

Received February 10, 2022, accepted February 23, 2022, date of publication March 2, 2022, date of current version March 11, 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3156124

# A Reduced Search Space Exploration Metaheuristic Algorithm for MPPT

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**ABSTRACT** The necessity for clean and sustainable energy has shifted the energy sector's interest in renewable energy sources. Photovoltaics (PV) is the most popular renewable energy source because the sun is ubiquitous. However, PV's power transfer efficiency varies with different load's electrical characteristics, temperatures on PV panels, and insolation conditions. Based on these factors, Maximum Power Point Tracking (MPPT) is a mechanism formulated as an optimization problem adjusting the PV to deliver the maximum power to the load. Under full insolation conditions, varying solar panel temperatures, and different loads MPPT problem is a convex optimization problem. However, when the PV's surface is partially shaded, multiple power peaks are created in the power versus voltage (P-V) curve making MPPT non-convex. Unfortunately, all optimization strategies for MPPT under partial shading applied in previous works, from traditional techniques to Machine Learning and the recently proposed Nature-inspired algorithms, were either computationally expensive or/and led to extensive power losses. To this end, this work presents an algorithm that builds upon metaheuristic optimization algorithms to reduce their complexity further and mitigate the power losses during power tracking. Our experimental results demonstrated that the proposed algorithm converges faster to maximum power point with lower power losses during tracking compared to two very recently proposed MPPT algorithms under partial shading conditions.

**INDEX TERMS** Metaheuristic algorithms, improved limited search strategy (iLSS), photovoltaic (PV), partial shading (PS), maximum power point tracking (MPPT).

## I. INTRODUCTION

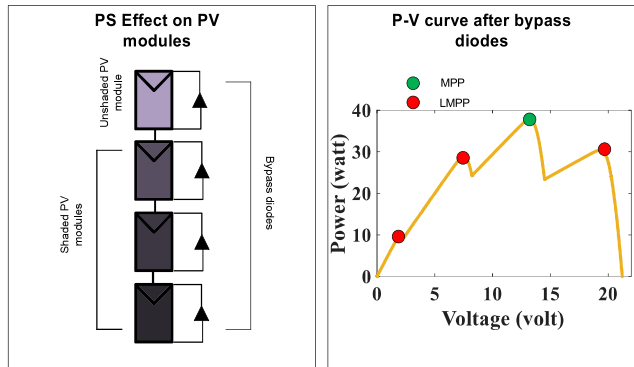
Photovoltaic (PV) arrays, owing to their clean and renewable nature, are one of the most potent sources for electricity generation. Although PV arrays are popular, they cannot straightforwardly meet the best power transfer. PV's power transfer efficiency depends on load's electrical characteristics, temperatures on PV panels, and insolation conditions. The load's electrical characteristics that lead to the maximum power transfer vary based on these factors. Maximum Power Point Tracking (MPPT) is a mechanism formulated as an optimization problem adjusting the PV to deliver the maximum power to the load.

Moreover, PVs present several power losses when the sun's rays partially shade PV surface. Because solar panels in a solar array are connected in series and generate different current values under different shading conditions, bypass diodes

are connected at their outputs to reverse bias (disable) hierarchically (according to the load's power demand) those panels providing the least current (see Fig. 1). However, these diodes also create several power peaks in the Power versus Voltage (P-V) curve rendering the MPPT problem non-convex.

Several conventional optimization algorithms [1]–[5] have been proposed to adjust the PV array to deliver the maximum output power when PV panels receive full insolation, in which case the MPPT problem is convex. However, these algorithms converge almost always to local maxima under PS conditions because of their limited exploration capability. Artificial intelligence (AI) algorithms [6], [7], on the other hand, have successfully managed to track the MPP under PS conditions, but at the cost of adding more computations. Metaheuristic iterative algorithms [8]–[26] then attracted the attention of researchers and have been applied for Maximum Power Point Tracking (MPPT) [10]–[26]. Although they cannot theoretically guarantee convergence to the global maximum, these algorithms reduce the probability of sticking to local maxima

The associate editor coordinating the review of this manuscript and approving it for publication was Alfeu J. Sguarezi Filho<sup>1</sup>.



