worst}}$ : The participant associated by the worst fitness value.

$F^{\text{norm}}$ : The stabilized value of fitness functions.

$\rho_i$ : The possibility function specific to the  $i$ th player.

After each iteration, players can be updated based on their scores, the scores of each player are determined based on the fitness function and the player's probability function are dependent on their respective normalized values. Afterwards, the scores are allocated to each player using the following process:

$$C_i = \text{round}(82 \times (1 - \rho_i)) , \quad (12)$$

$$SC_i = \begin{cases} S(1 : C), & \text{rand} < \rho_i \\ S(C + 1 : 82), & \text{rand} \geq \rho_i \end{cases} ' \quad (13)$$

$$S_i = SC_i(\text{area}), 1 \leq \text{area} \leq 82 , \quad (14)$$

$$S_i^{\text{norm}} = \frac{\sum_{\text{throw}=1}^3 S_i^{\text{throws}}}{180} . \quad (15)$$

The candidate score for the  $i$ th player is denoted as  $SC_i$ . Matrix  $S$  represents the sorted scores in ascending order.  $S_i$  represents the result per throw of the  $i$ th player, and  $S_i^{\text{norm}}$  is the normalized result of the  $i$ th player. To update the players' matrix for the next iteration, the following equation is used:

$$p_{\text{ite}+1} = p_{\text{ite}} + \text{rand}(1, m) \times (P_{\text{best}} - 3S_i^{\text{norm}} \times F_{\text{fitness}}) . \quad (16)$$

Once the fitness function for a specific problem is established, DGO can be utilized to identify the players that minimize this function. Before starting the optimization process, two key parameters need to be configured: The sum of players and the sum of iterations are both important factors to consider. At the beginning of the process, an initial set of players is formed randomly to start the optimization. The proposed algorithm depicts each player as a vector consisting of  $m$  elements, representing the difficult variables. These variables are assessed by plugging them into the actual task to obtain a fitness value for each player.

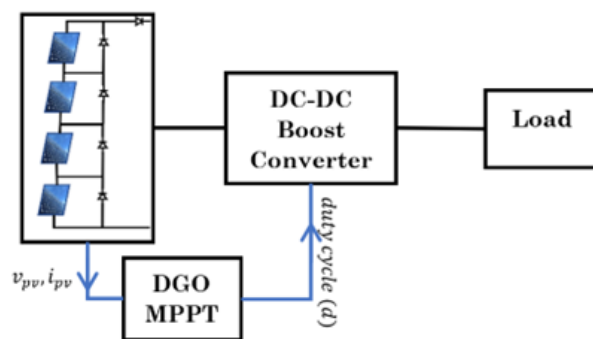
The DGO implementation involves the following steps:

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**Algorithm 1:** Pseudocode of DGO Algorithm.

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- 1: **Start DGO**
  - 2: Creating the initial population of players.
  - 3: Calculating the fitness function.
  - 4: Updating  $F_{\text{best}}$ ,  $P_{\text{best}}$ ,  $F_{\text{worst}}$ , and  $P_{\text{worst}}$  using equations (6) to (9).
  - 5: Updating  $F^{\text{norm}}$  and  $\rho_i$  using (10) and (11).
  - 6: Calculating  $S_i^{\text{norm}}$  using (12) to (15).
  - 7: Updating the players using (16).
  - 8: Checking the stop condition.
  - 9: Printing solution.
  - 10: **End DGO**
-



**Figure 5.** Boost converter with DGO MPPT.

### 3.2. DGO improved MPPT

Figure 5 demonstrates the utilization of DGO (Distributed Global Optimization) to optimize the output power of the PV (Photovoltaic) system, aiming to attain peak efficiency. The inputs provided to the DGO MPPT (Maximum Power Point Tracking) are the PV voltage ( $v_{pv}$ ) and PV current ( $i_{pv}$ ). Achieving To attain the highest power output from the PV system, it is essential to accurately tune the output voltage of the boost converter to align with the voltage at the MPP. By employing the DGO algorithm based MPPT controller, this task can be effectively achieved. In this context, the problem dimensions are simplified to 1 since the sole parameter subject to optimization is the DC output voltage ( $v_{dc}$ ) of the boost converter.

The simulation involves the utilization of 10 players, and the number of iterations is predefined as 20. The optimized  $v_{dc}$  has specific lower and upper bounds, and an array of casual values with the dimension of the population size serves as the initial  $v_{dc}$  configuration. The fitness value of the PV output power is assessed for each  $v_{dc}$  value. The player with the highest PV output power among the random values is chose as  $P_{best}$ , and the corresponding maximum power is denoted as  $F_{best}$ . Conversely, from the random values, the player with the lowest PV output power is selected as  $P_{worst}$ , and the corresponding minimum power is denoted as  $F_{worst}$ .

