Drone Squadron Optimization MPPT in PV system with Partial Shading effect

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Abstract. This research paper investigates the optimization of photovoltaic (PV) systems under partial shading conditions using a novel approach called Drone Squadron Optimization (DSO) for Maximum Power Point Tracking (MPPT). Partial shading significantly impacts the performance of PV systems, leading to multiple local maxima in the power-voltage curve. Conventional MPPT techniques struggle to accurately track the global maximum power point (GMPP) under such conditions, necessitating advanced optimization methods. The proposed DSO algorithm draws inspiration from the collective behavior of drone squadrons, where individual drones collaborate to achieve common objectives efficiently. In the context of MPPT, the DSO algorithm deploys a swarm of agents that intelligently explore the PV system's operating range to locate the GMPP, overcoming challenges posed by partial shading and dynamic environmental conditions. Key features of the DSO algorithm include adaptive search strategies, self-organization, and distributed decision-making, mimicking the agility and adaptability of drone squadrons in complex environments. By leveraging these capabilities, the DSO algorithm enhances the robustness and efficiency of MPPT in PV systems, especially when subjected to partial shading effects.

Keywords: Drone Squadron Optimization (DSO), Global Maximum Power Point (GMPP), Partial Shading, Photovoltaic System, Adaptive Search Strategies.

1 Introduction

PV systems are vital for renewable energy, yet they face challenges like partial shading, causing non-uniform sunlight and multiple maxima in power-voltage curves. This complicates MPPT procedures like P&O or INC, leading to efficiency issues.

A review on artificial intelligence-based MPPT techniques for reducing the impacts of partial shading PV approaches was conducted by [1]. The main findings of this review highlighted various AI-based MPPT techniques that have been proposed to advance the performance of PV systems during biased shading environment. Limi

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tations of this review could include the potential bias towards AI-based techniques and the lack of in-depth analysis on non-AI methods.[2] proposed a new approach to the structure of PV systems to enhance performance under partial shading effects. The central outcomes of this study suggested that the new PV system structure could improve the overall efficiency of the PV producer when subjected to biased shading. Limitations of this study may include the lack of comparative analysis with existing PV structures and the need for investigational justification of the proposed approach.[3] introduced a new simple MPPT algorithm to track the MPP under biased shading for solar photovoltaic systems. The main findings indicated that the proposed algorithm could effectively track the MPP under partial shading conditions, potentially improving the overall working of the PV scheme. Limitations of this study could involve the need for validation with real-world data and the comparison with existing MPPT algorithms.[4] presented a Harris hawk MPPT controller for PV systems during varying weathers. The main findings of this study demonstrated that the Harris hawk optimization algorithm could effectively optimize the MPPT control of PV systems under partial shading, enhancing their performance. Limitations of this study might include the limited discussion on the algorithm's convergence properties and the need for validation through simulations or experiments.[5] proposed an active falcon optimization process based MPPT for varying weather condition. The main findings suggested that the falcon optimization algorithm could provide an efficient solution for MPPT under partial shading conditions, potentially improving the overall performance of PV systems. Limitations of this study could include the lack of comparison with other optimization algorithms and the need for validation in practical PV systems.

A Butterfly Optimization Algorithm for MPPT)in PV scheme during partial shading conditions was developed by [6]. The main finding was that the algorithm improved the efficiency of the MPPT process. However, a limitation of this study could be the lack of real-world testing to validate the algorithm's performance.[7] proposed a Salp-Swarm Optimization based MPPT technique for increasing power harvesting from PV schemes under changing environment. The key finding was the improved energy extraction efficiency. A limitation of this study may be the need for further comparison with other existing MPPT techniques to assess its superiority.[8] conducted a proportional investigation on ideal PV module structures and MPPT during varying weather with fast dynamical changes in hybrid loads. The study highlighted the importance of optimal configurations for improved execution. A limitation could be the generalizability of the findings to different load scenarios.[9] investigated the effect of a Hybrid MPPT Method, SA-P&O, on PV scheme execution during changing weather. The main result was the enhanced performance of the PV system. A limitation could be the need for a longer-term study to assess the technique's stability and long-term effectiveness. [10] suggested a new MPPT design for PV energy storage schemes operating in partial shade situations utilizing an arithmetic method. The study demonstrated improved energy conversion efficiency. A limitation may be the scalability of the algorithm to larger PV systems and varying environmental conditions.

