A Novel Approach to the Maximum Peak Power Tracking under Partial Shading conditions

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***Abstract*—Electricity generation using photovoltaic (PV) technology has become highly popular recently. However, natural barriers such as trees, buildings, bird drops, etc., cause partial shading (PS) on the PV surface resulting in high power losses. Bypass diodes used to mitigate the PS effect cause multiple peaks in the PV power delivery. The tracking of the optimal power peak can be considered an optimization problem with a continuously changing objective function due to different insolation conditions. All optimization strategies applied in previous works spanning from mathematical programming techniques to Machine Learning and the recently proposed Nature-inspired algorithms led to either sub-optimal maximum power or required extensive computations. This work presents an algorithm that combines the advantages of the previous works and avoids their loopholes. Experimental results indicate the superiority of the proposed algorithm over the state-of-the-art algorithm for the Maximum Power Peak Tracking problem.**

***Index Terms*—Nature inspired (NI) algorithm, gradient descent (GD), Advanced limited search strategy (ALSS), photovoltaic (PV), partial shading (PS), Maximum power point tracking (MPPT).**

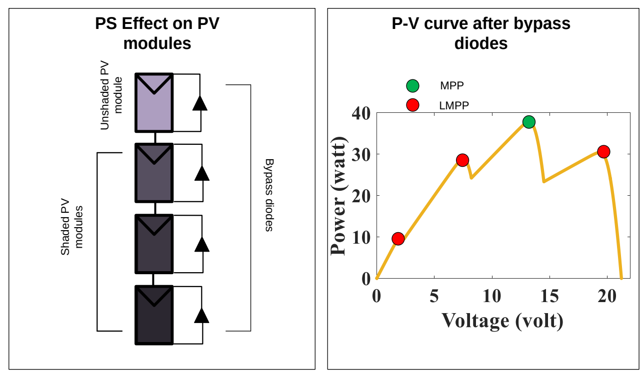

Fig. 1. Bypass diodes used to mitigate the Partial Shading effect and the corresponding P-V curve. The green dot corresponds to the maximum power point (MPP), while the red dots correspond to the local maximum power points (LMPPs).

I. Introduction

The high surge in technological advancements causes a significant reduction in the limited available energy sources. This calls for a shift towards the abundantly available sources of energy (renewable energy sources). Photovoltaic (PV) technology is one popularly used renewable source for electricity generation. Despite its high popularity, several loopholes exist that open different research areas, like PV efficiency, PV operation during the night, using the optimal available energy out of the PV array, etc. In this work, the emphasis is on extracting the highest available power out of the PV array (a process known as Maximum Power Point Tracking (MPPT)). MPPT becomes explicitly challenging when the sun's rays cannot completely strike the PV surface due to barriers like clouds, buildings, tree branches, etc. This results in the partial shading (PS) effect, which causes high power losses. Bypass diodes are connected at each PV module output to eliminate the PS effect. These diodes successfully avoid power losses but give rise to multiple power peaks in power versus voltage (P-V) curve, making the Maximum Power Point Tracking (MPPT) problem complex (see Fig. 1).

Several algorithms have been proposed in the literature for the MPPT problem. Due to their robustness, established iterative optimization algorithms [1]–[5] were very attractive to be employed at first for that problem under full insolation conditions. However, all these algorithms are stuck on local maxima when subjected to PS effect. Also, they converge very slowly when the initialization value (iterative algorithm requires an initial value) is far from the best solution. Artificial intelligence (AI) algorithms, when applied to MPPT [6], [7] outperformed the previous optimization algorithms but failed to fulfill the constraint of low computational resources existing in the PV control system. The focus then was shifted towards the nature-inspired (NI) algorithms i.e., inspired by natural phenomena, like birds flock, match league, glow-worm illumination, etc. A lot of NI techniques have been applied for MPPT [8]–[22]. Owing to their exploration property, they were very successful in tracking the maximum power among several peaks of P-V curve. Moreover, NI algorithms involve fewer computations than AI algorithms. However, the computational complexity of NI algorithms is still higher compared to the established optimization algorithms, and also depend on random number generation for exploring the search space, which may cause convergence to local maxima or continuous power fluctuations. Moreover, they exhibit 3-5 solutions to be updated, which results in slow convergence since all the solutions have to become approximately equal until then. Finally, the NI-based