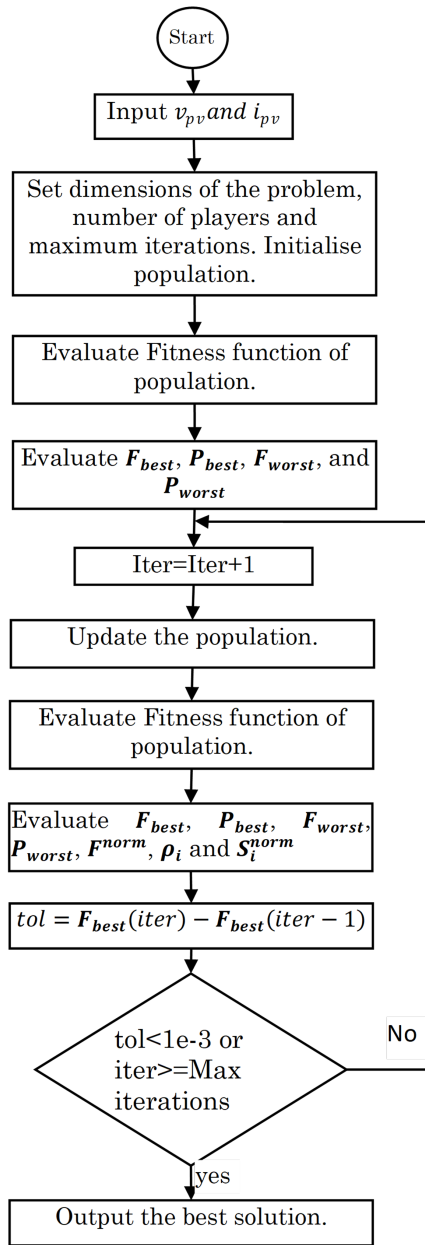
After calculating  $F^{norm}$  and  $\rho_i$  for the first players, a while round is started. In each repetition of the loop,  $F_{best}$ ,  $P_{best}$ ,  $F_{worst}$ ,  $P_{worst}$ ,  $F^{norm}$ ,  $\rho_i$  and  $S_i^{norm}$  are computed using equations 6 to 15. The players are then updated using equation 16, and the fitness values (PV turnout power) are recalculated for all players. This process continues until the specified stopping criterion is met. During each iteration, the maximum power ( $F_{best}$ ) is related with the maximum power got from the preceding duplication.

When the discrepancy between the previous and current maximum powers diminishes below a predefined threshold value, the iterations will be halted. The optimal fitness value associated with a particular player signifies the solution to be employed as the output voltage of the boost converter. The obtained value corresponds to the real DC voltage, which is then utilized in conjunction with a PI control to generate the duty cycle. Subsequently, the boost converter's switch generates pulses according to the calculated duty cycle, thereby sustaining the optimized  $v_{dc}$  at the output. This guarantees the maximum power output from the PV arrays. The flow for the DGO-based MPPT can be observed in Figure 6.

## 4. Simulation results

The efficiency of an MPPT system using the Differential Group Optimization (DGO) algorithm was evaluated through simulations of a Photovoltaic (PV) generation system allied to a load using a DC-DC boost converter. The optimized MPPT algorithm applied PV voltage and current as its input parameters. MATLAB/SIMULINK was employed for the PV simulation, utilizing the configuration illustrated in Figure 7 the arrangement consisted of PV arrays connected in series, which provided power to a DC load





**Figure 6.** Flowchart for DGO MPPT.

via a DC-DC boost converter. The boost converter was governed by a process based on the DGO algorithm, functioning as the MPPT controller. Every PV array comprised four modules interconnected in series, forming two parallel strings. Table 1 provides the specifications of the PV array, while Table 2 presents the details of the boost converter. The optimization algorithm utilized in the study is outlined in Table 3. The subsequent sections consist of multiple case studies that demonstrate the enhanced performance of the DGO optimization method, as validated by simulation outcomes, when compared to other MPPT techniques.

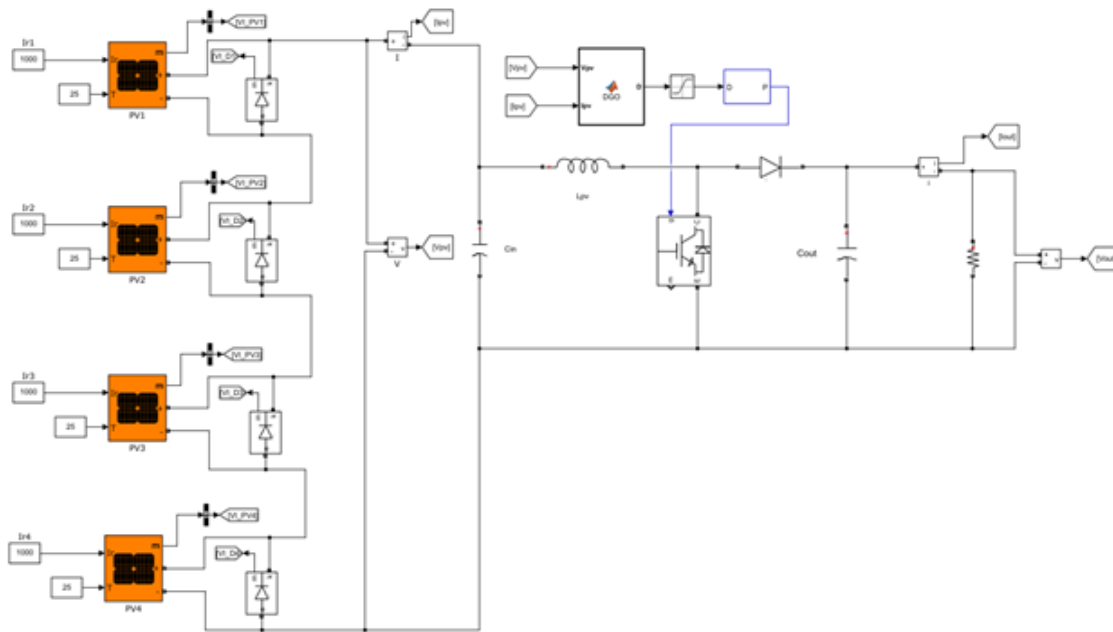


Figure 7. Simulation setup.

Table 1. PV Array’s parameters.

