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Mitigation of Power Losses in Solar Photovoltaic Systems Under Partial Shading Using Optimization-Based MPPT

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ABSTRACT

Partial shading is one of the crucial bottlenecks in solar photovoltaic (PV) system. The performance of a PV system is affected due to partial shading. This paper highlights the impact of partial shading condition (PSC) on the performance of PV systems with an experimental analysis using a PV emulator. A reduction of 37% in maximum power, 38% in fill factor, and 60% in efficiency as a result of PSC was observed in the experimentation work. PSC also results into multiple peaks on power-voltage (P-V) curve. One of these peaks is the Global Maximum Power Point (GMPP) and other peaks are local MPPs. The GMPP cannot be tracked using conventional MPPT algorithms. This paper proposes a new optimization method called as Firefly Algorithm (FA) built on a metaheuristic approach for Maximum Power Point Tracking (MPPT). Results obtained through the simulation show the enhancement in the tracking efficiency and tracking time over the conventional MPPT methods by achieving the tracking efficiency of 98.12% with a response time of less than 1ms. The proposed system is also able to reduce the oscillations around MPP and achieve stable performance under dynamically varying environmental conditions.

1. INTRODUCTION

Energy has become a crucial aspect in everyone's life. The world is facing an energy crisis because of the huge growth in population and industrialization. The difference between the demand and production of energy is continued to increase. To meet the energy demand, the conventional energy sources like coal, gas, etc., have been used from the past. But these energy sources are harmful for the nature as these are responsible for toxic pollution. The reports of the Annual Energy Outlook state that conventional energy sources like gas, coal, uranium, and oil will deplete in just a few decades [1]. To overcome the limitations of conventional energy sources, an alternative energy sources are needed. Renewable energy sources like wind, solar, biomass are used during the past two decades [2]. Natural resources that provide renewable energy are abundant and don't harm the environment. Renewable energy sources will soon dominate the energy landscape because of advances in harvesting technology. Solar energy harvesting offers several advantages in terms of less complex installation, simplicity of use, low maintenance requirements, etc. A solar photovoltaic system transforms photons into electricity. The power output of a PV system is greatly reliant on solar irradiation. A variety of problems, including PSC, minor flaws, diode failure, etc., restrict the power from the PV system. The effect of partial shading on PV system and hotspot problem is well discussed in the literature. Some of these difficulties are diagnosable. However, some elements, such as hotspots and partial shade, cannot be avoided [3-5]. Partial shading on PV panels reduces the maximum power from the system and can also cause PV cell damage due to hot spots. The effect of PSC can be minimized by using suitable MPPT. Conventional MPPT methods include the Perturb and Observe (P&O) and Incremental Conductance (IC). These techniques track the MPP by using iterative processes for adjusting the duty cycle. Conventional MPPTs are able to track the MPP in normal environmental conditions. But these methods are slower in tracking the MPP and also have less tracking efficiency in the range of 80% to 90% in case of PSC. When the PV system is subjected to PSC, multiple local MPPs are present on the P-V curve of the system. The conventional methods are get stuck at local MPP instead of GMPP and may fail to track GMPP. These methods cannot handle high dynamics in PV systems and nonlinearities due to PSC. Conventional MPPTs use fixed step size. Larger step size can be used for increasing the convergence speed, but it decreases accuracy. On the other hand, the smaller step size increases the accuracy, but decreases the convergence speed. To overcome the problems with conventional MPPT methods, the optimization methods are needed for MPPT. The proposed FA-based method can track the GMPP effectively under PSC. The FA-based method dynamically adjusts the step size to balance the accuracy and convergence speed. It can also handle non-linearity due to the PSC. It explores the entire search space that can increases the maximum power extraction.

Various reconfiguration techniques are implemented to track the GMPP under partial shading [6, 7]. The optimization techniques Particle Swarm Optimization (PSO), Neural Network (NN), Artificial Neural Network (ANN), Ant Colony Optimization (ACO), and Cuckoo search are merged with these methods [8]. The MPPT is dependent on the dynamics of uncontrollable operational circumstances. Intermittent solar energy puts a strain on the grid's stability and power quality as PV system penetration increases. PV systems' reliance on solar radiation can occasionally result in technical problems, including overloading the grid during periods of peak electricity output [9]. The PV system is affected by multiple mismatches, including cloud and dirt that creates multiple peaks on the P-V curve. This presents a challenge for these simple controllers. Unfortunately, simple controllers are unable to handle mismatch events [10]. Many researchers have looked at soft computing approaches to deal with difficult problems. Since their job is to find the global maxima rather than the local, they have been created to cope with global MPPT. In other words, they can potentially offer the best solution for a characteristic function with numerous peaks. The most recent research studies provide some sophisticated GMPPT approaches [11].

2. RELATED WORK

Many researchers have contributed to the development of various MPPTs. The Perturb and Observe (P&O) MPPT based on a novel linear tangent developed by the authors was able to achieve higher accuracy, improved efficiency, low oscillations, and improved dynamic and steady-state response [12]. An extensive review of the various hardware solutions to achieve maximum power under partial shading was done by the researchers. The research provided the economic viability and challenges for the various solutions [13]. The performance of the traditional P&O approach under rapidly varying solar irradiation is comprehensively examined by the researchers. Four out of sixteen example studies involving abrupt changes in solar irradiation show that the traditional P&O approach does not correctly track MPP. Under a ramp shift in irradiation level, the conventional P&O tracker is unable to function effectively. A modified P&O-based-MPP tracking system is presented and evaluated under step and ramp variations of irradiation. The said method tracks the MPP under fast varying conditions [14]. Başoğlu [15] has done a comprehensive review of distributed MPPT techniques and the module-level and submodule-level. In this work, distributed MPPT (DMPPT) is highlighted. Full and differential power processing (FPP and DPP) are two classes of hardware MPPT solutions based on power electronics that are explored. Additionally, a variety of parameters have been looked at when evaluating commercially available power optimizers. A thorough analysis and evaluation of the relevant literature have been conducted. Mahato et al. [9] has reviewed the active power control methods. They examined several active power control strategies, such as fixed and variable horizons. The main objective was to examine the dependability aspect while obtaining energy from solar plants. To determine which approach meets the requirements best, the two methods have been compared. The authors also briefly discussed how both systems affect the grid system. In addition, benchmarking has been suggested as a way to switch between modes based on the power supply. A novel extreme control-seeking framework was suggested by the authors. They provided ordered excitation (OE) and non-linear function-based PSO methods to track the MPP. For the improvement of steady-state response when carrying out the extreme searching task, the novel algorithms of nonlinear function (NF) based PSO and OE are introduced. The programs can quickly implement explicit control functions. The suggested controller is assessed using a variety of control performance indicators using statistical simulation-based analysis and experimental investigation. A comparative examination of the statistical data demonstrates that the simulation and experimental findings support the notion that both the NF-PSO and OE algorithms contribute to the enhancement of the global extreme seeking's steady state and transient responses [10]. MPPT design using swarm intelligence under the partial shading effect was developed by the researchers. The proposed system is tested in four distinct scenarios to validate system performance against simulation results. The recommended TLABC approach is found to provide better performance than other investigated methods [16]. Pal and Mukherji [17] have suggested another improved MPPT method. To maximize the power from the PV array under diverse climatic situations, the study suggests an enhanced chaotic PSO. To prevent regular PSO from becoming trapped in local MPPs, the chaotic mutation is incorporated into the algorithm. The suggested approach also significantly reduces tracking time, iteration count, and efficiency. The acquired findings also demonstrate that the tracking effectiveness of the suggested strategy is, in the majority of circumstances, superior to other methods, which gives it a better perspective for usage in the control block while looking for the overall MPP of the PV system. Nassef et al. [18] developed a modified MPPT using a honey-badger algorithm. Metaheuristic algorithms (MHs) have been developed recently to address a wide range of optimization issues. The benefit of the MHs is not only their ease of implementation, which aids in dealing with numerous and various real-world applications but also their simplicity of understanding. One of the more recent MHs is the Honey Badger Algorithm (HBA). The HBA algorithm effectively tackles difficult problems with high dimensions.