**FIGURE 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).

due to their extensive search space exploration. On top of that, they are also computationally cheaper than AI algorithms.

Several metaheuristic algorithms are available in the literature tackling MPPT under PS. The objectives of all these algorithms are the avoidance of converging to local maxima due to the non-convexity, accelerating the convergence rate for faster adaptability to dynamically changing conditions, and reducing the power losses during MPP tracking. For instance, [10] first finds the global optimum solution using the Particle Swarm Optimization (PSO) and then removes the steady-state oscillations using Fuzzy Logic Control (FLC). Also, the re-initialization of PSO particles under dynamic insolation conditions was introduced in this work to make the PSO time variant. In [11], a modified deterministic Jaya (DM-Jaya) proposed removing the random coefficients in the update equation of the original Rao and Jaya [8], improving the convergence speed. In [12], an adaptive PSO mitigates the local convergence of PSO when insolation changes by theoretically approximating the optimum duty ratios at each re-initialization. In [13], the convergence rate is enhanced by combining a full insolation detection technique with the Rat Swarm Optimizer (RSO) algorithm [9]. Reference [14] proposes a differential evolutionary algorithm hybrid with the PSO (PSO-DV) to reduce the probability of converging to the local maxima like in PSO by re-initializing possible solutions after a few iterations. In [15], a Modified Butterfly Optimization Algorithm (MBOA) limits the search area and avoids exploring useless regions. In [16], an enhancement of the Jaya algorithm, named Levy flight (JayaLF), is proposed. The algorithm is divided into two phases: the exploration and exploitation phases. It makes larger update steps to the candidate solutions during exploration and smaller steps during exploitation. Due to this two-phase split, the global exploration and the convergence are improved compared to the simple Jaya algorithm. Moreover, in [17], another improved variant of the Jaya algorithm known as adaptive Jaya (AJaya) is proposed that uses varying iteration weighting coefficients in the Jaya update equations, improving the convergence

speed of the simple Jaya algorithm and reducing the number of power fluctuations. Finally, in [18], a Most Valuable Player Algorithm (MVPA) algorithm uses a clever strategy based on the sensitivity of the Power versus Voltage and duty ratio to limit the search space to a set of solutions with a high probability of finding the global maximum there, and thus significantly improving the convergence speed and reducing the power losses.

However, all previous metaheuristic algorithms despite their advantages, they still present some drawbacks e.g.

- 1) Though metaheuristic algorithms are less complex than AI techniques, they generally update 3 to 5 solutions in each iteration to explore the search space thoroughly and arrive at the best solution. However, dealing with more candidate solutions increases the computations cost. Moreover, multiple solutions result in slow convergence to MPP. The microcontroller has to configure the PV array with all these possible solutions to measure their power and select the best during the tracking. However, all these configurations lead to fluctuations in power and consequently to power losses.
- 2) In addition, these algorithms to further improve the search space exploration include some stochasticity in picking the different regions of the search space. However, by doing so, they explore some useless regions, causing again power fluctuations that result in power losses.

This work proposes a metaheuristic-based algorithm called the Low Burden Narrow Search (LBNS) to mitigate the power fluctuation and provide a more power-efficient MPP tracker. In addition, the Limited Search Strategy (LSS) proposed in [18] is modified to confine the search space around the actual optimum. By doing so, we reduce the number of update equations to one that avoid searching useless regions and reduce computational burden. Finally, we evaluated the LBNS against two recently proposed algorithms we mentioned before ([16] and [17]), and the results showed that it significantly outperforms them. In addition, the proposed solution reduction technique can be applied to other metaheuristic techniques to further improve their performance in MPP tracking. The contributions of this work are summarized below

- A universal solution reduction technique that can be applied to any metaheuristic algorithm
- A power-efficient tracker. Fewer and smaller-size power fluctuations during MPP tracking that lead to low power losses
- A computationally cheap MPPT algorithm
- Fast convergence to the MPP