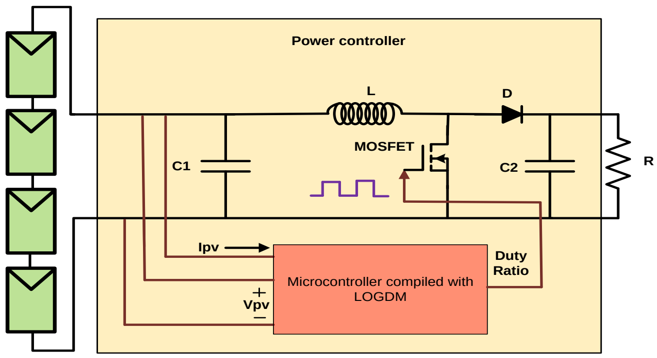

Fig. 2. Maximum Peak Power Tracking control system.

MPPT techniques exhibit large power fluctuations during their initialization phase. Therefore, although NI techniques are considered state of the art for the problem of MPPT, they present a couple of weak points.

To this end, in this work we present an algorithm with reduced power losses, due to a clever space exploration specific to the design of a PV controller in MPPT, as well as a gradient descent with momentum (Low Oscillatory Gradient descent with Momentum) algorithm that resolves the drawbacks of the NI algorithms. The proposed technique was compared with the Adaptive Jaya (AJaya) algorithm [13], which is considered state of the art for the problem of MPPT. The results demonstrate that the proposed method significantly outperforms the AJaya algorithm in convergence time, the convergence value to the maximum power, the magnitude, and the number of power fluctuations. The contributions of this work are an MPPT algorithm with (1) Low computational complexity, (2) High robustness against varying insolation, (3) Rapid convergence, (4) no dependence on random number generation, and (5) Negligible power oscillations.

II. Background

A. Maximum Power Peak Tracking

In MPPT, a PV array is connected to and controlled by a microcontroller (see Fig. 2) to deliver the maximum power to the load. The microcontroller senses the PV voltage and current values, computes the power, and switches the DC-DC boost converter according to the optimal duty cycle (current solution of the optimization algorithm), leading to new PV voltage and current values, and so on.

B. Gradient Descent with Momentum

Gradient descent is an iterative optimization algorithm that in each iteration updates the current solution taking a step in the direction of the function's gradient at the current point, as shown in equation (1).

$$X_i^{t+1} = X_i^t - \epsilon \frac{\partial f(x)}{dx}\Big|_{X_i^t} \tag{1}$$

,where X_i^{t+1} is the updated solution, $\frac{\partial f(x)}{dx}\Big|_{X_i^t}$ is the gradient, at the current point and ϵ is the gradient step parameter.

A problem with GD is that it may bounce strongly while exploring the space due to noisy gradients or get stuck in flat spots at points of space with zero gradient. Momentum is an extension of GD that dampens these oscillations by adding a fraction of the sum of past update vectors to the current gradient, as shown in equation (2).

$$J_{t+1} = \gamma J_t + \epsilon \frac{\partial f(x)}{dx}\Big|_{X_i^t}$$

$$X_i^{t+1} = X_i^t - J_{t+1} \tag{2}$$

,where J_{t+1} is the update vector and γ is the momentum term.

III. Low Oscillatory Gradient descent with Momentum (LOGDM) Algorithm for MPPT

The proposed algorithm LOGDM resolves several drawbacks of the previous works exploiting the strong points of both the traditional iterative optimization algorithms and the Nature Inspired (NI) algorithms and combining them into one algorithm. The proposed algorithm consists of three stages (see Algorithm 1). In the first stage, we confine our exploration to the duty cycles, where the best solution is expected more probably to be found. In the second stage, we perform a careful space exploration (which we call solution redistribution) to approach the best solution, and in the last stage, we employ the GD with momentum algorithm.