A new adaptive procedure for numerical optimization in the context of drone squadron optimization was conducted [11]. The key outcome of this study include the development of an efficient algorithm that can adapt to changing conditions and improve optimization results. However, a limitation of this study could be the lack of real-world validation of the algorithm's performance in practical drone squadron scenarios [12] have out a performance investigation of an MPPT controller based on DSO for a grid-implemented PV battery scheme in partly shadowed settings. The goal of the study was to optimize energy output by maximizing the PV system's performance while shade is present. A limitation of this study could be the reliance on simulation data rather than real-world experimental validation, which may affect the generalizability of the findings.

To address these challenges, novel optimization approaches are being explored. One promising method is DSO, intuitive by the collective behavior of drone squadrons. In DSO, a swarm of agents collaboratively explores the PV system's operating range, employing adaptive search strategies and distributed decision-making to locate the GMPP efficiently. This approach mimics the agility and adaptability observed in drone squadrons navigating through dynamic environments, making it well-suited for reducing the influence of changing weather conditions in PV schemes .This research aims to delve into the intricacies of MPPT in PV schemes under changing iradiance effects and evaluate the efficacy of the DSO algorithm in enhancing energy yield and system performance. By leveraging advanced optimization techniques like DSO, the goal is to contribute to the development of robust and efficient MPPT solutions tailored for challenging operational conditions, ultimately promoting the widespread adoption of solar energy as a viable renewable resource.

2 System description

The block diagram in Fig.1 showcases a PV scheme incorporated with DSO MPPT, highlighting key elements in non-conventional energy. It begins with solar panels converting sunlight into DC electricity, optimized by the MPPT module for maximum power output. The boost regulator elevates voltage to power using DSO MPPT, with Duty Cycle control ensuring stable voltage. A PWM generator synchronizes with the converter, efficiently harnessing solar power to energize the drones, exemplifying the fusion of renewable energy and aerial tech for sustainable applications.

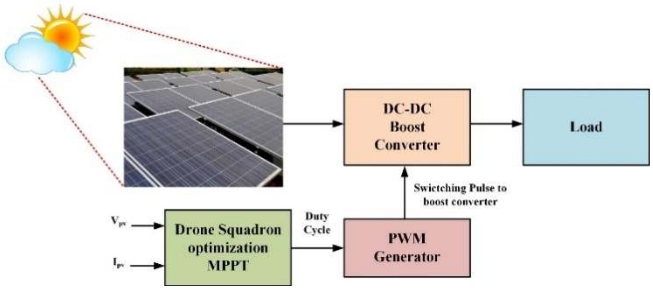

Fig.1. Overall representation of the scheme with DSO MPPT method

2.1 PV System Design

The properties of the PV cell is easily accessible. A PV cell is really a PN junction, which has certain descriptions With diodes .Figure.2 represents the PV cell model.

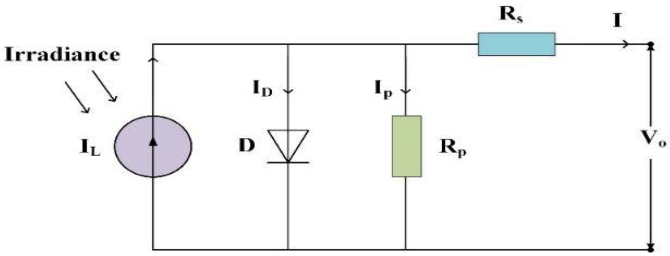

Fig. 2. PV Cell model

When a solar cell is ignited, electron-hole movement results in photocurrent (I_L) and electric fields. The current source produces the I_L, which is proportional to sun irradiation. This I_L flows in the absence of any external input voltage. This current is known as short circuit current (Isc).