The rest of the paper is organized as follows. Section II describes a PV energy system and defines the MPPT Problem. Section III offers the necessary background to justify the steps in our algorithm. Section IV explains the proposed algorithm (LBNS). Section V provides experimental results

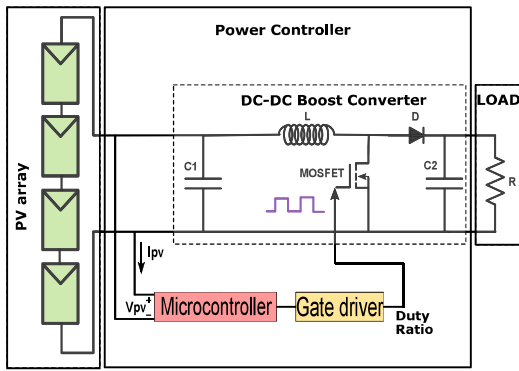


FIGURE 2. Maximum Power Point Tracking photovoltaic system.

that demonstrate the efficiency of LBNS, while conclusions are drawn in Section VI.

II. PV ENERGY SYSTEM AND PROBLEM FORMULATION

MPP tracker is a closed-loop control system that enforces a PV to deliver the maximum power to the load (see Fig. 2). The controller consists of a DC-DC boost converter, a microcontroller, voltage and current sensors, and a gate driver circuit. The microcontroller reads the PV current and voltage through the sensors circuit and generates a duty ratio driven to the MOSFET switch through the gate driver circuit. In essence, the duty ratio is the solution of an optimization algorithm executed in the microcontroller.

A rigorous definition of the MPPT problem is the following:

$$D^* = \underset{D}{\operatorname{argmax}} \operatorname{POWER}(D) \quad \text{s.t. } 0 < D \leq 1 \quad (1)$$

where  $D$  is the duty ratio and  $\operatorname{POWER}(D)$  is the power at this duty ratio. Because the insolation conditions may be altering continuously, the above optimization problem must be solved inside an infinite loop. Therefore, the runtime for obtaining the solution designates the system’s adaptability to the insolation changes. Moreover, the algorithm is going to be executed on a weak (small memory and a weak CPU) microcontroller. Thus, a computationally efficient optimization algorithm has to be developed for this problem.

III. BACKGROUND

In this section we provide the appropriate background for better understanding the proposed algorithm.

A. METAHEURISTIC OPTIMIZATION ALGORITHMS

The metaheuristic techniques are well-suited for solving non-convex optimization problems, like the problem in (1). These techniques aim to provide near-optimal solutions (they do not guarantee globally optimal solutions) while exploring the search space efficiently (update a couple of candidate solutions in each iteration). Usually, they draw their intuition in search space exploration from nature. We take as an example

the Jaya algorithm to show the basic structure of metaheuristic techniques. Jaya first initializes several possible solutions ( $X_i$ ) to begin search space explorations from all of these. Then, for each possible solution ( $X_i$ ), in each iteration ( $t$ ), first finds a candidate solution for the next iteration ( $X_i^{(t+1)}$ ) as follows:

$$X_i^{(t+1)} = X_i^t + r_1 * (X_{best}^t - X_i^t) - r_2 * (X_{worst}^t - X_i^t) \quad (2)$$

where  $X_{best}^t$  and  $X_{worst}^t$  are the best and the worst solutions seen until iteration  $t$ , respectively and,  $r_1, r_2$  are two random numbers to adjust the search space exploration around  $X_i^t$ . Then, it compares the value of the Fitness function of the candidate solution ( $X_i^{(t+1)}$ ) with the corresponding value of the Fitness function of the previous solution ( $X_i^t$ ) (in our problem, the Fitness function is the Power) and updates the solution for the next iteration ( $X_i^{(t+1)}$ ) with that one that has better Fitness value (in our problem with the highest value), as shown below

$$X_i^{t+1} = \begin{cases} X_i^{t+1}, & \text{Fitness}(X_i^{t+1}) \text{ better than } \text{Fitness}(X_i^t) \\ X_i^t, & \text{otherwise} \end{cases} \quad (3)$$