Parameter	Value
Maximum Power	250 W
Cells per module	60
Open Circuit Voltage ( $V_{oc}$ )	37.92 V
Short Circuit Current ( $I_{sc}$ )	8.62 A
Voltage at Maximum Power Point ( $V_{mpp}$ )	30.96 V
Current at Maximum Power Point ( $I_{mpp}$ )	8.07 A
Temperature coefficient of $V_{oc}$	-0.33969 %/ °C
Temperature coefficient of $I_{sc}$	0.063701 %/ °C
Shunt Resistance $R_{sh}$	247.2351 $\Omega$
Series Resistance $R_{se}$	0.29588 $\Omega$

Table 2. Parameters of the Boost Converter.

Parameter	Value
Inductor ( $L_{pv}$ )	2 mH
Input Capacitor ( $C_{in}$ )	10 $\mu F$
Output Capacitor ( $C_{out}$ )	680 $\mu F$
Switching Frequency	10 kHz

Table 3. DGO optimization parameters.

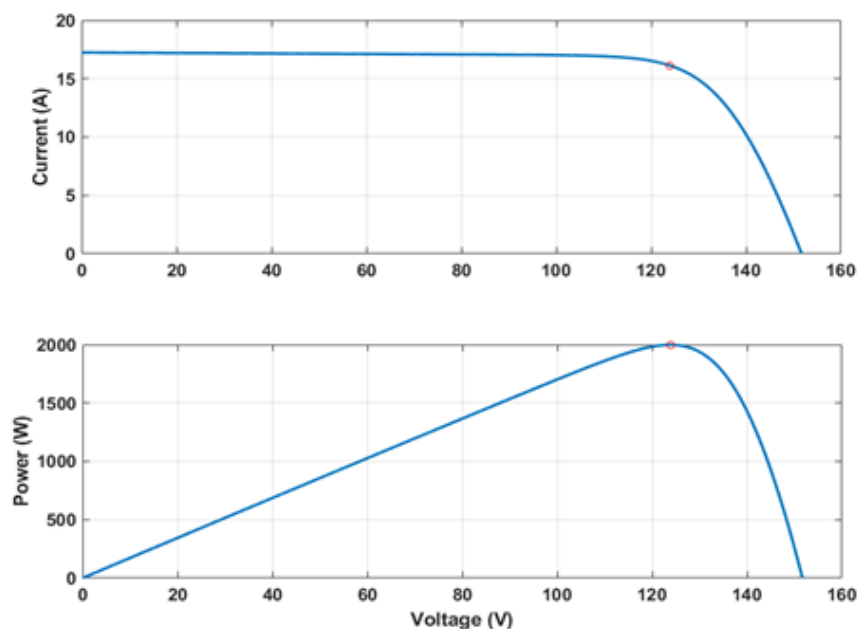
Parameter	Value
No. of players	50
No. of repetitions	100

### 4.1. Case 1 Equal Irradiance

In Case 1, the use of the DGO-created MPPT to pursue the global maximum power point was evaluated by considering varying irradiance levels. Table 4 shows the variation of the irradiance pattern. The four PV arrays are subjected to equal irradiance conditions, and the irradiance level changes every 2 seconds. In the initial interval (first 2 seconds), the irradiance is fixed at 1000 W/m<sup>2</sup>, leading to the following power outputs for the PV arrays: The power outputs achieved for P&O, PSO, and the proposed DGO MPPT are 1951.2W, 1982.36W, and 1998.7W, respectively. The corresponding efficiencies for DGO, PSO, and P&O are 99.98%, 98.12%, and 96.33%, individually. Figure 8 shows the IV and PV characteristics of the PV array under uniform irradiance conditions. The output power, energy, and current comparison for the three algorithms can be seen in Figures 9, 11, and 13, respectively. Under conditions of equal irradiance, conventional MPPT algorithms like P&O demonstrate effective performance with fewer computations. However, the fluctuations in the duty cycle result in ripples around the global maximum. The optimized parameters of conventional MPPT algorithms, like P&O, cause oscillations around the maximum power point. DGO demonstrates effective tracking of the maximum power point with reduced oscillations when compared to PSO and P&O. Figures 10, 12, and 14 offer a closer look at the power, current, and voltage comparisons, providing further evidence of the stable output achieved by DGO. For P&O, the settling time to reach the maximum power point is 0.1214, while for PSO, it is 0.3503, and for DGO MPPT, it is 0.2014. To evaluate the converter’s efficiency, the method described in [29], is employed.

**Table 4.** Irradiance in W/m<sup>2</sup> for case 1.

	0 to 2 sec	2 to 4 sec	4 to 6 sec	6 to 8 sec
PV1	1000	600	400	800
PV2	1000	600	400	800
PV3	1000	600	400	800
PV4	1000	600	400	800



**Figure 8.** I-V and P-V characteristics.

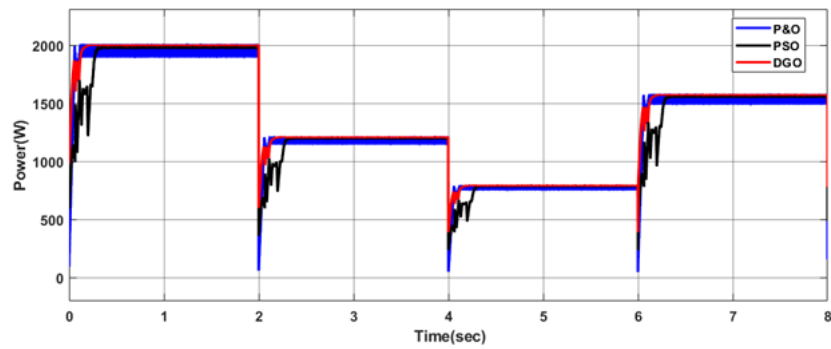


Figure 9. Performance of Power Delivery to Load under Uniform Irradiance.

