

MODIFIED PARTICLESWARM OPTIMISATION ALGORITHM FOR PHOTOVOLTAIC MAXIMUM POWER POINT TRACKING UNDER PARTIAL SHADING CONDITIONS

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ABSTRACT

The common problem associated with the PV systems is partial shading of the PV modules due to clouds or blocking objects, such as buildings or tree leaves. For a PV system to be effective, maximum power point tracking (MPPT) algorithm that can track the global maximum power point is necessary, since causes the output power of a PV system to reduce drastically. Meta-heuristic algorithms (MHA) can track the maximum power point in a power-voltage (P-V) curve with multiple peaks. Particle swarm optimisation (PSO) algorithm is a new optimisation algorithm based on MHA. Is use to solve optimisation problems in many applications including MPPT for a PV system. However, the accuracy and tracking time in the original PSO can be further improved for various partial shading conditions (PSCs). Therefore, a proposed modified PSO, named modified particle swarm optimisation is use for this study. The proposed method adds the weighting average, the swooping behaviour, and nonlinear convergence factor in the PSO. The maximum power tracked by the MPSO method during PS1, PS2, PS3, and PS4 were 500.502 W, 399.6840 W, 285.0341 W and 180.8662 W respectively while for the PSO algorithm values were 463.0465 W, 398.4245 W, 195.7191 W and 176.4084 W respectively, The results showed that the MPSO algorithm was able to achieve better tracking accuracy, faster dynamic response and more robust under the partial shaded conditions than the conventional PSO technique. The MPSO has reduced the tracking time up to 45.5% of the PSO and the dynamic tracking efficiency is improved by more than 2%, compared to the PSO. The findings can be applied to improve real-world photovoltaic systems. By implementing the modified PSO approach, solar energy producers can enhance their profitability and sustainability, ultimately contributing to a greener future.

Keywords: Maximum Power Point Tracking, Modified Particle Swarm Optimisation, Partial Shading Condition, Photovoltaic Array and Booster Converter.

1 INTRODUCTION

According to [1], there has been a notable interest in renewable resources among scholars due to factors such as rising fuel prices, global warming, and increased demand for energy. Solar, wind, geothermal, fuel cell hydrogen, and many other forms of energy are examples of renewable energy sources. According to [2], there appears to be a greater inclination toward solar energy among them. Globally, renewable energy has risen quickly as a means of mitigating the negative consequences of fossil fuel consumption. Solar energy is one type of renewable energy that produces little emissions and an abundance of resources. Photovoltaic (PV) systems and concentrated solar power (CSP) are two categories into which solar energy can be divided. Utilizing solar thermal power, CSP produces electricity by converting solar radiation into heat power during the day, storing the heat for