B. MODELING

In this subsection, our purpose is to arrive at a formula that gives the PV output power concerning the duty ratio to justify the decisions in the proposed algorithm. The Thevenin equivalent circuit of the PV circuit model is shown in Fig. 3. In Fig. 3b, the DC-DC boost converter subcircuit has been substituted with an equivalent resistance  $R_{eq}$ , including the output load  $R_o$ . The DC-DC boost converter output voltage ( $V_o$ ) is given by:

$$V_o = \frac{V_{pv}}{(1 - D)} \quad (4)$$

Also, owing to its high efficiency, DC-DC boost converter input and output power remains almost equal i.e.

$$\frac{V_{pv}^2}{R_{eq}} \approx \frac{V_o^2}{R_o} \quad (5)$$

Substituting (4) into (5) we obtain

$$R_{eq} = (1 - D)^2 R_o$$

Finally, the PV output power (power consumed on  $R_{eq}$ ) is given by:

$$P_{pv} = \frac{V_{pv}^2}{R_{eq}} = \frac{(1 - D)^2 V_{th}^2 R_o}{(R_{th} + (1 - D)^2 R_o)^2} \quad (6)$$

where  $P_{pv}$  is the PV output power,  $D$  is the boost converter duty ratio,  $V_{th}$  and  $R_{th}$  are the Thevenin equivalent voltage and resistance respectively, and  $R_o$  is the output load. In Fig. 4, we have plotted  $P_{pv}$  for different duty ratios. From Fig. 4 it can be seen that (6) results in a concave relation between the power of the PV module and the duty ratio of the controller, a result that we rely on to develop the steps of our proposed algorithm.

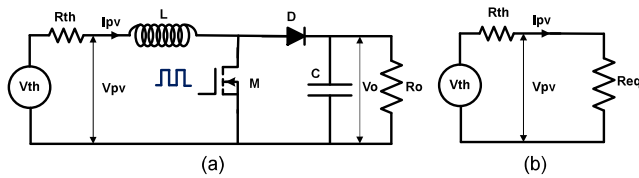


FIGURE 3. Thevenin circuit model of the PV system.

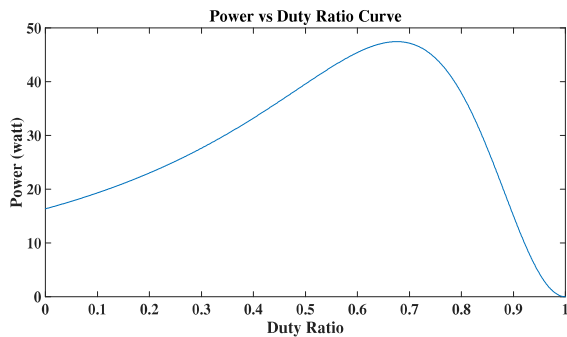


FIGURE 4. Power vs duty ratio curve. See the concave relation between the power and the duty ratios.

During partial shading conditions, the shaded modules provide significantly reduced current. Moreover, because all modules are connected in series, even full insolation modules cannot increase the current value. Bypass diodes are connected in anti-parallel with each module to mitigate that problem. The shaded modules generate negative voltages that forward bias the bypass diodes, while the unshaded modules deliver the maximum current because their bypass diodes remain reverse biased.

### C. PARTIAL SHADING

Depending on the load connected at the output, the PV can generate several possible voltage and current values. The operating voltage ranges from zero to the maximum voltage generated by the summation of voltages across each module. The maximum possible voltage that the unshaded modules can deliver is the sum of voltages across each unshaded module. The bypass diode across the least shaded module becomes reverse biased once the PV output voltage exceeds the sum of voltages across the unshaded modules. This reverse biasing of bypass diodes across the shaded modules grows with increasing voltages until the maximum possible voltage is reached. The current dips due to the reverse biasing of the shaded modules in Fig. 5 correspond to almost the same voltage ranges because each module's maximum voltage is approximately equal. However, the full insolation does not correspond to the same voltage range as the other modules (see Fig. 5 in which one panel that receives full insolation is considered). Due to the negative voltage drop across the shaded modules' forward-biased bypass diodes, the full insolation modules start from higher non-zero total voltage. Finally, as shown in the I-V curve, these current dips also cause multiple power humps. To sum up, if we