Various optimization methods have also been implemented to improve the performance of MPPT algorithms. Premkumar et al. [19] have used the whale optimization technique for MPPT. To maximize the PV output under PSC, they have presented an effective technique for MPPT. The recommended strategy is based on the whale-optimization (WO) algorithm, which aims to detect the global peak (GP) despite its quick convergence speed and poor tracking efficiency. This recommended approach lessens the computational complexity faced by the many MPPT algorithms that have been studied in the literature and aid in lowering the oscillation of power during environmental changes. Another Global MPPT using the teaching-learning method was introduced by the study [20]. A unique population-based optimization approach inspired by the learning environment of the classroom, is used in this method to extract GMPP. Regarding tracking effectiveness and steady-state oscillations, the suggested technique improves upon the drawbacks of current traditional MPPT tracking systems. It was discovered that TLBO satisfied the requirements for a heuristic technique, performed better than the PSO method with less computational work, and demonstrated high consistency. Another MPPT technique based on a tuned adaptive fuzzy PID controller using grey wolf optimization (GWO) was suggested by the researchers. A GWO approach has been used in their work to optimize the parameters of an adaptive fuzzy-based PID (AFPID) controller that has been developed for the frequency regulation of power systems. Throughout the search process, the original GWO method's simplicity is introduced by discarding the wolves in the poorest category and giving precedence to superior wolves. By using benchmark functions for unimodal, multimodal, and fixed dimensions, projected SGWO's advantage over GWO is shown in terms of better results with shorter execution times [21].

Recent advancements in MPPT research involve various reconfiguration techniques to track the global MPP. The physical relocation procedures are challenging since they need labor-intensive work. The ideal switching matrix design for EAR is still difficult to achieve. An extensive review of reconfiguration strategies for MPPT is done by the authors. The performance of various reconfigurations is simulated and compared by the study [22]. Patro and Saini [23] have used static array reconfiguration for GMPPT. Analysis has been done on the effectiveness of various photovoltaic static array topologies. It has been discovered that a static PV array with a bypass diode and a TCT (Total Cross Tied) configuration may increase output power to 1.14 kW. As a result, the MPPT controller is connected to the static PV array with TCT configuration. Finding the GMPP, which is a difficult challenge for the control algorithm due to several peaks. To perform an inspection approach, the MPPT technique incorporates social learning differential evolution (SLDE), which significantly increases the tracking capabilities. Another new metaheuristic method called Adaptive-JAYA optimization for the best reconfiguration of the PV array is used to get over the problems associated with the traditional reconfiguration methods. Because it is dependable and easy to use, adaptive-JAYA uses less memory and puts less strain on processors [24]. The selection of the suitable MPPT technique is necessary for solar PV system under PSC.

3. MODELLING OF PV CELL

A single diode model may be thought of as a current source and a parallel linked diode operating in the opposite direction as shown in Figure 1. Each parallel and series resistance in a model is unique. Series resistance stands for the obstruction to the passage of electrons from the n to the p junction and parallel resistance for leakage current. In the absence of incoming light, the PV cell operates as a diode and produces a current.

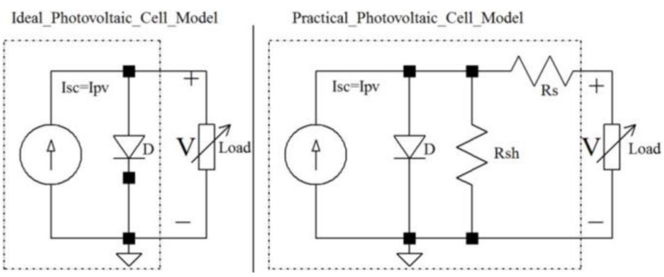

Figure 1. PV cell equivalent model

For an ideal PV cell, the current is given by Eq. (1).

$$I_d = I_{pv} - I_s\left(\exp\frac{qV}{kT} - 1\right) \tag{1}$$

where, I_d is diode current (A), I_{pv} is the PV current (A), I_s is saturation current (A), q is charge on electron, V is the PV cell voltage (V), k is Boltzmann constant (1.380649×10^{-23} J/K), and T is temperature (K).

The MPP of a solar module, as illustrated in Figure 2, shows non-linear Current-Voltage (I-V) and Power-Voltage (P-V) characteristics and can alter in response to changing radiation and temperature. In real-world situations, PV cell connections in series and/or parallel must be used to provide the necessary voltage and current. A greater output current results from a parallel connection, but a greater output voltage arises from the series connection.