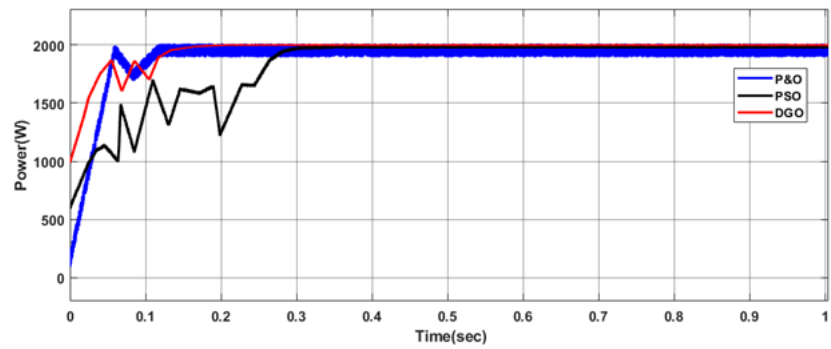


Figure 10. Power delivered between 0 to 1 secs.

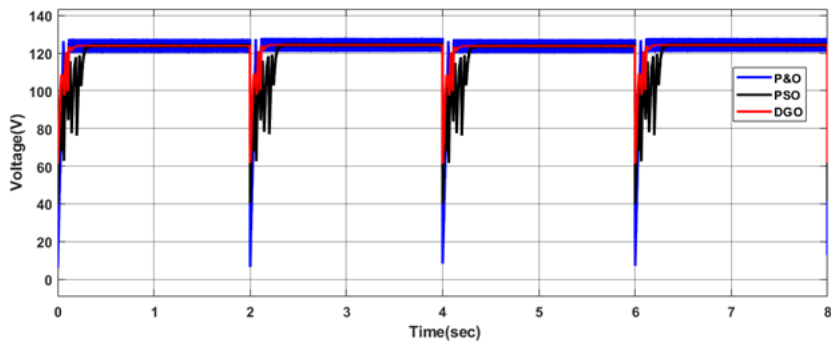


Figure 11. Voltage around the load.

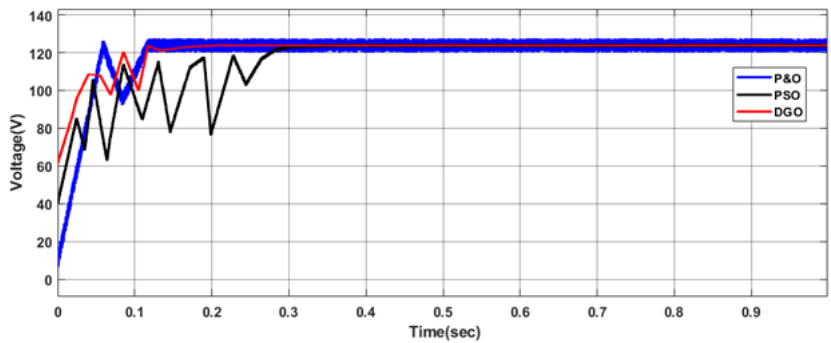


Figure 12. Load voltage.

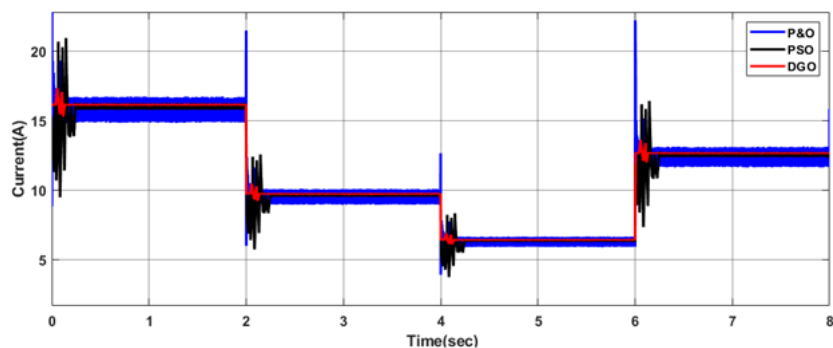


Figure 13. Load current.

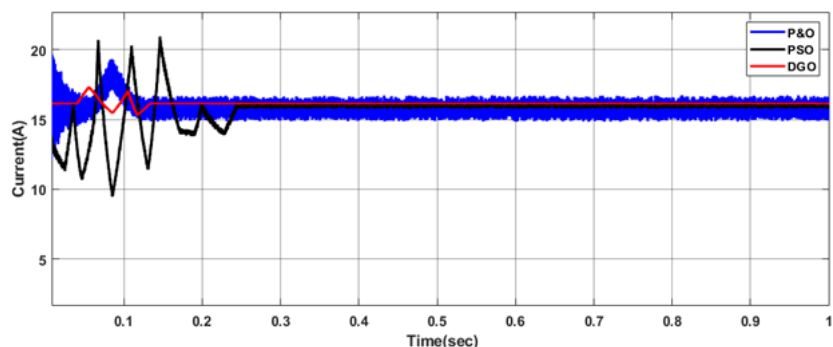


Figure 14. Load Current between 0 to 1 secs.