A. Initialization and Search Region Estimation

Since GD with momentum cannot differentiate between the local and the global peaks of the P-V curve, its global convergence depends on the closeness of the initial solution to the final solution. Thus, the initialization strategy used in NI algorithms is employed to resolve the local convergence of GD with momentum algorithm (line 3 in Algorithm 1). However, to fix the large oscillations during initialization, the duty ratios were initialized such that the power evaluation takes place only in the region close to where it is most likely to find the best solution (lines 4-9 in Algorithm 1).

First, the two duty ratios are set to $D_1 = 0.4$ and $D_2 = 0.6$ to explore their nearby region. They are initialized to these values because they lie in the mid-region of the search space. Thus, we expect the least power oscillations on average for whatever load is connected at the output. Suppose the power corresponding to D_1 is higher than that corresponding to D_2. In that case, this indicates that the region containing the global maximum is closer to D_1; thus, the third duty ratio D_3 will then be a value closer to D_1. The same procedure is followed if the power corresponding to D_2 is higher than that of D_1. In this work, we pick a duty ratio closer to 0.4 the 0.2 and closer to 0.6 the 0.8.

Algorithm 1 Low Oscillatory Gradient descent with Momentum (LOGDM) Algorithm for MPPT

1: **function** $D^* = \text{LOGDM}$
2: *Initialization and Search Region Estimation*
3: $D_1 = 0.4,\ D_2 = 0.6$
4: $D^* = \underset{\{D_1, D_2\}}{argmax POWER(x)}$
5: **if** $D^* == D_1$ **then**
6: $D_3 = 0.2$
7: **else**
8: $D_3 = 0.8$
9: **end if**
10: *Solution Redistribution*
11: $D^* = \underset{\{D_1, D_2, D_3\}}{argmax}\ POWER(x)$
12: $D^*_+ = D^* + \delta D$
13: $D_4 = \underset{\{D^*_+,\ D^*\}}{argmax POWER(x)}$
14: **if** $D_4 == D^*_+$ **then**
15: $D_{temp} = D^* + c$
16: $D^*_{new} = \underset{\{D_{temp},\ D^*\}}{argmax}\ POWER(x)$
17: **if** $D^*_{new} == D_{temp}$ **then**
18: $D^* = D_{temp} + c''$
19: **else**
20: $D^* = \frac{D_{temp} + D^*}{2}$
21: **end if**
22: **else**
23: $D_{temp} = D^* - c$
24: $D^*_{new} = \underset{\{D_{temp},\ D^*\}}{argmax}\ POWER(x)$
25: **if** $D^*_{new} == D_{temp}$ **then**
26: $D^* = D_{temp} - c''$
27: **else**
28: $D^* = \frac{D_{temp} + D^*}{2}$
29: **end if**
30: **end if**
31: $D^* = \underset{\{D^*,\ D^*_{new}\}}{argmax}\ POWER(x)$
32: *Gradient descent with momentum Algorithm*
33: D^* = Update rule in eq. (2) beginning from D^*
34: **end function**

B. Solution Redistribution

Apart from solving only the local convergence of GD algorithm, we have to take care of its slow convergence. When the initial best solution (D^* in line 11 of Algorithm 1) is far away from the optimum solution, GD with momentum algorithm takes a very long time to converge. To solve this problem, we employ a modified version of the LSS algorithm [16] (lines 11-30 in Algorithm 1) to fit with our method that entails a GD algorithm (updates one value) instead of a meta-heuristic algorithm (updates multiple values). After finding the best value D^* (corresponds to the maximum Power) between D_1, D_2 and D_3, our modified version of LSS adds to D^* a positive or negative constant value according to the optimal direction concerning the maximum power (lines 12, 13 and either 15 or 23 in Algorithm 1). The new solution candidate D_{temp} (either line 15 or 23 in Algorithm 1) is then compared against D^* again, with respect to the maximum power (either line 16 or 24 in Algorithm 1). Now, if the best candidate (from that comparison) is the D_{temp} (either line 17 or 25 in Algorithm 1), then the final solution (D^*) will be farther apart from D_{temp} by a constant (either line 18 or 26 in Algorithm 1) in the optimal direction we have taken earlier (either line 14 or 22 in Algorithm 1), while in the opposite case the best solution will be in the middle between D_{temp} and D^* (either line 20 or 28 in Algorithm 1).