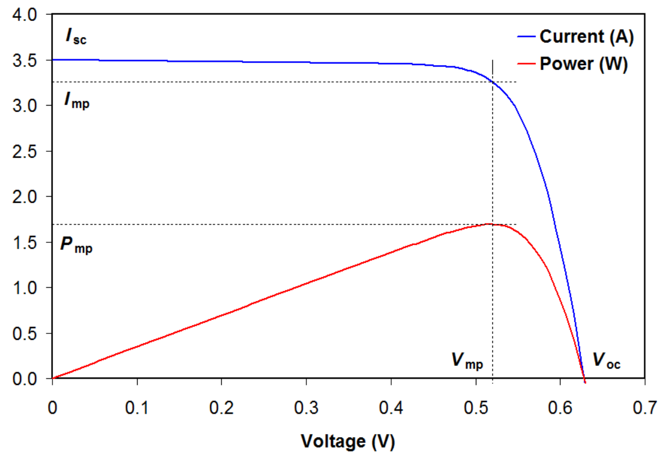

Figure 2. I-V and P-V curves for a typical PV system

With practical factors considered, the equation can be modified as Eq. (2).

$$I_d = I_{pv} - I_s\left(\exp\frac{q(V + IR_s)}{N_s kT\alpha} - 1\right) - \frac{V + IR_s}{R_{sh}} \tag{2}$$

where, R_s is the series resistance (Ω), N_s is the number of PV cells connected in series, α is diode ideality factor, and R_{sh} is the shunt resistance (Ω).

Series resistance and shunt resistance values are calculated as Eq. (3) and Eq. (4).

$$R_s = \frac{V_{oc} - V_m}{I_m} \tag{3}$$

$$R_{sh} = \frac{V_m}{I_{sc} - I_m} \tag{4}$$

where, V_{oc} is open-circuit voltage (V), I_{sc} is the short-circuit current (A), V_m is the voltage (V) at MPP, I_m is the current (A) at MPP.

4. EXPERIMENTAL ANALYSIS OF THE EFFECT OF PARTIAL SHADING USING PV EMULATOR

The effect of PSC was analyzed using PV Emulator. Figure 3 depicts the actual setup utilized for the experiment. Four various shading schemes were used in a series of studies. The performance parameters were noted, and the PV Emulator's parameters were configured as shown in Table 1. Figure 4 and Figure 5 demonstrate, respectively, the P-V and I-V Curves in four different PSCs using a PV Emulator. Table 2 contains a summary of these observations.

In case 1, all the panels are fully illuminated with solar irradiance of 1000 W/m^2. It indicates no shading condition. This represents the ideal conditions where all PV panels receive maximum and uniform solar irradiance. It serves as a baseline to observe the maximum power extracted from the PV system.

Table 1. PV emulator configuration parameters

Sr. No.	Parameter	Value
1	V_{oc}	36.3V
2	I_{sc}	7.84A
3	T_c	0.102
4	A	0.98117
5	R_s	0

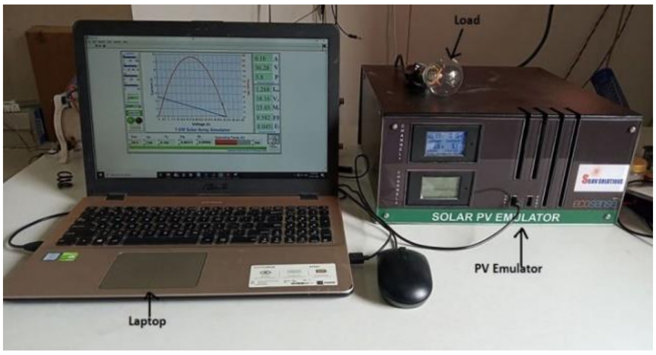

Figure 3. The experimental set-up using PV emulator

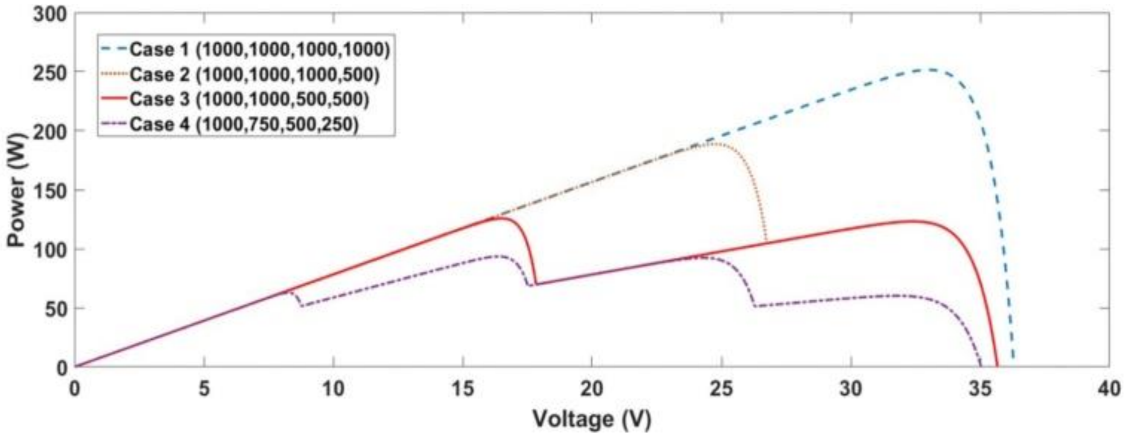

Figure 4. P-V curves using PV emulator

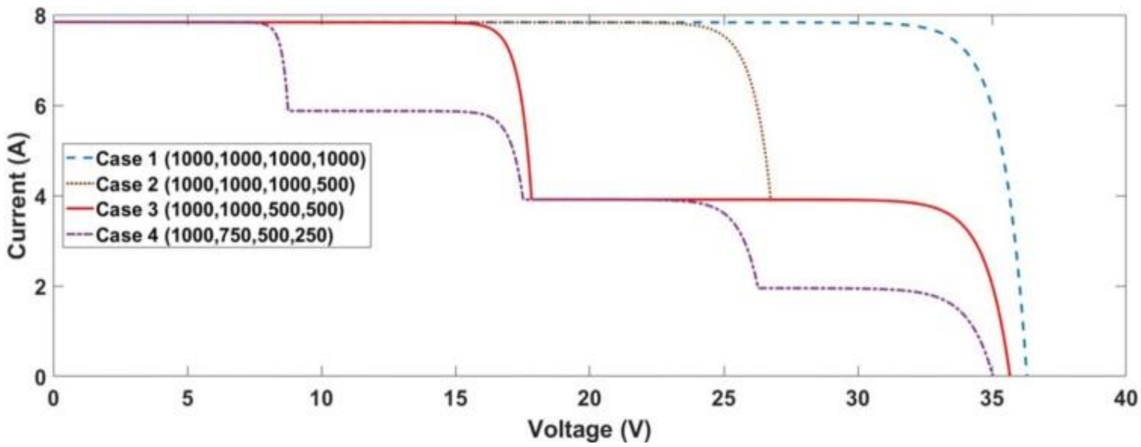

Figure 5. I-V curves using PV emulator

Table 2. PV array performance using PV emulator

Case	Irradiance Levels (W/m^2)	I_{MPP} (A)	V_{MPP} (V)	MPP (W)	Fill Factor	Efficiency
1	1000, 1000, 1000, 1000	7.618	33.02	251.6	88.37	0.4006
2	1000, 1000, 1000, 500	7.620	24.77	188.7	67.46	0.3432
3	1000, 1000, 500, 500	7.618	16.50	125.9	44.98	0.2671
4	1000, 750, 500, 250	5.713	16.39	93.52	34.03	0.2384