Table 5. Performance summary of MPPT algorithms in case 1

	P&O	PSO	DGO
Optimization Time (sec)	0.0856	0.2856	0.092
Settling Time (sec)	0.1214	0.3503	0.2014
Ripples (%)	5.13	0.76	0.21
Global Maximum (W)			
0 to 2 sec	1998.7	1998.7	1998.7
2 to 4 sec	898.0135	898.0135	898.0135
4 to 6 sec	596.1377	596.1377	596.1377
6 to 8 sec	1195.564	1195.564	1195.564
Maximum power (W)			
0 to 2 sec	1951.2	1982.36	1998.7
2 to 4 sec	850.59	880.512	898.001
4 to 6 sec	545.67	581.265	596.1285

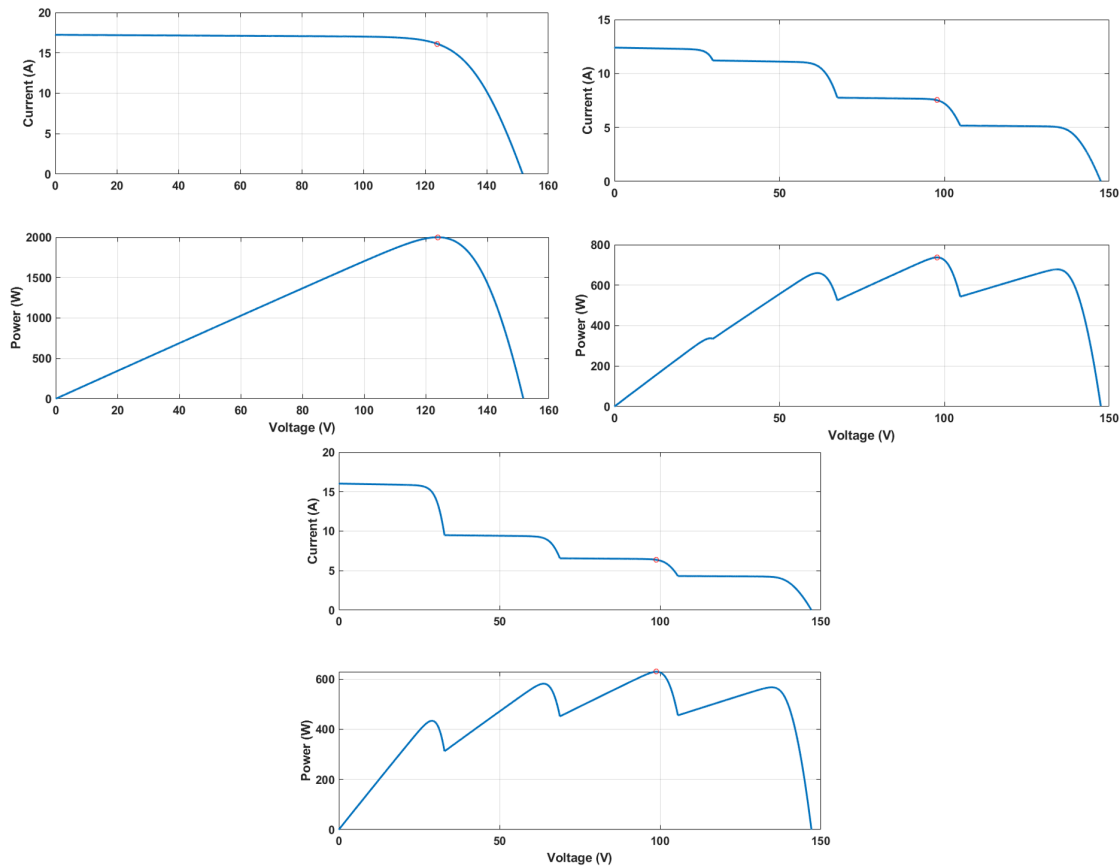
#### 4.2. Case 2 Partial Shading

The PV system’s response under partial shading conditions is examined by adjusting the irradiance levels, as presented in Table 6. Between 2 and 3 seconds, as well as between 3 and 4 seconds, under particular irradiation values, the power and voltage characteristics of the PV array display three local maximum power points and one global maximum power point. Between 2-3 seconds interval, Figures 16, 18, and 20 showcase three local maximum points at 337.2744, 659.7958, and 677.764, with the global maximum

**Table 6.** Irradiance in W/m<sup>2</sup> for case 2.

	0 to 2 sec	2 to 4 sec	4 to 6 sec
PV1	1000	650	930
PV2	1000	300	380
PV3	1000	450	250
PV4	1000	720	550

at 736.836. The MPPT algorithms successfully follow the global maximum, and the DGO-based MPPT proposed in this study exhibits fewer ripples compared to the other two methods. Similarly, during the 3-4 seconds interval, Figure 15 exhibits three local maximum points at 433.726, 581.4655, and 566.966, with the global maximum at 629.168. The PV arrays and their characteristics under partial shading conditions are depicted. Figure 16 presents the proposed MPPT technique, which effectively tracks the global maximum while reducing ripples to a minimum. Due to its superior performance in terms of oscillations, maximum power point tracking, and overall effectiveness, this approach emerges as the most effective method for dealing with partial shading conditions. The voltage, current and power waveforms are depicted in Figures 17, 19 and 21, with zoomed-in versions between 1 to 3 seconds. In Table 7, a comparison of the three MPPT methods is presented, considering convergence time, stability time, maximum power capability, and overall effectiveness.