later use, and producing the necessary amount of electricity [3]. Conversely, photovoltaic (PV) systems convert solar radiation directly into electricity without requiring any heat conversion. This advantage draws residential users to install PV rather than CSP because PV is a more cost-effective technology. As a result, PV has increased in proportion to the decrease in the cost of production and installation [4]. Nevertheless, a common problem for PV systems is partial shading on the PV modules due to clouds or blocking objects, such as buildings or tree leaves. Partial shading conditions (PSCs) cause hotspot issues by limiting the performance of the unshaded module and making the shaded modules operate in reverse bias and burden the unshaded module. A PV panel may exhibit a multi-peak power-voltage (P-V) characteristic curve when partial shading conditions exist in some of the modules. A 70% power loss could occur if the Global Maximum Power Point (GMPP) is not reached by the Maximum Power Point Tracker (MPPT) [1]. For a PV system to be effective, an MPPT algorithm that can calculate the GMPP is necessary. A number of solutions have been put out to address the impacts of partial shade. In general, they can be divided into two categories: software solutions and hardware solutions. Rather than installing a single central inverter to control the entire PV system, the hardware solutions use several microinverters coupled to the PV modules/panels [5, 6]. Each panel or module's MPPT can be separately tracked by the micro inverters. The amount of electricity produced by a panel using a microinverter is independent of the amount of power produced by the other panels. As a result, PSCs that happened on any particular module or panel are no longer able to limit the maximum power generated at the system level. However, a few disadvantages prevent microinverters from being widely used by owners of PV systems. These include their high cost when compared to a standard central inverter, different environmental conditions because they are installed outside, as opposed to standard inverters, which are typically housed inside buildings, making them less vulnerable to the effects of the environment and more easily accessible for maintenance, and their installation have an impact on the roof structure of homes when it comes to rooftop PV systems since, in large-scale deployments, the combined weight of these devices plus the PV panels can increase the loading on the roofs of homes and buildings. The main goal of the software solutions is to create sophisticated MPPT algorithms that track the GMPP at the system level. These methods don't involve installing new hardware and are inexpensive. Most of the material was written with the intention of recommending various software techniques. Meta-heuristic algorithms (MHAs) are the most popular and sophisticated software used for MPPT tracking under PSC [7]. As a result of the shortcomings of traditional MPPT algorithms, many research studies have used artificial intelligence (AI) techniques to address the stated limitations. Such as Fuzzy Logic Controller (FLC) and Neural Network (NN). The FLC which is based on rational data interpretation can find means of retrieving the maximum power under partially shaded and rapidly varying atmospheric conditions. Even though these techniques are efficient when dealing with the nonlinear characteristic I - V curves, they require a significant amount of computation. FLC, for example, deals with operations such as fuzzification, rule-based storage, inference mechanisms, and defuzzification. The enormous amount of data needed for training is a major constraint for NN. More so, since the operational conditions of the PV system change continuously, MPPT must respond instantaneously to changes in irradiance and temperature. Therefore, low -cost processors cannot be employed in such a system. Their tracking efficiencies are affected by high control circuit complexity and large data processors for training the system [8]. The Ant Colony Optimisation (ACO) algorithm also has certain limitations, particularly when there is partial shading. Specifically, ACO may become trapped in local optima while attempting to find the global maximum power point, despite being an effective method for tracking the maximum power point in PV systems. The power-voltage curve of the PV module may have several local maxima in partially shadowed conditions. As opposed to the real GMPP, the ACO may converge to one of these local maxima [9], which would result in a slower rate of convergence than with conventional MPPT techniques. ACO depends on pheromone trails to direct its search, and when dealing with quickly changing shade circumstances, this sluggish convergence might result in inferior tracking performance [10]. It also limits its adaptability. Nevertheless, the MPPT accuracy may be impacted if these trails are unable to adjust rapidly enough to abrupt changes in shade patterns [9]. Despite being useful for MPPT in PV systems, the Cuckoo Search (CS) algorithm exhibits significant failure rates, takes a long time to converge, and has strong oscillations around the GMPP, which can result in inefficiencies and power loss [11]. Particle Swarm Optimization (PSO) is a widely used optimization technique in many domains, including photovoltaic system design. It is modeled after the social behavior of flocks of birds. Like any technique, PSO has drawbacks, though. Among the few

drawbacks are local optima imprisonment and slow convergence. Despite the setback, PSO is still a useful tool for adjusting the parameters of PV systems, and researchers are still looking for ways to improve its functionality and deal with these issues [8]. Due to its capacity to efficiently navigate intricate search areas and discover fresh, ideal solutions whenever they arise, it is still extensively utilized for PV system MPPT [12]. Global convergence may be ensured using particle swarm optimisation, however there are drawbacks, including longer settling times and persistent oscillations in PV output power while tracking. Consequently, the PSO needs to be changed. The proposed method in this paper, named as modified PSO (MPSO), is a MHAs and an improved version of the PSO algorithm. It is developed to improve the convergence speed and reduce the GMPP tracking time. The main contributions of the paper include A new procedure, swooping, is added to the PSO to improve convergence speed in the late search period. Since a prey bird may engage in swooping during hunting, this newly added procedure completes the PSO. The paper also investigates some previously proposed procedure such as nonlinear convergence factor, and shows that convergence factor with concave-up is more suitable for MPPT. The developed MPSO can lower the tracking time up to 45:5% and increase the dynamic efficiency more than2%, compared to the PSO.