In case 2, first three panels are fully illuminated, but one panel is shaded with solar irradiance of 500 W/m^2. This Simulates a scenario where one panel is partially shaded while the others receive full sunlight. Such condition commonly occurs due to small obstructions like a tree branch, or debris on one part of the array.

In case 3, two panels are fully illuminated, but remaining two panels are equally shaded with 500 W/m^2. This represents increases level of partial shading, but it's less complex in variations. This represents conditions where shading affects two consecutive panels. Such condition is commonly caused by shadows from nearby buildings, poles, or larger obstructions at certain times of the day. It demonstrates how increasing shading reduces the system's power output more significantly compared to case 2.

In case 4, only one panel is fully illuminated and other three panels are shaded differently having unequal solar irradiance of 700 W/m^2, 500 W/m^2, and 250 W/m^2. This represents the complex shading pattern with varying levels of solar irradiance. This case simulates a situation where shading occurs progressively across all panels, such as during early morning, late evening, or with moving clouds. This condition is common during partial sunlight conditions or dynamic shading patterns. This is important for analyzing the PV system's performance under highly non-uniform irradiance and designing suitable mitigation strategies such as MPPT algorithms.

As illustrated in case 1, the system produces a MPP of 251.6 W with consistent solar irradiation across all PV panels. In the ensuing situations, as solar irradiation non-uniformity grows, the maximum power drops. Additionally, there are other local maxima. The experimental findings confirm the effect of PSC on the maximum power and local maxima of the PV system.

5. PROPOSED MPPT METHOD

A Firefly Algorithm is a metaheuristic approach to achieve optimization. The flow for the FA algorithm to track GMPP is described in Figure 6. According to the inverse square law, as stated in Eq. (5), light intensity diminishes as firefly distance rises.

$$I_r = \frac{I_s}{r^2} \quad (5)$$

where, I_r is solar light intensity (W/m^2) at distance r (m).

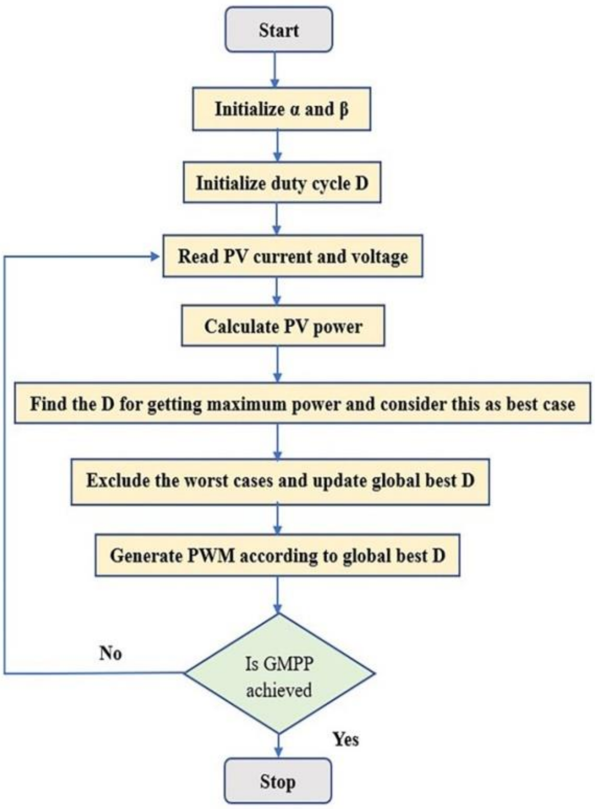

Figure 6. Flowchart for FA

The rules used by Firefly Algorithm are:

1. Fireflies attract each other regardless of their gender.
2. The attraction is proportional to light emitted. It decreases with an increase in the distance. In case of no brightness by any firefly, the fireflies move randomly.
3. Objective function determines the light emitted by firefly.

In addition, the air also absorbs light, making it dimmer as it travels farther. The selection of appropriate parameter values is essential to enhance convergence to the global optimum. Computational inefficiency might stem from poor decisions. The parameter of attractiveness is an additional element. The firefly is drawn to and tends to migrate toward a firefly that is more visible. Eq. (6) provides a quantitative description of the attractiveness.

$$\beta_r = \beta_0 \, e^{\gamma r^m}, \; m \geq 1 \quad (6)$$

The distance between i and j is represented by Eq. (7) and the position x_i is represented by Eq. (8).

$$r_{ij} = \left\| x_i - x_j \right\| \quad (7)$$

where, β_r is attractiveness at distance r, β_0 is initial attractiveness, γ is absorption parameter, and m is integer value,

$$x_i = x_i + \beta_0 \, e^{-\gamma r_{ij}^{\;2}} \; x_i - x_j + \alpha \varepsilon_i \quad (8)$$

where, α is randomization term, and ε_i is random number distributed in [0,1]. The β_0 stands for initial attractiveness. The absorption coefficient γ governs how much light intensity is reduced. Its value is critical in deciding how the FA algorithm will behave and how quickly convergence will occur. Integer m is set to a value of 2. α serves as a term for randomization.

Population size is taken as 40 and an algorithm is simulated for 50 iterations to ensure the better convergence and speed for the GMPPT. The γ is taken as 0.1 for MPPT to maintain a balance between local and global search. The value of α is taken as 0.2 to focus on a deterministic search while retaining minimal randomness. The value of β_0 is taken as 1 to stronger convergence toward brighter fireflies, improving tracking accuracy.

6. RESULTS AND DISCUSSION

The proposed MPPT is tested in a MATLAB SIMULINK environment. The system uses the PV array having three panels with 60.003W maximum power capacity and other specifications as listed in Table 3.