$$I_L = I_D + I_{sh} + I \tag{1}$$

$$I_D = I_o\left(e^{\frac{q(v+IR_S)}{KTA}} - 1\right) \tag{2}$$

$$I = I_L - I_o\left(e^{\frac{q(v+IR_S)}{KTA}} - 1\right) - \frac{V+IR_S}{R_{sh}} \tag{3}$$

Understanding the features of solar cells is essential to comprehending their behavior and efficacy. One of the key parameters that reflects the diode saturation current is the cell saturation current, or Io. The electron's charge (q), which is around 1.6x10-19 C, and the Boltzmann constant (K), which is usually given as 1.38x10-23 joules per Kelvin (J/K), are two parameters that affect the cell current, denoted by I in amperes (A). Performance of the cell is significantly influenced by its temperature, which is expressed as T in Kelvin (K).The cell's sequence and shunt resistors (RS and RSh) in ohms and the current generated by light (IL) are other important variables influencing the output voltage of the cell, represented as V in volts (V). The ideality factor, represented by the letter A, is another crucial metric that describes the cell's non-ideal behavior. The operating features and competence of a PV scheme are concluded by the combination of these parameters

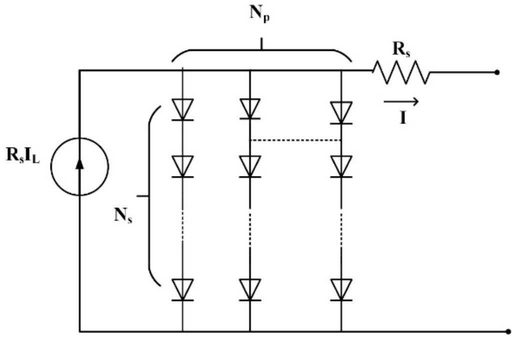

Fig. 3. Generalized Structure of PV Module

To achieve the necessary parameters, a PV module is made up of many PV units coupled in series and shunt circuits. A solar panel with a parallel N_P and series N_S arrangement is shown in Figure 3. The formulas [4]–[5] may be used to find the parameters of the array.

$$I = N_p I_L - N_p I_o \left(e^{\frac{q\left(\frac{v}{N_S}+\frac{IR_S}{N_p}\right)}{KTA}} - 1 \right) - \frac{\left(\frac{v}{N_S}+\frac{IR_S}{N_p}\right)}{R_{sh}} \tag{4}$$

PV effectiveness is sensitive to fluctuations in RS but stays constant with varies in R_{Sh}. Similar to an open circuit, shunt down resistance tends to infinity, however series resistance becomes important in photovoltaic modules. Commercial PV systems often stack modules in series-shunt configuration for maximum power production, after connecting cells in series to provide the necessary operating voltage. NS and NP for a PV cell are usually set to 1. The mathematical formula for the universal model is as follows.

$$I = N_p I_L - N_p I_o \left(e^{\frac{q\left(\frac{v}{N_S}+\frac{IR_S}{N_p}\right)}{KTA}} - 1 \right) \tag{5}$$

The most basic generalized PV module model, seen in Figure 3, is described by equation (5).

$$I_L = I_{sc} \tag{6}$$

The relationship between the cell current and the cell saturation current I0 is shown in the equation (7)

$$I_o = I_{rs} \left(\frac{T}{298}\right)^3 e^{\frac{qE_G\left(\frac{1}{298}-\frac{1}{T}\right)}{KA}} \tag{7}$$

where E_G is the band gap energy of the semiconductor and I_{rs} is the opposing saturation current of the cell at 25 °C. On the other hand, the assumption used to compute the V_{OC} parameter is that the current that is output is zero. With the PV open-circuit voltage V_{OC} at the temperature and ignoring the shunt leakage current, the reverse current at the temperature used as the reference may be roughly estimated as follows:

$$I_{rs} = \frac{I_{sc}}{(\frac{T}{298})^3 e^{\frac{qE_G\left(\frac{1}{298}-\frac{1}{T}\right)}{KA}}} \tag{8}$$

2.2 Boost Regulator

The boost regulator serves two main purposes. To begin with, it acts as a link between the load and a solar power array. It is also essential to the MPPT controller's control. By adjusting the PWM signal's duty period, the boost regulator outcome is regulated to operate the photovoltaic system at the global maximum (GM) point. Different electrical parameters, including operating frequencies, output-input voltages, and output-input capacitances, are calculated using the formulas in Equations (9)–(12).