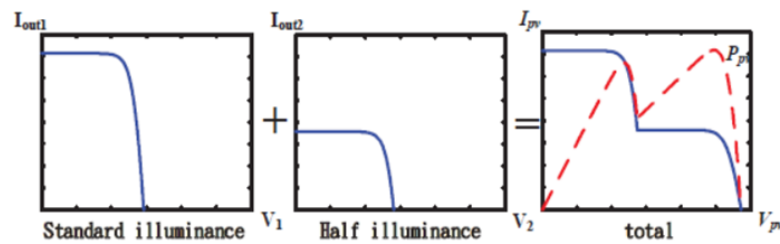


Figure 1. The cause of the multiple peaks characteristic curves (Adopted) [13]

1.1 PSO Algorithm Review

PSO algorithm is a swarm technique that is inspired by the collective behaviour of flocks of birds [12]. It is one of the most popular population-based MHAs. Due to its simple structure and easy implementation, PSO has been applied for MPPT tracking in PV systems. However, it may guarantee global convergence, but it has the disadvantages of increased settling time and sustained PV output power oscillations during tracking. Therefore, it is necessary to modify the PSO method for MPPT. The PSO drives each particle throughout the search space, updating the best solution based on each particle's neighbouring experience. The PSO starts by randomly initializing particles, then searching for optimum solutions through iteration, and then evaluating the solution quality with a fitness function. The particle position is influenced by the position of the best particle in a neighbourhood. The initial particle position in the neighbourhood can be represented by equation (1), the particle position is then modified using equation (2).

$$X_{ij}^{t+1} = X_{ij}^t + V_{ij}^{t+1} \tag{1}$$

The step size is represented by the velocity component, V_i . The velocity is determined using the formular.

$$V_{ij}^{t+1} = w^t V_{ij}^t + c_1 r_1 (X_{pbest.ij}^t - X_{ij}^t) + c_2 r_2 (X_{Gbest.i}^t - X_{ij}^t) \tag{2}$$

Where $i = 1, 2, 3 \dots, n$. Therefore, the other two changes made to the old speed function are c_1 , c_2 , c_3 , and c_4 , which are called constant parameters, and the random numbers of MPSO, r_1 , r_2 , r_3 , and r_4 , which are between (0, 1).

1.2 Modified Convergence Factor

The proposed convergence factor is stated in equation (3) and plotted in Figure 2. As shown in the figure, the convergence factors α decrease rapidly in the beginning and decreases slowly at the end of the iteration. The purpose is to shorten unnecessary exploration and reduce the searching time. This concept is also proposed by [14] here the convergence factor α is modified to a nonlinear function.

$$\alpha = 2 \left(1 - \frac{t}{T} \right)^2 \tag{3}$$

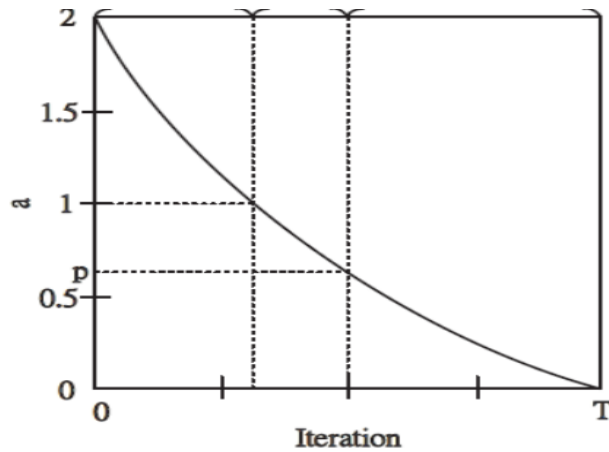


Figure 2. The change of convergence Factor α of the MPSO

2 MATERIALS AND METHOD

2.1 Materials

The materials used in this research are Matlab R2020b (version 9,9,0,1467703) programme simulation of the PV cell of module type PS-P310-36, the manufacturer cell datasheet of monocrystalline photovoltaic modules type of PS-P310-36, under STC, temperature of 25°C, 50W/m² to 1000W/m² of irradiance level and 1.5 of the air mass (AM). The technical characteristics of the photovoltaic modules used for this model are shown in Table 1 and the PSO, MPSO parameter values shown in Table 2.