Table 3. PV array specifications

Sr. No.	Parameter	Value
1	Maximum power	60.003 W
2	Cells per module	60
3	V_{oc}	22 V
4	I_{sc}	3.8 A
5	V_{MPP}	17.7 V
6	I_{MPP}	3.39 A
7	R_p	67.2783 Ω
8	R_{sh}	0.46132 Ω

The system is applied with three different levels of solar irradiance. The corresponding levels of maximum power obtained, the Pulse Width Modulation (PWM) signal applied to the converter, and output voltage variations are noted for these three levels of partial shading. In case 1, two PV panels are fully illuminated with 1000 W/m^2, but the third panel is shaded by applying 800 W/m^2 solar irradiance. The FA algorithm optimizes the output by using the population of fireflies, random value, and multiple iterations. Finally it reaches to 60.03W output power with 98.12% tracking efficiency as shown in Figure 7. The required PWM variations and the output voltage are shown in Figure 8 and Figure 9 respectively. In case 2, only one PV panel is fully illuminated with 1000 W/m^2, and remaining two panels are shaded by applying 900 W/m^2 and 800 W/m^2 solar irradiance. The FA algorithm optimizes the output for this partial shading condition. Finally it reaches to 58.23W output power with 97.05% tracking efficiency as shown in Figure 10. The required PWM variations and the output voltage are shown in Figure 11 and Figure 12 respectively.

In case 3, all three panels are shaded by applying 700 W/m^2, 900 W/m^2, and 800 W/m^2 solar irradiance. The FA algorithm optimizes the output and reaches to 57.12W output power with 96.48% tracking efficiency as shown in Figure 13. The required PWM variations and the output voltage are shown in Figure 14 and Figure 15 respectively.

The performance parameters are noted in Table 4. The proposed system is able to avoid the oscillations and achieve stable performance.

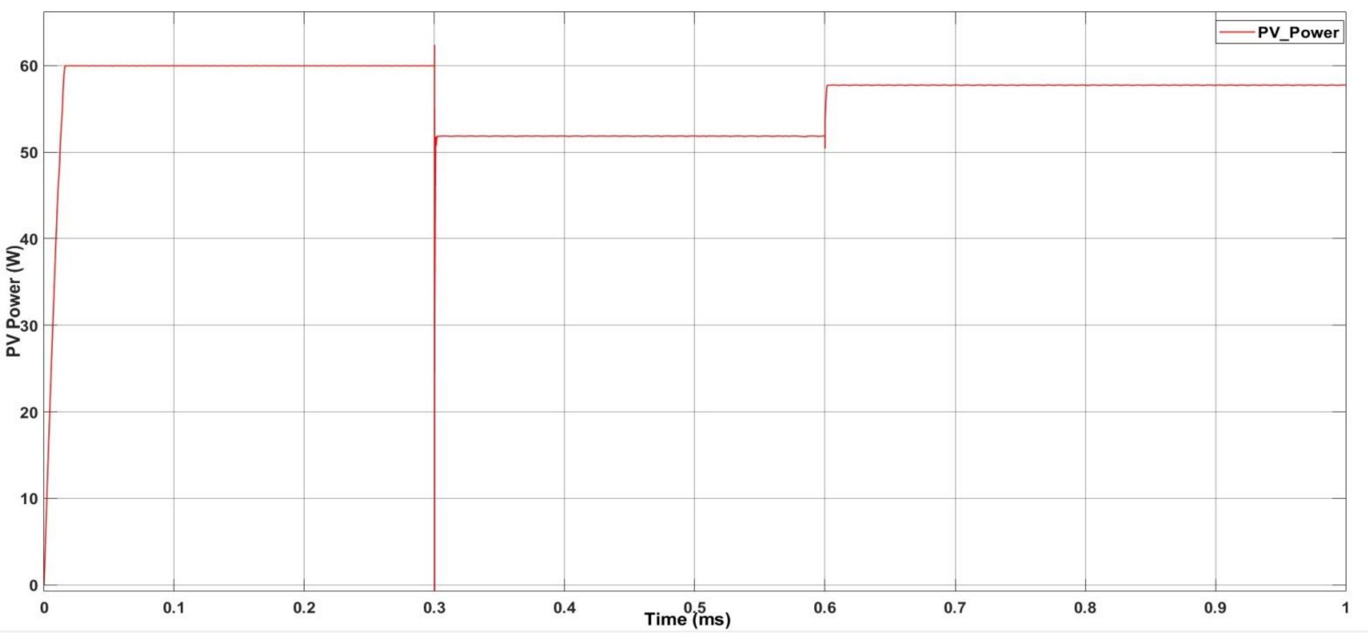

Figure 7. PV power (case 1)

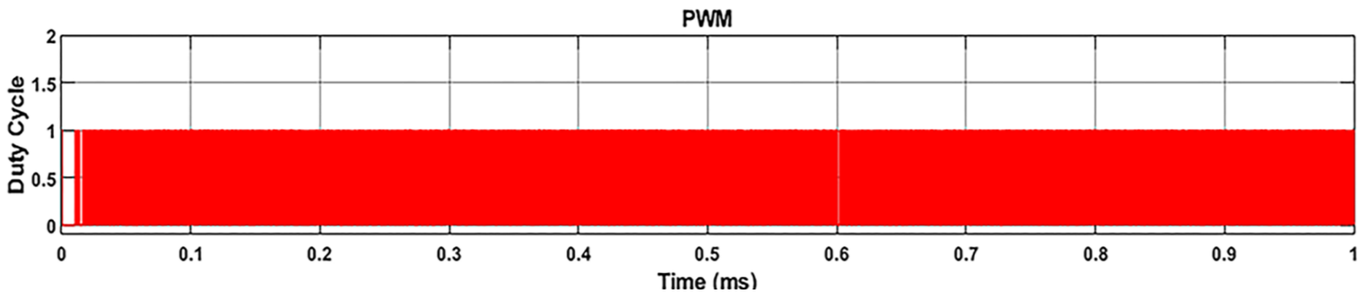

Figure 8. PWM variation (case 1)