IV. Results & Discussion

The performance of the proposed technique is validated and compared with one of the most recently proposed algorithms for the problem of MPPT, the AJaya algorithm [13]. The results are shown for a four module PV array with open circuit voltage (V_{ov}) = 5.425V, short circuit current (I_{sc}) = 5.34A, voltage at MPP (V_{MPP}) = 4.35V, and current at MPP (I_{MPP}) = 5.02A, while the specifications of the DC-DC boost converter (Fig. 2) are: input capacitance (C_i) = 47uF, output capacitance (C_o) = 470uF, inductor (L) = 1.15mH, and load resistance (R) = 10Ω.

For the demonstration of the proposed technique, we designed one static and one dynamic partial shading scenario. The insolation values on the four modules of the PV array for the static insolation condition were kept as 1000, 900, 750, and 620 W/m^2, respectively. Also, the simulation for the dynamic scenario was executed for nine sec assuming three different PS conditions lasting three seconds each, while the PV panels' insolation conditions assumed during each time slot are shown in Table I. Finally, we picked the different partial shading conditions to cover all three cases in which the power peak can exist in power versus voltage (P-V) curves (at the left, in the middle, and at the right).

Fig. 3 and 5 show the performance of the AJaya algorithm. Despite its successful convergence to the MPP, it exhibits a couple of issues, as we elaborated in the Introduction for the NI algorithms. First, there are two large power fluctuations present, one in the initialization phase and the other one in the tracking phase, and second, multiple solutions make the final convergence (after MPP tracked) slow, as shown in Fig. 3. Both problems lead to power losses and reduce the system efficiency.

Fig. 4 and 6 show the performance of the proposed algorithm (LOGDM). LOGDM significantly outperforms the AJaya algorithm in convergence time while achieving the same MPP. First, there are fewer power fluctuations, even in the initialization phase. The fluctuations during the tracking phase vanish due to the idea of search space redistribution and the update of only one solution (see III-A), while in the initialization phase, they are eliminated due to the idea of search region estimation (see III-B). Second, instead of 3-4 solutions like in meta-heuristic algorithms, convergence is significantly faster because of updating only one solution. Third, the single solution update dampens the fluctuations between the tracked and the converged instant, making the final convergence even faster. Tables II and III summarize the proposed and AJaya algorithm results for the static and dynamic partial shading scenarios, respectively.

TABLE I
THE DYNAMIC PS SCENARIO UNDER TEST.

PV panels	Time Instants		
	t = 0s	t = 3s	t = 6s
P1	1000	1000	1000
P2	920	650	920
P3	830	500	230
P4	760	250	160

TABLE II
RESULTING MPP TRACKED AND CONVERGENCE TIME OF THE ALGORITHMS UNDER TEST IN THE STATIC PS SCENARIO.

Algorithm	MPP tracked (Watt)	CVG. time (sec)
Proposed	60.332	0.3
Ajaya	60.31	1

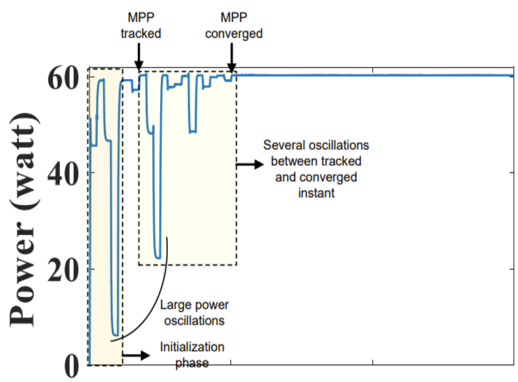

Fig. 3. Convergence behavior of the AJaya algorithm. See the two large power fluctuations at the beginning and during the tracking phase.