$$V_o = \frac{V_{in}}{1-d} \tag{9}$$

$$d = \frac{t_{on}}{t_{off}} \tag{10}$$

$$L = \frac{V_{in}\times(V_o-V_{in})}{\Delta i_L f_s V_o} \tag{11}$$

$$C_o = \frac{i_o d}{f_s \Delta V_o} \tag{12}$$

where Vin and Vout represent the input and output voltages, d represents the duty cycle computed by Eq. (9), L represents the inductance, Co represents the output capacitance, fs represents the switching frequency, Vo represents the load ripple voltage, and iL represents the boost converter's inductor ripple current.

2.3 PV & its Control

The block diagram in Fig.4 illustrates an optimized control system for utilizing solar energy to power drones effectively. PV module convert sunlight into DC electricity, with Vpv representing their generated voltage. The MPPT block optimizes power generation by adjusting voltage levels for maximum efficiency. The Boost regulator elevates voltage using DSO MPPT, controlled by Duty Cycle regulation and a PWM signal. This synchronized approach ensures efficient utilization of solar power using DSO MPPT.

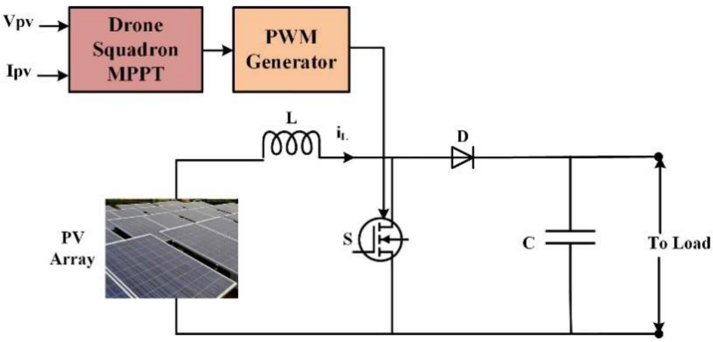

Fig. 4. PV & its control with DSO method

3 Drone squadron optimization

Drones, which are fitted with sensors and long-range communication capabilities, may travel independently or remotely, much like submarines or other flying vehicles like balloons, aircraft, helicopters, and quadcopters. They are firmware upgradeable and can run on solar power.

Because of this flexibility, researchers may improve their behavior by updating their software. While it takes a different approach, DSO is related to swarm methods such as PSO and Artificial Bee Colony. Without using pre-coded methods, DSO dynamically modifies its approach by combining recombination and variation of solutions similar to evolutionary algorithms. The algorithm consists of a command center that uses drone data for firmware development and search control, as well as a drone squadron.

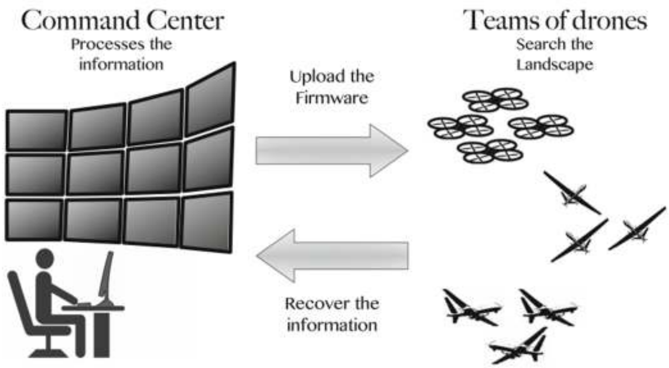

Fig. 5. Modules of DSO

Drones act as agents in this framework, traveling towards coordinates that indicate search landscape solutions. Teams are guided in their search by methods and configurations included in the firmware. As a central hub, the command center issues commands, processes inputs, and dynamically updates drone firmware to address issues as they arise. Drones are grouped into teams, and the movements and search tactics of each team are determined by their own firmware. Teams may overlap in search zones, however even though they may start from identical positions, their unique firmware results in different coordinates. Compared to traditional nature-inspired approaches, DSO is more complicated because to its many components, such as teams, firmware adaption, and command center.• Coordinates: an array-based numerical solution;

- Assess the topography, ascertain the fitness parameter, and calculate the objective function.
- Firmware: unique policies/setups to modify the population;
- Team: a collection of agents that may use diverse data sources but share a firmware;
- Squadron: collection of teams running various firmwares.