Table 1. Electrical specification of PS-P310-36 Photovoltaic Modules provided by manufacturer in operating condition.

Characteristic Value	Cell	Module
Open Circuit Tension (V_{oc}), [V]	1.1920	42.9
Short Circuit Current (I_{sc}), [A]	4.6600	9.31
Maximum Rated Tension (V_{max}), [V]	1.008	36.3
Maximum Rated Current (I_{max}), [A]	4.2700	8.54
Maximum Power (P_{max}), [W]	4.3040	310
Series Resistance (R_s), [Ω]	0.0254	0.457
Thermal Tension (V_t), [V]	0.0257	0.9252

Table 2. PSO MPSO parameter value

Parameter	PSO	MPSO
iteration weight (W)		0.4
acceleration coefficients 1 (C_1)		1.6
acceleration coefficients 2 (C_2)		1.8

2.2 Methods

The methods use in this research was base on Modified PSO Algorithms, Boost converter, and four different shading patterns. The modified particle swarm optimisation (MPSO) technique, which is a modified version of the conventional PSO technique. The MPSO technique used a new update strategy and a novel mutation operator to enhance the performance of PSO under partial shading conditions. The update strategy which considers both the current position and the previous best position of each particle, which can balance the exploration and exploitation abilities of the swarm and avoid being

trapped in local optima. The proposed MPSO algorithm was compared with the convectional particle swarm optimisation (PSO), The performance of both methods was evaluated under several scenarios of partial shading conditions and non-uniform irradiation levels using Matlab. The performance criteria which included convergence speed, tracking accuracy, and robustness. The operating principles of a standard PSO method can be described as stated below:

Step 1: The Initialisation. Initialise a population of particles and randomize their positions and velocities on the D-dimensional.

Step 2: Fitness Evaluation. The fitness of each particle is evaluated by supplying the candidate solution to the objective function.

Step 3: Update Individual and Global Best Data. Compare the current fitness of each particle with the previous one and update the values of the best global fitness G_{best} and the private local fitness P_{best} .

Step 4: Update the velocities and the positions. The position x_i and the velocity v_i of each particle are updated using the equations (1) and (2) respectively.

Step 5: Convergence Determination. Loop to step02 until the convergence criterion is satisfied then stop the optimisation after checking the end conditions.

2.2.1 Modeling of PV array under PSC

The configuration of PV array consists of four modules connected in series (4S configuration) and protected by bypass diodes. The simulation of PV model was implemented in MATLAB/Simulink model as it is illustrated in Figure 3.