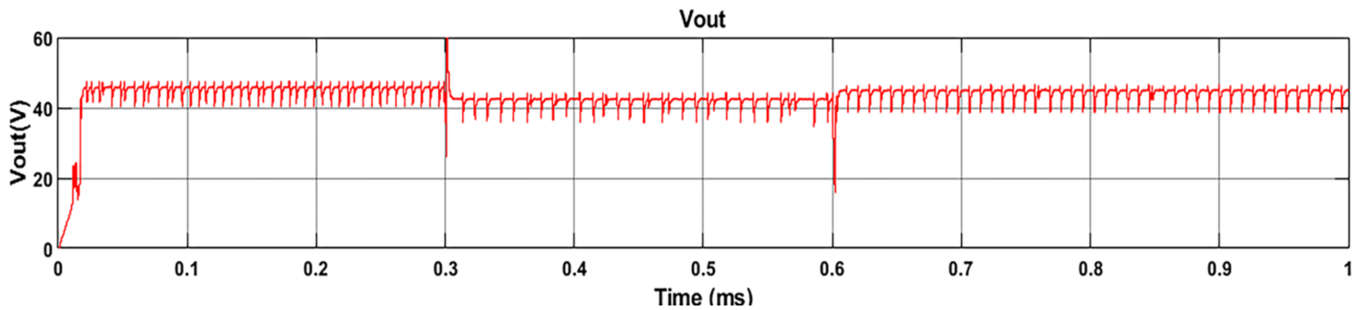

Figure 9. Output voltage (case 1)

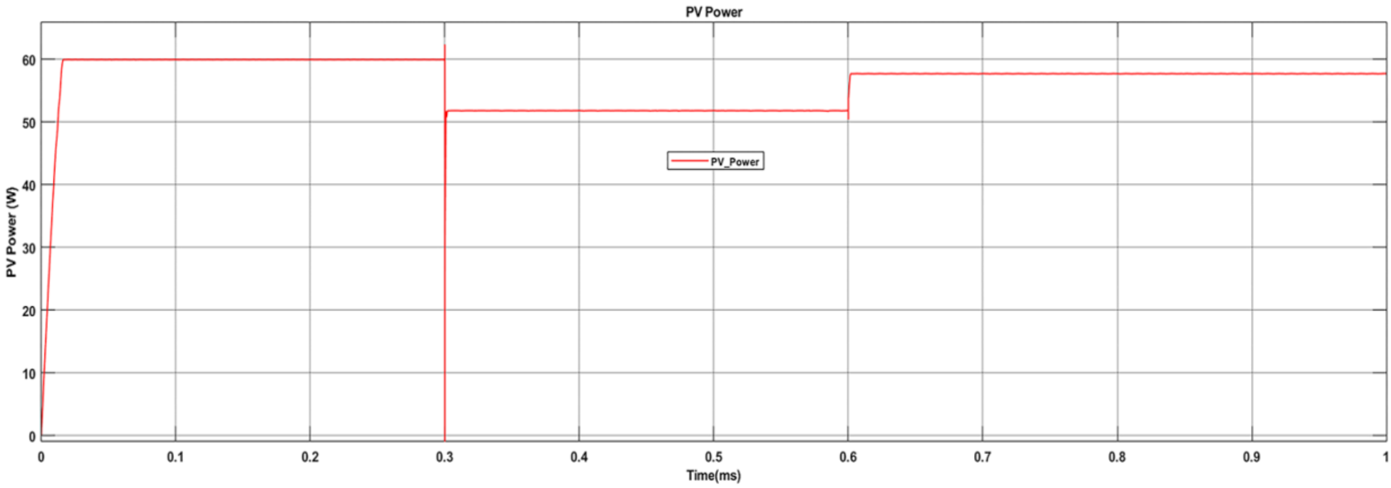

Figure 10. PV power (case 2)

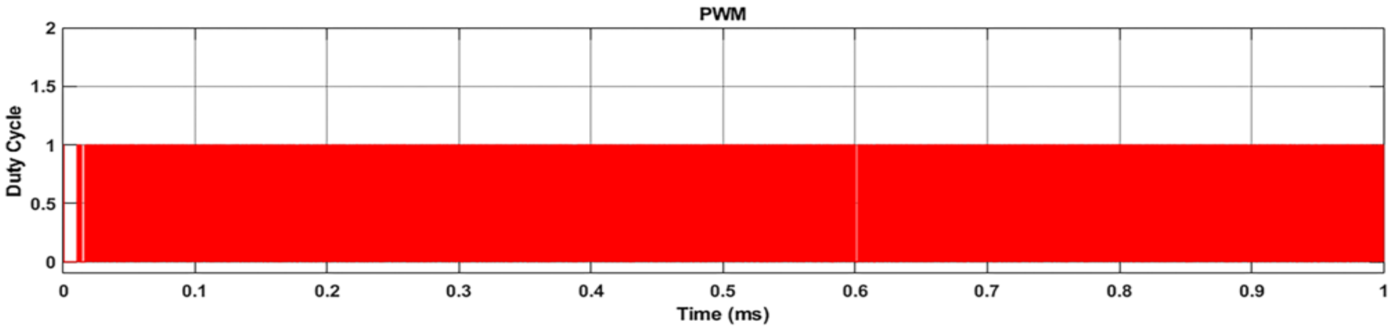

Figure 11. PWM variation (case 2)

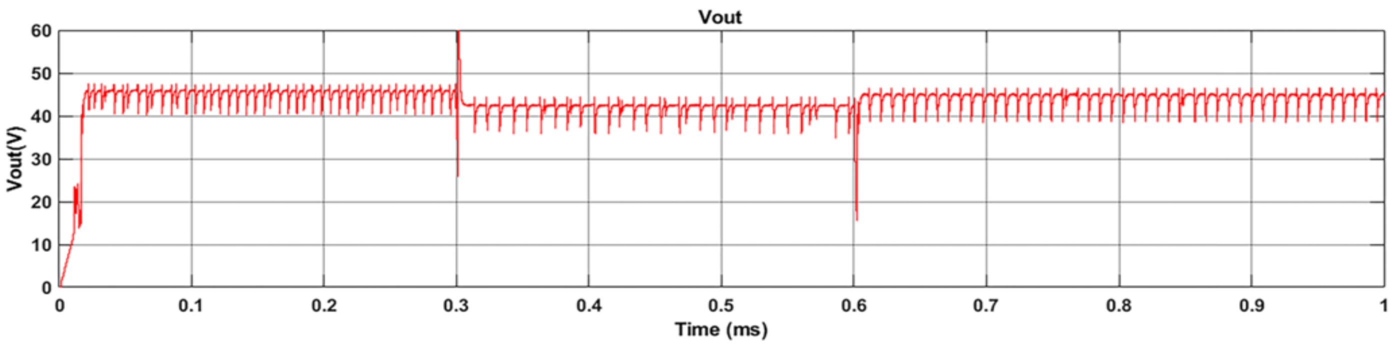

Figure 12. Output voltage (case 2)