**Figure 15.** I-V and P-V characteristics of the PV arrays.



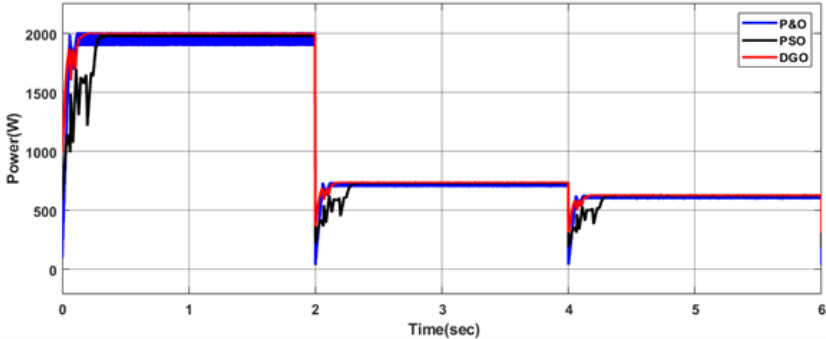


Figure 16. Power Carried to Load during partial shading.

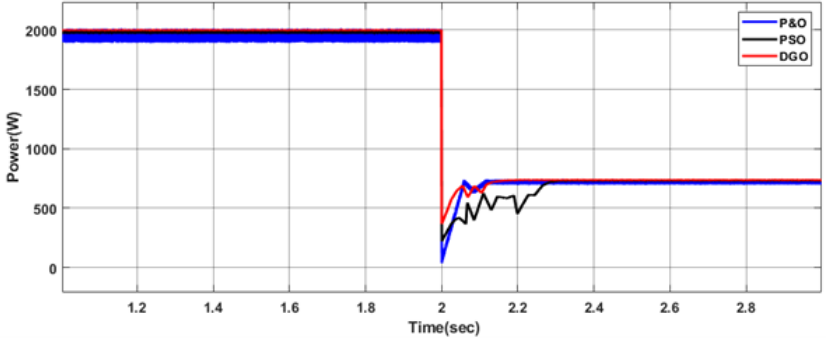


Figure 17. Power during partial shading.

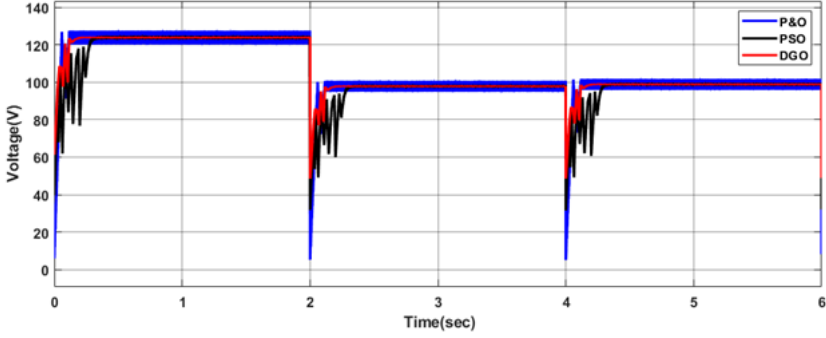


Figure 18. Load voltage during partial shading.

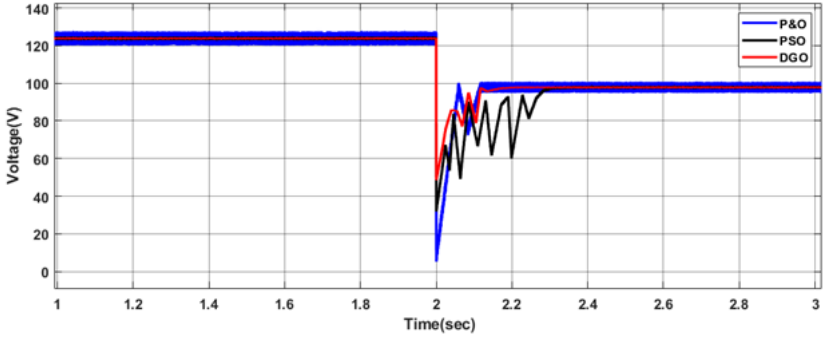


Figure 19. Zoomed Load voltage during partial shading.

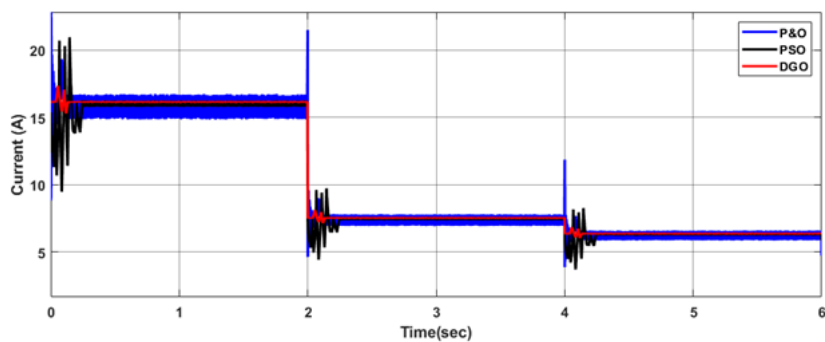


Figure 20. Load Current during partial shading.