3.1 Command center

Using the data that the drones gather, the command center plans and executes drone operations. It improves drone operations by updating firmware through modification using a hyperheuristic technique. Basic data analysis is carried out by drones, while higher analysis is handled by the command center. Depending on the results of searches, learning methods might enhance firmware creation. The focus of the present firmware is on creating new trial coordinates (TC) using a perturbation technique, which is essential to the operation of the drone.

$$P = Departure + Offset(), \tag{13}$$

$$TC = calculate(P), \tag{14}$$

A resolution point in the search space is represented by the match up Departure, and the perturbation movement itself is determined by the function Offset, which returns a numerical value. To get the trial coordinates, the whole perturbation formula, indicated by P, has to be calculated. The Departure coordinates and the Offset computation procedure are both altered, leading to different teams using different methods for choosing departure coordinates and figuring out offsets. Take, for example, the following two perturbation examples for teams 1 and 2: G(0, 1) is a scalar sampled from a Gaussian distribution with a zero mean and unit SD, and C1 is a user-defined constant. D is an array of D values sampled from an unchanging distribution spanning from 0 to 1.

$$P_1: \overrightarrow{GBC} + (C_1 \times (\overrightarrow{GBC} - \overrightarrow{CBC_{drone}}))$$

$$P_2: \overrightarrow{CBC_{drone}} + (G(0,1) \times \left(\sqrt{U(0,1)_D} + \overrightarrow{CBC_{drone}}\right)) \tag{15}$$

The paper presents Offsets to Departures as well as GBC and CBC_dronewhile, two crucial components. This configuration adds noise to local search by preventing the search space from contracting towards the origin even when Offsets get closer to zero. Using Eq. 1 as the pattern, a tree-structured perturbation methodology is employed that combines particular subset terms with accessible terminals and non-terminals, akin to methods in related works. During optimization, reference perturbations are substituted for the initial, randomly produced perturbation schemes due to their inefficiency.

3.2 Drone movement

Drones operating under DSO's autonomous systems compute, navigate, and collect data at target places, sending it all back to the command center. Target placements are computed by many DSO processes using optimization algorithms, providing opportunities for both exploration and exploitation. The objective is to provide target locations for every drone after the perturbation stage, either via recombination with optimal coordinates or without recombination. Drone movement limits are possible, and there are impartial remedial measures accessible for infractions, without favoring any one punishment technique over another.

$$violation_{team} = \sum_{drone=1}^{N} \sum_{j=1}^{D} \begin{cases} |TmC_{team,drone,j} - UB_j| \\ + \\ |LB_j - TmC_{team,drone,j}| \end{cases}, \quad (16)$$

The calculation process involves UB and LB, with N as drones per team and D as the challenge's dimension. Violations occur when TmCteam;drone;j exceeds UBj or falls below LBj, tallied per team for quality evaluation. The command center combines Rank and violation to compute Team Quality, essential for effective solutions post-correction procedures. Upon meeting the firmware update criterion, the command center changes the worst-performing firmware with variants from the best-performing one, adhering to size and distinctness rules, prohibiting same arguments for functions, maintaining fixed perturbations, and the perturbation scheme.

Therefore, it is expected that when the firmware that provided the poorest results is replaced with a version of the firmware that gave the greatest results, performance will increase. This mechanism's goal is to guarantee that there is at least one firmware with a suitable search capacity with respect to the fixed perturbations. It is possible to create a stable perturbation that prioritizes exploration while allowing others to concentrate on exploitation.