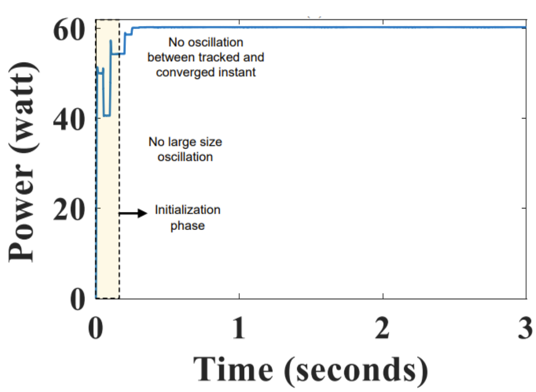

Fig. 4. Convergence behavior of the proposed algorithm. Notice the fast convergence of the algorithm as well as, the small number and the milder strength of power fluctuations.

V. CONCLUSION

The paper focuses on developing a computationally efficient optimization strategy for tracking the maximum power point under the presence of Partial Shading while resulting in fewer power losses in a Photovoltaic system. Our proposed optimization strategy blends the advantages of the Gradient descent with momentum algorithm with the most recently proposed Nature Inspired algorithms. Because GD with momentum algorithm may converge to local maxima, we make an exploratory search borrowing ideas from NI algorithms to reach as close as possible to the optimal solution before running GD with momentum. The performance of the proposed algorithm was compared with the state-of-the-art algorithm under partially shaded conditions. It was shown that the proposed method significantly outperforms the state-of-the-art algorithm in convergence time, the convergence value to maximum Power, the magnitude, and the number of power fluctuations (which contribute to power losses).

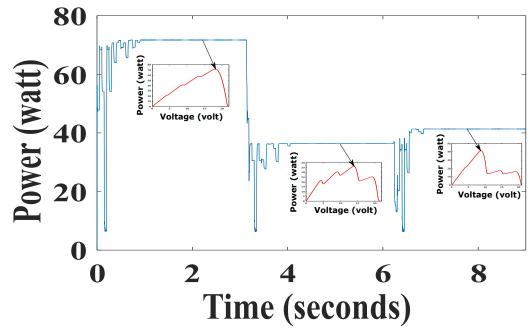

Fig. 5. Convergence behavior of the AJaya for dynamic insolation condition. Again, observe the large power fluctuations at the beginning and during the tracking phase.

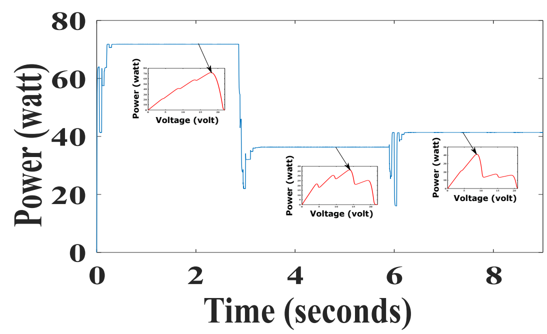

Fig. 6. Convergence behavior of the proposed algorithm for dynamic insolation condition. See the better adaptation of the proposed algorithm to changing partial shading conditions.

TABLE III
RESULTING MPP TRACKED AND CONVERGENCE TIME OF THE ALGORITHMS UNDER TEST IN THE DYNAMIC PS SCENARIO.

Time Instants	Algorithms			
	Proposed		Ajaya	
	MPP tracked (W)	CVG. time (sec)	MPP tracked (W)	CVG. time (sec)
t = 0s	71.81	0.3	71.716	0.92
t = 3s	36.322	0.4	36.338	0.91
t = 6s	41.382	0.4	41.35	0.61

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