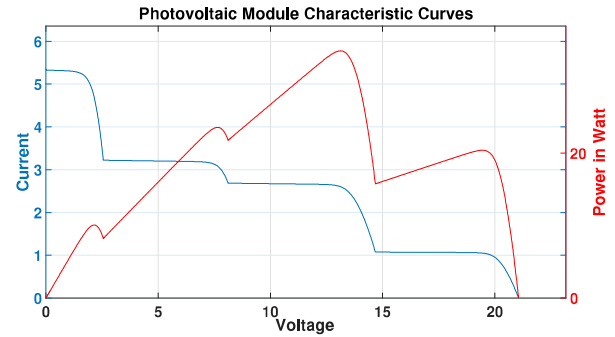


FIGURE 5. The current and the power curves by sweeping the voltage from zero to the maximum voltage the PV array can deliver.

study the operation of the photovoltaic between the current dips (or power humps in the P-V curve), which correspond approximately to equal voltage ranges, then the equations explained in the previous subsection can be used.

## IV. THE PROPOSED ALGORITHM

### A. LOW BURDEN NARROW SEARCH

The proposed algorithm (LBNS) is presented in Algorithm 1. The rest of the subsection explains the three main steps of LBNS, namely the initialization, the solution redistribution technique, and the metaheuristic solution update equation.

#### 1) INITIALIZATION

The algorithm starts by initializing four duty ratios in the search space (line 4). Then, the power corresponding to each one is evaluated, and the duty ratio with the highest power is selected as the initial best duty ratio (line 5). Unlike metaheuristic techniques that randomly spread solutions in the search space, just after the initialization, in this work, an improved version of the Limited Search Strategy (LSS) [18] (we call it Modified Limited Search Strategy (MLSS)) is proposed to redistribute the solutions between a lower and an upper bound.

#### 2) SOLUTION REDISTRIBUTION WITH MLSS

In MLSS, we limit the search space exploration in a narrow region with high certainty of finding the optimum solution there. Therefore, the metaheuristic techniques' required number of solutions to be updated in each iteration are reduced. The MLSS initially makes a tiny increment in the initial best duty ratio and finds a new duty ratio (line 7). Then, it evaluates the power of the new duty ratio and computes the finite difference (sensitivity) between the new and the initial best duty ratio power values (line 8). A positive finite difference value indicates that the optimum solution resides in the region of higher duty ratios and vice-versa, which is in total agreement with the power versus duty ratio relation (see (6)). In case that the indication is toward the region of higher (lower) duty ratios, the initial best duty ratio is set as the lower (upper) bound. Also, a duty ratio between the initial best duty ratio and the following (previous), from the