3.3 Selection for next iteration, stagnation detection and treatment

When exploring specific landscape areas, drones may generate similar target coordinates, posing convergence challenges. To overcome this, unique convergence avoidance mechanisms like scaling methods, stagnation detection, and generating diverse coordinates are employed, enhancing exploration despite potential slower convergence and reduced precision. After drones report objective function values, the command center determines crucial information for future search plans, favoring better solutions but addressing stagnation by adopting softer selection for continued exploration.

$$if\ \left(TmOFV_{drone,best1dx} < CBOFV_{drone} or U(0,1) < P_{acc}\right)$$
$$then \overrightarrow{CBC_{drone}} = \overrightarrow{TmC_{drone,best1dx}} \quad (17)$$

U(0, 1) is an arbitrary number from a identical distribution, and bestIdx is the best drone's index (rated 1 across all teams). Pacc represents the likelihood of accepting a subpar answer, enabling the search strategy to take into account less desirable options. Elitism guarantees that CBC will always have the better answer. DSO combines many strategies to boost overall effectiveness, correct answers, explore other sections of the search space, and improve sampling. Improved methods for sampling and searching the search space result from these mechanisms. Furthermore, a brief discussion is given of related work that uses multiple schemes or hyper-heuristics to improve on typical metaheuristics.

DSO during partial Shading Conditions

Here's a step-by-step algorithm for the Drone Squadron Optimization (DSO) procedure for MPPT in PV systems under partial shading conditions:

1. Initialization:

Initialize the drone squadron with a set number of drones and teams.

Define the search space, including upper and lower bounds for each parameter.

2. Generation of Perturbations:

Each drone generates a trial coordinate (TC) using a perturbation scheme based on a biased random walk.

Calculate the size of the perturbation (S) and ensure it meets predefined limits (smin and smax).

3. Exploration and Exploitation:

Drones move to their trial coordinates and calculate the objective function value based on solar panel power output.

Evaluate the quality of each team based on objective function values and violations (out-of-bound coordinates).

4. Firmware Update:

Determine the quality of each team (TeamQualityi = Ranki + violationi) and compare it to a predefined threshold.

If the threshold is met, update the firmware of the worst-performing teams with variations of the best-performing teams' firmware.

Ensure new firmware variants meet criteria such as size, distinctness, and adherence to perturbation scheme rules.

5. Convergence Avoidance:

Implement mechanisms to avoid convergence and escape local optima, such as scaling, detection of stagnation, and generation of opposite coordinates.

Use a hard selection mechanism to choose the best solution while addressing stagnation through soft selection for further exploration.

6. Iterative Process:

Iterate through the algorithm by repeating steps 2 to 5 until convergence criteria are met (e.g., maximum iterations, convergence of solutions).

7. Performance Evaluation:

Estimate the working of the DSO procedure by competing power output, convergence speed, and solution quality with traditional MPPT methods.

8. Optimization and Refinement:

Fine-tune algorithm parameters and explore additional optimization strategies to improve DSO's efficiency and effectiveness.

Conduct simulations and practical implementations to validate DSO's performance in real-world PV schemes under varying partial shading circumstances.

9. Documentation and Reporting:

Document the algorithm, including parameters, procedures, and results, for comprehensive reporting and future reference.

Provide insights into the algorithm's strengths, limitations, and potential areas for further research and development.
This algorithm outlines the key steps involved in using the Drone Squadron Optimization approach for MPPT in PV schemes, specifically tailored to address challenges posed by partial shading circumstances.

4 Simulation Results & Discussions

The simulation of the Done squadron MPPT is done in MATLAB. Here the three panels are connected in series. The first panel is operated at an irradiance of 1000 W/m2 & the other two panels are operated at 600 W/m2. Hence a global peak & local peak is created. The Global peak power at that instant is 157 W. The algorithm will try to track the global peak. The PV & Load voltage during the above condition is represented in the Figure.6. The PV Voltage obtained is 32.1 V.