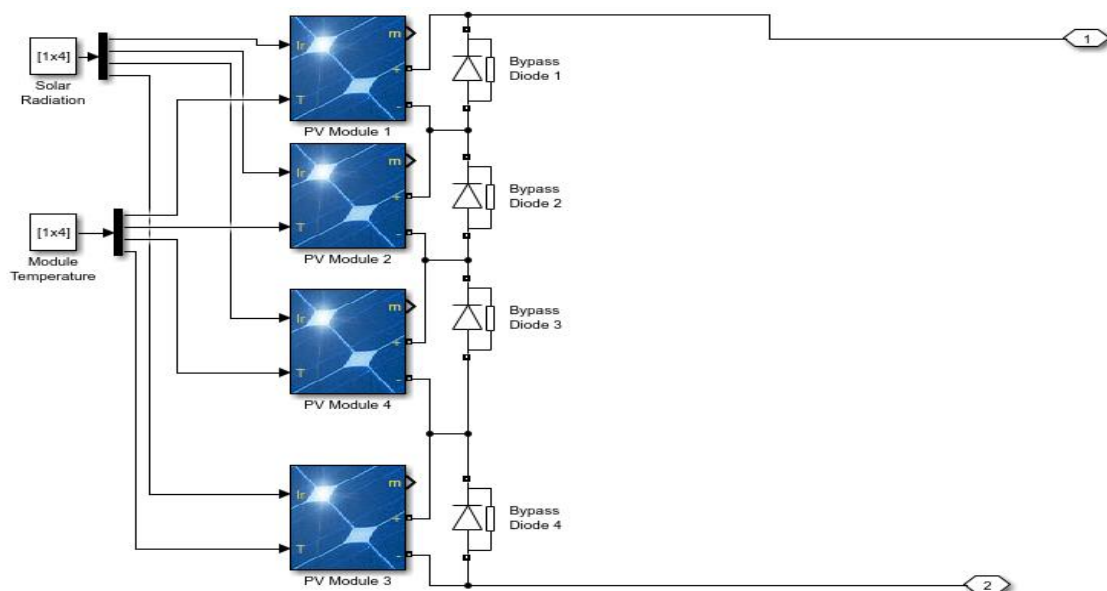


Figure 3. Simulink model of PV array under PSC

2.2.2 Modified particle swarm optimisation

In normal PSO, the part “particles” refers to population members, which have a small mass and small volume, and are subject to speeds or accelerations with the best performance. Every particle in the swarm represents a solution in a high-dimensional space with four vectors, which are: present position; after the acceleration of particles compared to the old position, it selected the personal best position of all particles; particle speed; and the global best position for all particles that have thus far originated in its neighborhood. Every particle regulates its position X_{ij} inside the limited search area based on the best position that is achieved by itself $X_{Pbest,ij}$ and the global best position that is achieved by all particles $X_{Gbest,ij}$.

2.2.3 Velocity step function

Conventional PSO employs step function V_{ij}^t , which is determined for every particle i th of every j th variable at every iteration t , where $V_{ij}^t \geq 0$, as seen in Equation (4), refers to a three-part equation. To move from one position to another in the search area; particles are fixed by three mean the inertia function ω , which could be counted in every iteration from Equation (5); the inertia operator limit values and the third term are the maximum fit iteration number t_{max} ; the second term refers to updating the present location's procedure, and the third represents the method of sharing information of the global best solution between old locations. Here, an important change is that global optimisation should also guide the individual optimisation to reach the optimal solution as the acceleration factor of the convergence process, which can be expressed mathematically using Equation (6). Therefore, the other two changes made to the old speed function are c_1 , c_2 , c_3 , and c_4 , which are called constant parameters, and the random numbers of MPSO, r_1 , r_2 , r_3 , and r_4 , which are between (0, 1).

$$V_{ij}^{t+1} = w^t V_{ij}^t + c_1 r_1 (X_{pbest.ij}^t - X_{ij}^t) + c_2 r_2 (X_{Gbest.i}^t - X_{ij}^t) \quad (4)$$

$$w^t = w_{max} - \left(\frac{(w_{max} - w_{min})}{t_{max}} \right) \times t \quad w \geq 0 \quad (5)$$

$$V_{ij}^{t+1} = V_{ij}^{t+1} + c_3 r_3 (X_{Gbest.j}^t + X_{pbest}^t - 2X_{ij}^t) + c_4 r_4 (X_{Gbest.i}^t - X_{pbest.ij}^t) \quad (6)$$

2.2.4 Updating the i th particle position

Ever particle should transfer towards the optimum by properly updating its location utilising the step function V_{ij}^t , as seen in Equation (7), where the step is added to the present location. The step may be positive or negative until it becomes zero, after which it is the optimum solution.

$$X_{ij}^{t+1} = X_{ij}^t + V_{ij}^{t+1} \quad (7)$$

2.2.5 Search space limit reduction strategy

Here, considering decreasing the search area to discover the optimum value, which is another modification added to the searching process, which requires the adjustment and modification of the limits of the controlled variables in each iteration. Therefore, for the X_i controlled variable, the limit is modified in a reducing way to make it converge to the global best location in every iteration compared to its old limit.