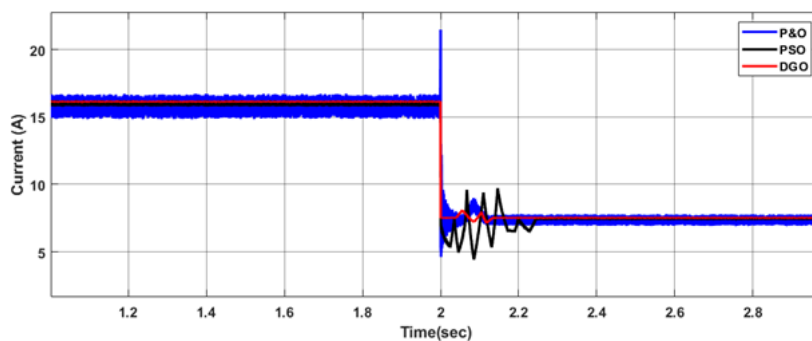


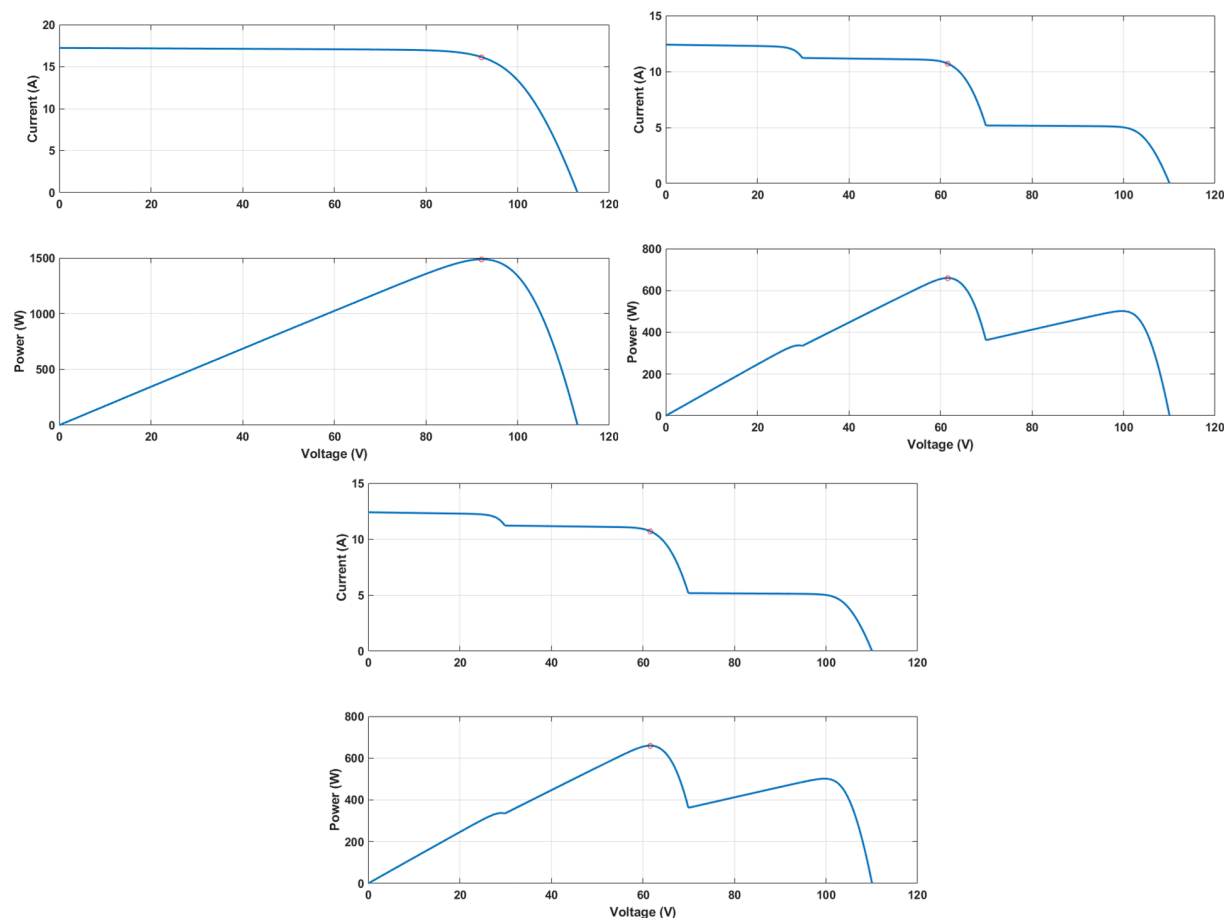
Figure 21. Zoomed Load Current during partial shading.

Table 7. Performance of MPPT Algorithms under Partial Shading Conditions (Case 2).

	P&O	PSO	DGO
Optimization Time (sec)	0.0886	0.2701	0.088
Settling Time (sec)	0.1305	0.3648	0.1956
Ripples (%)	5.08	0.781	0.195
Global Maximum (W)			
0 to 2 sec	1998.7	1998.7	1998.7
2 to 4 sec	736.836	736.836	736.836
4 to 6 sec	629.168	629.168	629.168
Maximum power (W)			
0 to 2 sec	1951.2	1982.36	1998.7
2 to 4 sec	695.21	736.152	862.59
4 to 6 sec	585.46	610.74	629.125
Efficiency (%)	96.33	98.12	99.98

### 4.3. Case 3 Faulty PV Array Analysis

To assess the efficacy of the proposed algorithm in reaching the global maximum, a fault is introduced in one of the PV arrays. Specifically, the third PV array is labeled as faulty and bypassed using a connected bypass diode. Table 8 shows the variation of the irradiance pattern. The irradiation values remain unchanged, like case 2. When the bypassed PV array is present, the power and voltage characteristics exhibit two local maximum points and one global maximum point at the time intervals of 2-3 seconds and 3-4 seconds,



**Figure 22.** I-V and P-V characteristics of PV arrays.

respectively. During the time interval of 2-3 seconds, the global maximum is observed at 659.712, while at 3-4 seconds, it is located at 629.168. Figure 22 presents the IV and PV characteristics of the PV array with the faulty PV array. In the figure, the MPPT algorithms efficiently follow the global maximum, and the proposed DGO-based MPPT exhibits fewer ripples compared to the other two methods. Tables 5, 7, and 9 present the outcomes of the DGO MPPT, PSO MPPT, and P&O MPPT algorithms, respectively. It is vital to note that the outcomes obtained for each algorithm were derived from distinct evaluation parameters and shading conditions. The reported optimization time, settling time, maximum power, ripples, and efficiency values in the tables represent the meaning of the computed outcomes.