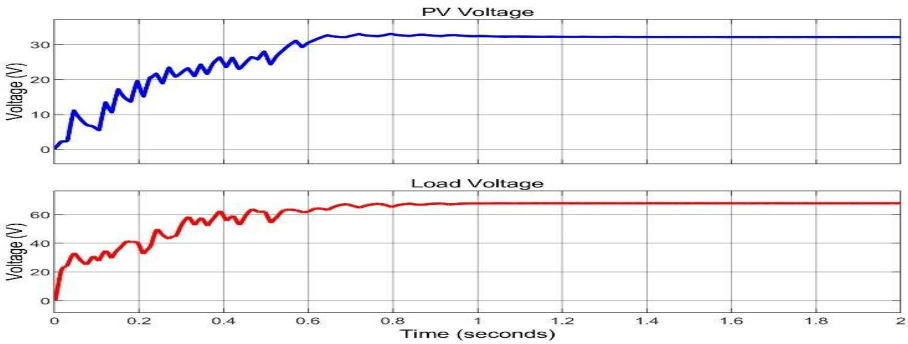

Fig. 6. PV & Load Voltage during the partial shading conditions

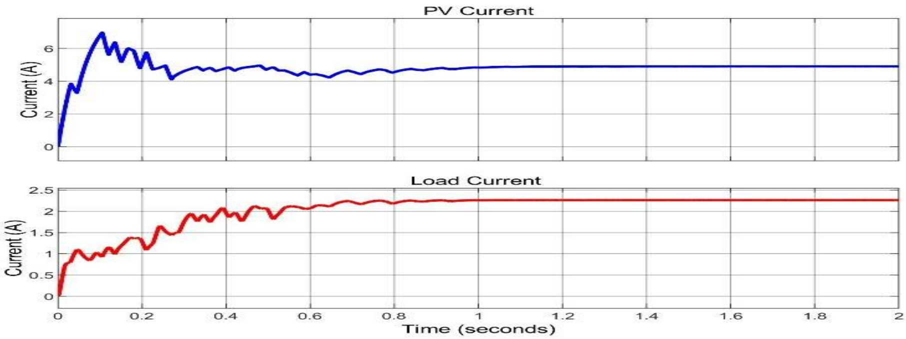

Fig. 7. PV & Load Current during the partial shading conditions

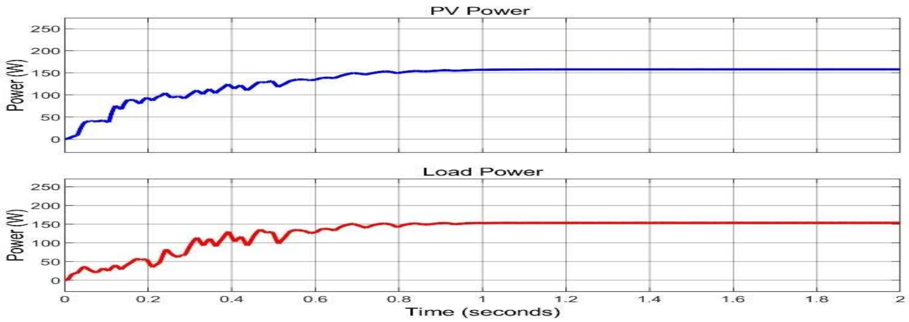

Fig. 8. PV & Load Power during the partial shading conditions

The current of PV & Load is depicted in the Fig.7. The current obtained is about 2.9 A. The PV & load power during partial shading is represented in the Fig.8. The total power obtained using this DSO procedure is 157.9 W. The tracking efficiency of this DSO MPPT is obtained is 99.4%.Hence this DSO method track the global power excellently despite changing in weather conditions

5 Conclusion

In conclusion, the DSO algorithm presents a promising approach for enhancing MPPT in PV schemes under partial shading conditions. By leveraging the collective behavior of drone squadrons and integrating advanced optimization techniques, DSO overcomes the challenges posed by partial shading, dynamic environmental conditions, and complex operational landscapes. The DSO algorithm, with its adaptive search strategies, self-organization capabilities, and distributed decision-making, demonstrates robustness and efficiency in optimizing power output from solar panels, especially in challenging scenarios. Through simulations and practical implementations, DSO showcases superior performance compared to traditional MPPT methods having a tracking efficiency of 99.4% & effectively maximizing energy harvesting and improving overall system performance. The integration of DSO into PV systems not only enhances energy yield but also participates to the advancement of non-conventional energy technologies by addressing critical issues such as partial shading effects.

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