3 RESULTS AND DISCUSSION

The P-V characteristics of the PV array under uniform and non-uniform weather conditions are shown in Figure 5 to 8. All PV modules were exposed to PSC. The P-V characteristic curves show that peaks were established for Cases 1, 2, 3, and 4 because the PV arrays were partially shaded by four different solar irradiances values, where the global MPP for the 1, 2, 3, and 4 cases are (500.5, 399.7, 285.0 and 180.9, respectively). The results for the PV system under a temperature of $T_{25} \text{ }^\circ\text{C}$ and different shading patterns of power for MPSO and PSO algorithms are shown in Table 3. These results are for transition from pattern 1 to pattern 4 and consist of several local maximum power points (LMPPs) and only one global maximum power point (GMPP) under PSCs. As shown in Table 4, MPSO tracks maximum values for Power as 500.502 W while the maximum values for PSO as 399.6840 W during SP1. The performance of MPSO and PSO algorithms in four patterns have been compared in Table 5, which shows that both algorithms succeeded in tracking GMPP but the convergence speed of MPSO is higher, its efficiency is slightly improved and has less tracking energy losses compared to PSO MPPT algorithms [15].

Table 3. Shading patterns for Maximum Power of MPSO and PSO techniques in Watt (W)

S/N	Pattern 1		Pattern 2		Pattern 3		Pattern 4	
	MPSO	PSO	MPSO	PSO	MPSO	PSO	MPSO	PSO
1	0	0	0	0	0	0	0	0
2	217.7	217.7	142.169	77.9472	100.866	58.3399	62.2337	33.0491
3	324.7	361.9	160.538	113.804	105.916	87.388	69.4813	48.9943
4	360.2	361.9	234.196	160.538	168.091	105.916	88.3952	69.4813
5	362.5	361.9	240.126	180.162	175.114	110.89	104.381	78.6138
6	426	414.9	243.534	225.979	190.251	141.596	109.259	82.4489
7	436.6	442.4	266.1	263.727	195.641	149.859	114.226	94.6538
8	441.7	443.6	295.495	303.659	195.645	151.739	114.739	103.171
9	442.7	447	311.797	307.369	195.649	152.389	122.529	109.693
10	448.5	463	315.94	310.924	195.656	158.617	123.295	109.945
11	450.5	463	336.795	330.114	195.662	161.689	130.213	121.14
12	454.1	463	337.707	334.247	195.665	169.902	135.442	129.964
13	471.9	463	338.215	335.273	279.011	195.693	137.91	130.864
14	473.8	463	339.031	336.921	279.861	195.695	139.81	134.35
15	474.6	463	340.037	337.26	279.952	195.695	141.456	135.554
16	474.6	463	341.1	339.335	280.135	195.696	159.722	158.192
17	474.8	463	341.484	340.612	280.169	195.697	160.632	158.282
18	479.8	463	352.923	341.738	281.955	195.699	161.13	158.753
19	488.6	463	360.166	342.476	282.758	195.702	168.938	162.394
20	490.8	463	392.103	390.159	283.835	195.704	170.578	162.583
21	492.4	463	395.761	391.853	284.259	195.717	171.953	162.659
22	493.2	463	395.967	392.66	284.816	195.717	180.808	173.158
23	500.5	463	399.684	398.424	285.034	195.719	180.866	176.408

Table 4. Comparison of power output between PSO and MPSO at different partial shading conditions

Shading patterns	Solar PV array				PV array output			PSO	MPSO
	PV module 1		PV module 2		Vmp	Imp	Pmp		
	1	2	3	4					
1	950	800	650	500	74.67	3.205	439.4	463.02	500.5
2	800	650	500	350	55.7	2.73	352.1	398.42	399.7
3	650	500	350	200	56.05	2.265	227	195.72	285
4	500	350	200	50	35.65	2.469	168	176.41	180.9