**Algorithm 1** Low Burden Narrow Search (LBNS) for MPPT

```

1: function  $D^* = \text{LBNS}$ 
2:   while true do
3:     Initialization
4:      $D_1 = 0.2, D_2 = 0.4, D_3 = 0.6, D_4 = 0.8$ 
5:      $D^* = \underset{\{D_1, D_2, D_3, D_4\}}{\text{argmax}} \text{ POWER}(D_i)$ 
6:     Solution Redistribution (MLSS)
7:      $D_+^* = D^* + \delta D$ 
8:      $\frac{\Delta P}{\Delta D} = \frac{\text{POWER}(D_+^*) - \text{POWER}(D^*)}{D_+^* - D^*}$ 
9:     if  $\frac{\Delta P}{\Delta D} > 0$  then
10:       $D_1 = D^*, D_2 = D^* + 0.03,$ 
11:       $D_3 = D^* + 0.065, D_4 = D^* + 0.105$ 
12:     else
13:       $D_1 = D^*, D_2 = D^* - 0.03,$ 
14:       $D_3 = D^* - 0.065, D_4 = D^* - 0.105$ 
15:     end if
16:      $D_1^* = \underset{\{D_1, D_2, D_3, D_4\}}{\text{argmax}} \text{ POWER}(D_i)$ 
17:      $D_{\text{imp}} = \{D_1, D_2, D_3, D_4\} - \{D_1^*\}$ 
18:      $D_2^* = \underset{D_{\text{imp}}}{\text{argmax}} \text{ POWER}(D_i)$ 
19:     Metaheuristic-update equation
20:      $D_3^* = \text{Update (7)}$ 
21:      $D^* = \underset{\{D_1^*, D_3^*\}}{\text{argmax}} \text{ POWER}(D_i)$ 
22:      $D_2^* = \{D_1^*, D_3^*\} - \{D^*\}, D_1^* = D^*$ 
23:     Convergence criterion of metaheuristic-update
24:     while  $\frac{|\text{POWER}(D_1^*) - \text{POWER}(D_2^*)|}{\text{POWER}(D_2^*)} \geq 5\%$  do
25:       $D_3^* = \text{Update (7)}$  for two iterations
26:       $D^* = \underset{\{D_1^*, D_3^*\}}{\text{argmax}} \text{ POWER}(D_i)$ 
27:       $D_2^* = \{D_1^*, D_3^*\} - \{D^*\}, D_1^* = D^*$ 
28:     end while
29:      $\text{POWER}_{\text{old}} = \text{POWER}(D^*)$ 
30:     Insolation change condition
31:     do
32:       return  $D^*$  and go to line 33
33:      $\text{POWER}_{\text{new}} = \text{POWER}(D^*)$ 
34:     while  $\frac{|\text{POWER}_{\text{new}} - \text{POWER}_{\text{old}}|}{\text{POWER}_{\text{old}}} < 1\%$ 
35:     end while
36: end function

```

initialization, duty ratio is set as the upper (lower) bound of the search space to be explored afterwards. Then, the duty ratios are redistributed uniformly within the above bounds (lines 9-15). Finally, the two duty ratios corresponding to the most significant power values initialize our metaheuristic solution update equation (lines 16-18).

**3) METAHEURISTIC SOLUTION UPDATE EQUATION**

After the MLSS step, we arrive at a window of duty ratios, where the power and duty ratios exhibit a concave relation, as shown in eq. (6). Then, we employ the following metaheuristic solution update equation (looks similar to the Jaya

**TABLE 1.** The dynamic PS scenario under test.

Dynamic PS cond.	PV Panels			
	P1	P2	P3	P4
1 <sup>st</sup>	1000 w/m <sup>2</sup>	680 w/m <sup>2</sup>	550 w/m <sup>2</sup>	400 w/m <sup>2</sup>
2 <sup>nd</sup>	1000 w/m <sup>2</sup>	900 w/m <sup>2</sup>	750 w/m <sup>2</sup>	600 w/m <sup>2</sup>
3 <sup>rd</sup>	1000 w/m <sup>2</sup>	650 w/m <sup>2</sup>	520 w/m <sup>2</sup>	300 w/m <sup>2</sup>
4 <sup>th</sup>	1000 w/m <sup>2</sup>	870 w/m <sup>2</sup>	700 w/m <sup>2</sup>	450 w/m <sup>2</sup>
5 <sup>th</sup>	1000 w/m <sup>2</sup>	950 w/m <sup>2</sup>	850 w/m <sup>2</sup>	550 w/m <sup>2</sup>
6 <sup>th</sup>	1000 w/m <sup>2</sup>	700 w/m <sup>2</sup>	500 w/m <sup>2</sup>	350 w/m <sup>2</sup>

update equation described in subsection III-A):

$$D_i^{(t+1)} = D_{\text{sbest}}^{(t)} - (D_{\text{sbest}}^{(t)} - D_{\text{best}}^{(t)}) * \left( 1 + r * \left[ \frac{(P_1 - P_2)}{|(P_1 - P_2)|} \right] \right) \tag{7}$$