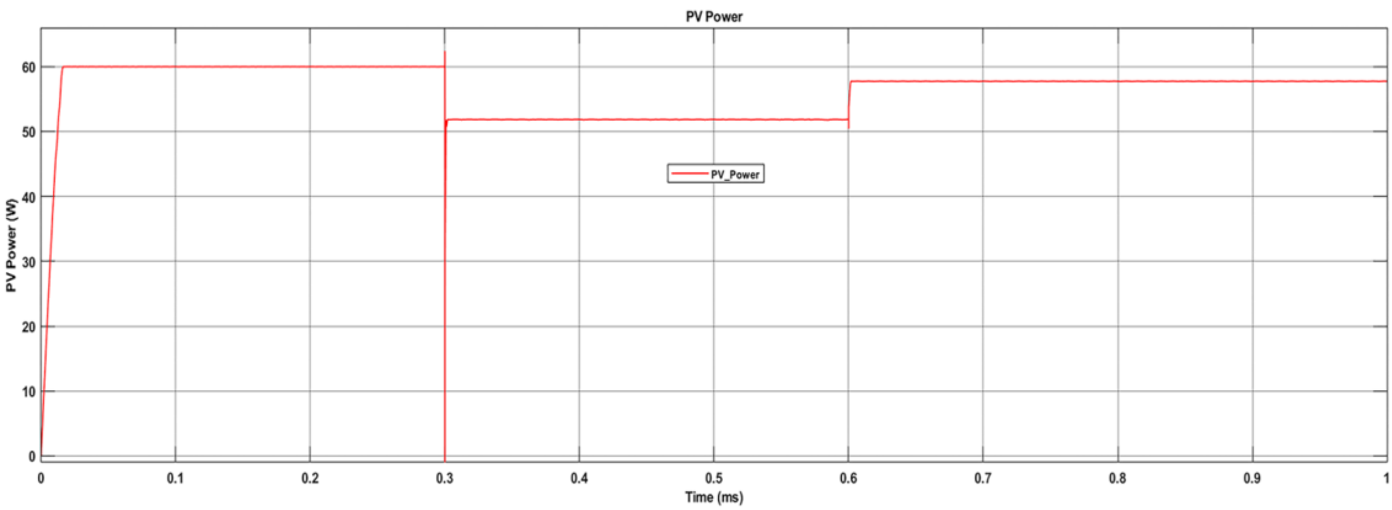

Figure 13. PV power (case 3)

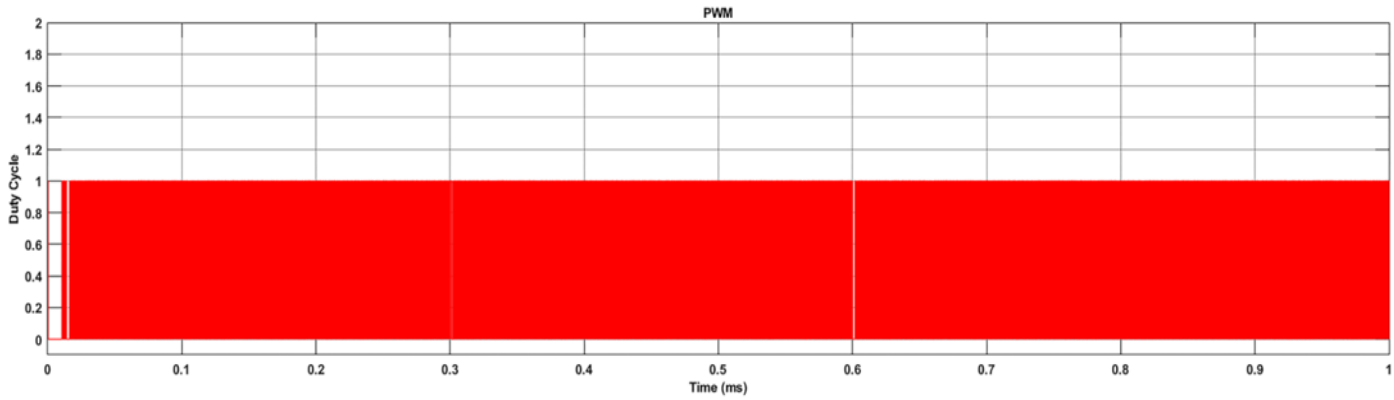

Figure 14. PWM variation (case 3)

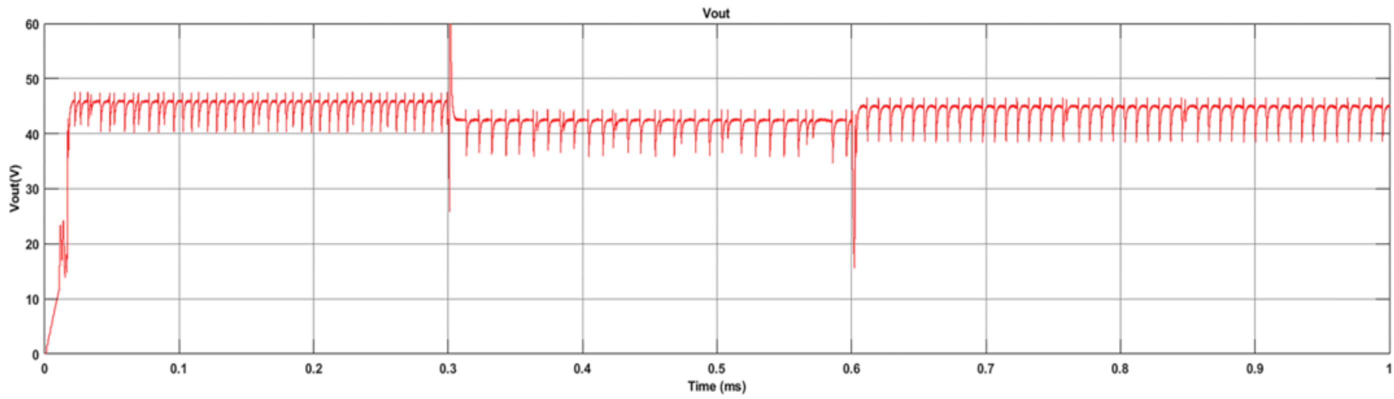

Figure 15. Output voltage (case 3)

Table 4. Performance of proposed MPPT

Case	Solar Irradiance on Panel 1 (W/m^2)	Solar Irradiance on Panel 2 (W/m^2)	Solar Irradiance on Panel 3 (W/m^2)	Output Power (W)	Tracking Efficiency (%)
1	1000	1000	800	60.03	98.12
2	1000	900	800	58.23	97.05
3	700	900	800	57.12	96.48

As can be seen from the results, the proposed FA-based MPPT system can track the GMPP with improved accuracy and less response time. The system is also tested for few conventional algorithms namely PID, P&O; and one optimization algorithm namely Particle Swarm Optimization (PSO). The performance of FA-based MPPT is compared with other conventional MPPT methods in Table 5.