Table 5. Summary of comparison results of PSO and MPSO methods

Shading patterns		Tracking time(s)	
		Pmp	
Pattern 1	PSO	463.0203	2.73
	MPSO	500.4717	1.72
Pattern 2	PSO	398.424	3.00
	MPSO	399.6844	2.01
Pattern 3	PSO	274.7226	3.95
	MPSO	285.034	2.41
Pattern 4	PSO	176.4083	4.13
	MPSO	180.8664	2.42

Table 6. Performance comparison of PSO and MPSO

Evaluation Criteria	PSO	MPSO
Steady state oscillations	Less	Almost zero
Tracking speed	Medium	Good
Tracking MPP under varying environment condition	Medium	Good
Hardware implementation	Yes	Yes

3.1 Performance comparison of MPSO with conventional PSO

The effectiveness of the MPSO, its performance is compared with conventional PSO in terms of power output. Table 6 summarizes the tracked power, voltage and current with PSO and MPSO from the table, it is evident that the MPSO method is capable of tracking global peak within few MPPT under any circumstances. However, the conventional PSO methods continue to operate at local peak resulting in continuous loss of power [8]. Figures (4-7) are the detailed simulations of results for the PV system under different shading patterns. The power curves for MPSO and PSO algorithms have been shown in Figure (4-7) for a transition from pattern 1 to pattern 4.

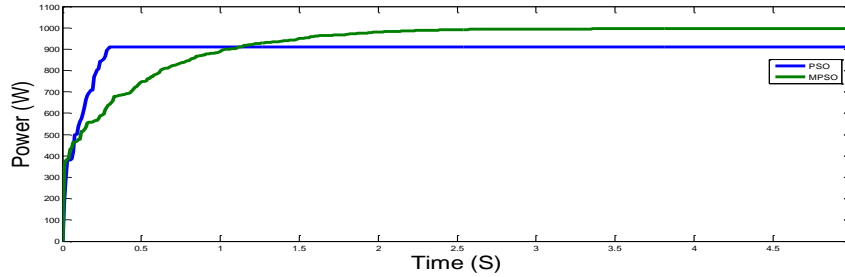


Figure 4. PV array under PSC case 1

In scenario 1, the PV system is exposed to nonuniform levels of irradiation and PSCs (950, 800, 650, and 500 W/m²) and at a constant temperature (25°C), which the MPPT trackers need to track and achieve this global peak. Figure 6 displays the output power the MPSO, and PSO which indicates that the proposed MPPT method (MPSO) is capable of efficiently tracking the actual maximum power under nonuniform levels of irradiation and PSCs. The output of MPSO is better than the output of the PSO [8].

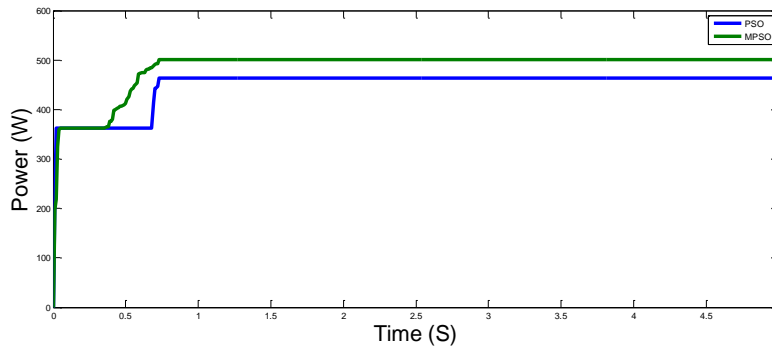


Figure 5. PV array under PSC case 2

In scenario 2, the PV system is exposed to nonuniform levels of irradiation and PSCs (800, 650, 500, and 350 W/m²) and a constant temperature (25°C), which the MPPT trackers are supposed to track to find this global peak. Figure 6 shows the output power and voltage for all the MPSO, and PSO, it illustrates the proposed MPPT method (MPSO) can efficiently track the actual maximum power under nonuniform levels of irradiation and PSCs [8].