**Table 8.** Irradiance in W/m<sup>2</sup> for case 3.

	0 to 2 sec	2 to 4 sec	4 to 6 sec
PV1	1000	650	930
PV2	1000	300	380
PV3	0	0	0
PV4	1000	720	550

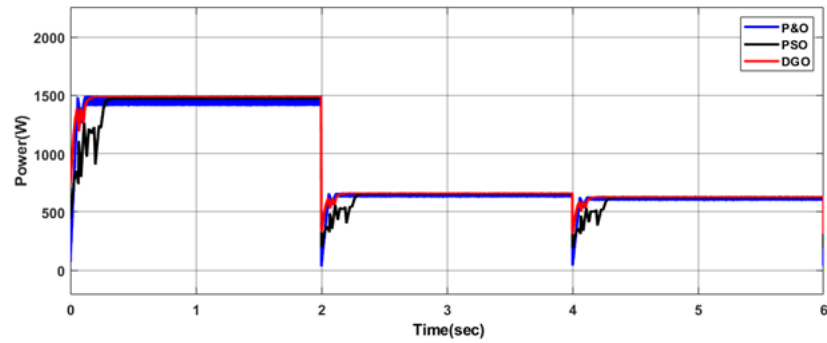


Figure 23. Load power.

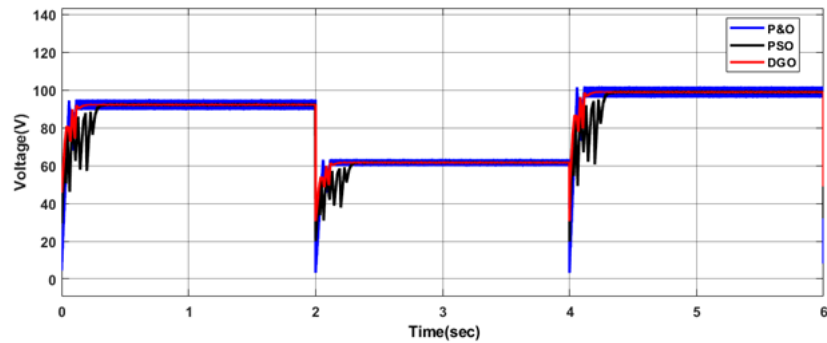


Figure 24. Load Voltage.

Table 9. Performance of MPPT Algorithms in Partial Shading with a Faulty PV Array (Case 3).

	P&O	PSO	DGO
Optimization Time (sec)	0.0873	0.2695	0.087
Settling Time (sec)	0.138	0.368	0.1912
Ripples (%)	5.18	0.852	0.198
Global Maximum (W)			
0 to 2 sec	1487.4738	1487.4738	1487.4738
2 to 4 sec	659.712	659.712	659.712
4 to 6 sec	629.168	629.168	629.168
Maximum power (W)			
0 to 2 sec	1430.12	1469.31	1486.9545
2 to 4 sec	615.85	641.08	659.054
4 to 6 sec	585.46	611.52	628.84
Efficiency (%)	96.33	98.12	99.98

### 5. Conclusions

Partial shading in a PV system can impact the strength of the arrangement and increase losses, resulting in a drop in efficiency. This paper presents a new optimization algorithm called DGO. Its main goal is to efficiently track the highest point of power globally, even in the presence of multiple local optimal peak powers, especially when partial shading occurs. The method uses PV voltage and PV current as inputs and produces the optimized voltage as the output. To achieve the maximum power output from the

PV system, it is essential for the DC-DC converter to maintain the optimized voltage. The PI controller uses the difference between the optimized voltage and the actual voltage as its input to calculate the duty cycle required for the DC-DC converter. The converter then utilizes the switching pulses produced by this duty cycle to extract maximum energy. This study recedes the application of the offered optimization process to achieve greatest power in three distinct scenarios: The efficiency of the DGO-based MPPT algorithm is evaluated by comparing it with the PSO and P&O methods under various conditions, including equal irradiance, partial shading, and faulty PV array scenarios. The comparison is carried out through MATLAB/SIMULINK simulations. The simulation results are presented on paper. The simulation results presented in tables show that compared to the PSO-based optimization, the intended process to track the global maximum with 30% less settling time and 96% reduced ripples and negligible steady-state error. Tuning the PI controller gains may be considered as future improvement to the presented work in this paper by the authors. A precisely adjusted PI controller for DC voltage regulation can further reduce the staying time and steady-state ripples and adjust the permanence of the system.

## Acknowledgments

**Funding:** No external funding.

**Author contributions:** Conceptualization - Keerthi Sonam Soma and R. Balamurugan; methodology - Keerthi Sonam Soma; validation – Karuppiyah Natarajan; investigation - Keerthi Sonam Soma; writing—original draft preparation - Keerthi Sonam Soma; writing—review and editing, Keerthi Sonam Soma, R. Balamurugan and Karuppiyah Natarajan.

**Disclosure statement:** The authors declare no conflict of interest.

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