Table 5. Performance comparison of MPPTs

Performance Parameter	PID	P&O	PSO	FA
Efficiency (%)	80.22	78.23	92.5	98.12
Convergence time (ms)	2.5	2.3	2.5	1
Oscillations around MPP (%)	3	5	1	0.1

The comparison depicts that the proposed FA-based MPPT outperforms in terms of efficiency, convergence speed, and oscillations around MPP than conventional MPPTs as shown in Figure 16, Figure 17, and Figure 18.

The computational complexity is also an important factor in selection of MPPTs as it decides the implementation cost and the suitability of MPPT for real time systems. Table 6 describes the comparison of computational complexities for FA and other optimization techniques.

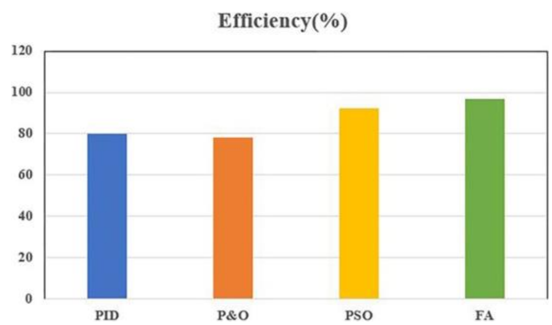

Figure 16. Comparison of efficiency

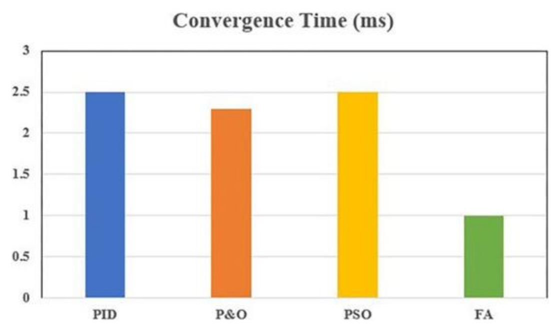

Figure 17. Comparison of convergence time

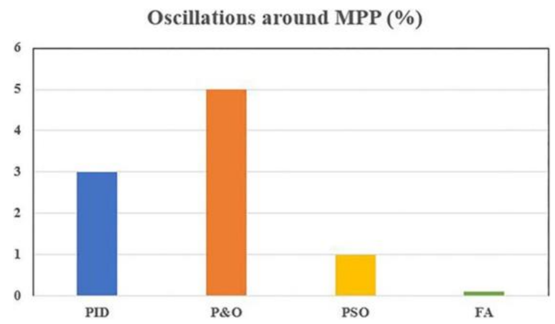

Figure 18. Comparison of oscillations around MPP

Table 6. Computational complexity of optimization-based MPPTs

Algorithm	Computational Complexity
FA	O (T. n^2)
Particle Swarm Optimization (PSO)	O (T. n)
Genetic Algorithm (GA)	O (T. n. m)
Grey Wolf Optimization (GWO)	O (T. n)
Differential Evolution (DE)	O (T. n. m)
Ant Colony Optimization (ACO)	O (T. n^2)

Here T is number of iterations, n is number of fireflies, and m is dimensionality of the solution space.

The FA has higher complexity as compared to PSO or GWO, making it slightly slower for real-time MPPT, but it is faster in convergence process. But the FA has lower computational complexity than GA and GE which makes is better suited for real-time MPPT.

7. CONCLUSIONS

The work focuses on the experimental analysis of the impact of partial shading on the performance of PV systems and the proposed method using Firefly Algorithm for GMPPT. A deep investigation is done with the experimentation by using PV emulator. A reduction of 37% in MPP, a reduction of 38% in fill factor, and a reduction of 60% in efficiency is observed due to partial shading. The proposed novel metaheuristic optimization approach using the Firefly Algorithm to track the global MPP is able to track the GMPP accurately. The algorithm efficiently explores the search space by focusing on the global peak and local peaks. The algorithm is tested under different levels of partial shading. The proposed method is able to achieve 98.12% tracking efficiency within 1ms tracking time. The developed MPPT outperforms conventional MPPT methods in terms of efficiency, convergence speed, and oscillations around MPP. The FA algorithm can also be scaled up for the larger and complex PV systems.

While the FA is effective in handling non-linear and multimodal problems in MPPT, it has several limitations. It has higher computational complexity as compared to few other optimization algorithms. The performance of FA depends heavily on parameter tuning. The higher complexity of FA may not be suitable with embedded systems having limited memory and computational power, especially for low-cost PV systems. To address these problems, the hybrid methods can be developed by incorporating FA with other algorithms such as PSO or GWO. Adaptive techniques such as Fuzzy logic or neural network can be used with the FA technique for adaptive tuning of parameters. Parallel computing technique can be used to reduce the computational complexity of FA method. Such future research directions ensure that the FA can be considered as a suitable choice for real time MPPT.

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NOMENCLATURE

I	Total current (A)
I_{pv}	PV current (A)
I_d	Diode current (A)
q	Charge on an electron
k	Boltzmann constant (1.380649×10^{-23} J/K)
V	PV cell voltage (V)
T	Temperature (K)
N_s	Number of PV cells connected in series
R_s	Series resistance (Ω)
R_{sh}	Shunt resistance (Ω)
V_{oc}	Open-circuit voltage (V)
I_{sc}	Short-circuit current (A)
V_{MPP}	Voltage at maximum power point (V)
I_{MPP}	Current at maximum power point (A)
I_r	Solar light intensity at distance r
I_s	Initial solar light intensity
r	Distance
β_r	Attractiveness at distance r
β_0	Initial attractiveness
γ	Absorption parameter
m	Integer value
i and j	Fireflies at positions x_i and x_j
x_i and x_j	Positions of fireflies i and j
r_{ij}	Distance between i and j
α	Randomization term
ε_i	random number distributed in [0,1]