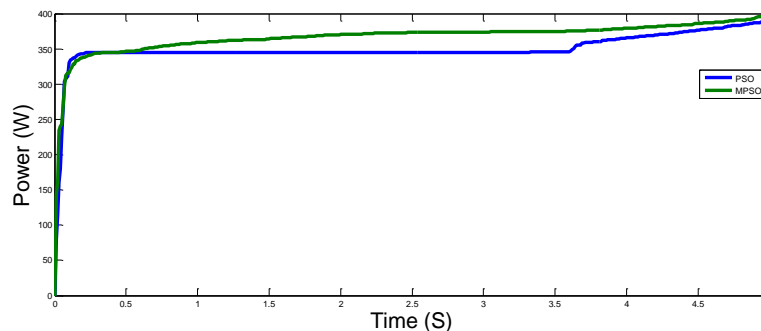


Figure 6. PV array under PSC case 3

In scenario 3, the PV system is exposed to the PSCs for which the radiations level are (650, 500, 350, and 200 W/m²) and a constant temperature (25°C), which the MPPT trackers are supposed to track to obtain this global peak. Figure 7 shows the output power and time for the MPSOs, and PSO, it indicates that the proposed MPPT method (MPSO) is perfect and able to track the actual maximum power under PSCs [8].

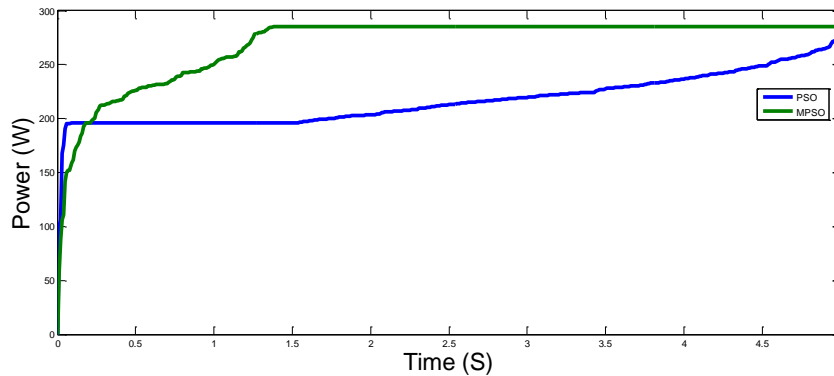


Figure 7. PV array under PSC case 4

In scenario 4, the PV system is exposed to nonuniform levels of irradiation and PSCs (500, 350, 200, and 50 W/m²) and a constant temperature (25°C), which the MPPT trackers are supposed to track to obtain this global peak. Figure 8 shows the output power and time for the MPSOs, and PSO, it shows that the proposed MPPT method (MPSO) is able to track the actual maximum power under PSCs. The above discussions and results conclude that the modified PSO technique can track the actual maximum power regardless of the shading conditions and scenarios. For all considered shading scenarios, it was observed that the proposed method can easily track the actual maximum power of system. Based on the results presented in Table 5, 6 and from Figures. 5 to 8, From the table results it is clear that the performance of the Modified PSO does comparatively well against conventional PSO method in terms of tracking speed, steady state oscillations, and the ability to accurately track global peak under varying environmental conditions [8].

4 CONCLUSIONS

The new MPPT algorithm modifies the linear convergence factor function into a nonlinear one and incorporates weighing average and whooping action in the position update formula for better performance. The convectional particle swarm optimization has been successfully modified for the determination of MPPT in PV system; the approach presents a viable solution for enhancing photovoltaic system performance under partial shading conditions. In the simulation result, the algorithm which was compared with an existing particle swarm optimisation algorithm under various PSCs and the main reasons for comparisons were convergence speed and accuracy. The results show that the algorithm (MPSO) can maintain an accurate result while significantly reducing the tracking time to find the exact GMPP compared with the conventional methods which being trapped in a local maximum. It can save up to 45.5% of the tracking time compared to the convectional PSO.

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