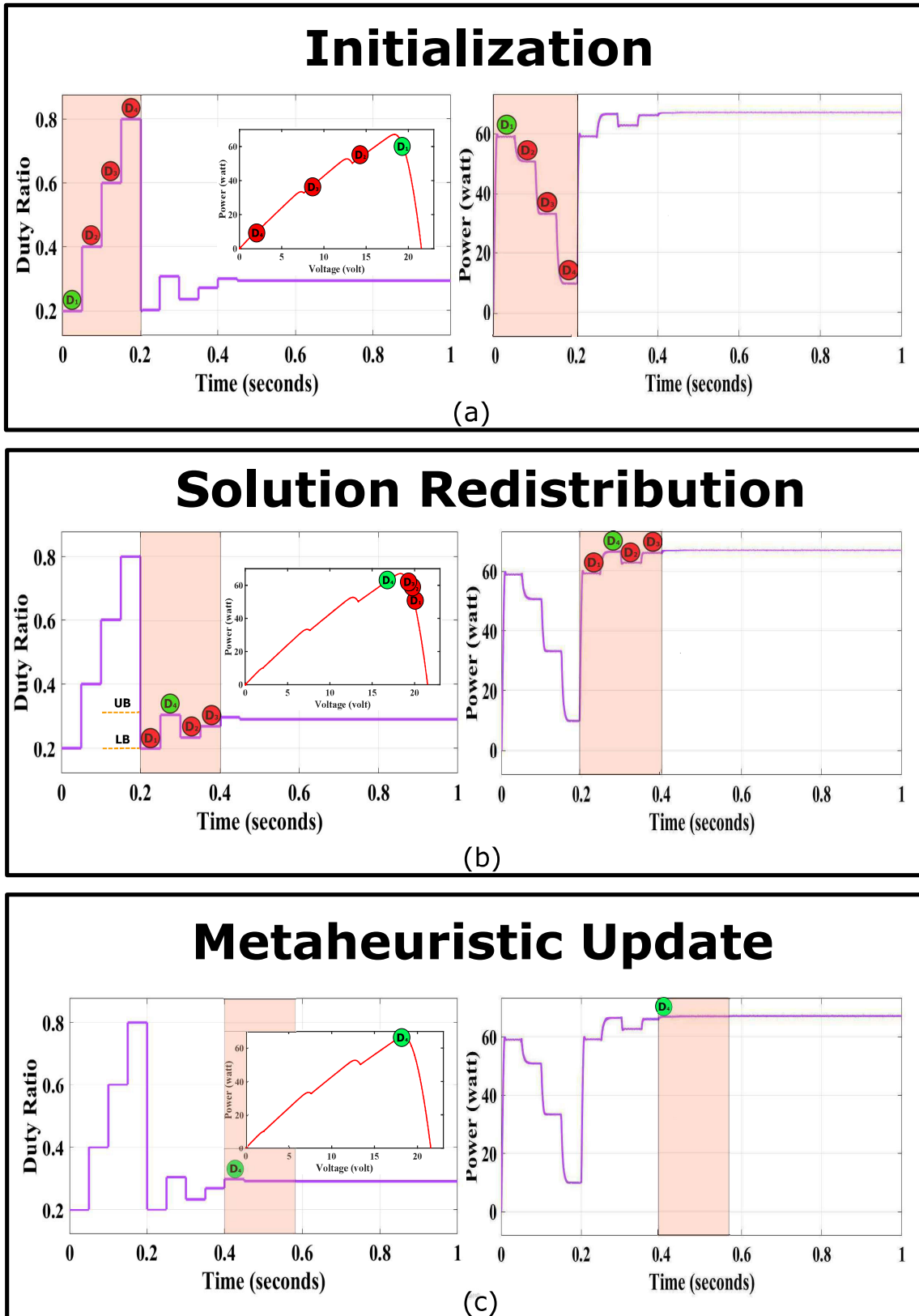
with

$$\begin{aligned}
 \begin{pmatrix} D_i^{(t+1)} \\ D_{\text{sbest}}^{(t+1)} \end{pmatrix} &= \begin{cases} \begin{pmatrix} D_i^{(t+1)} \\ D_{\text{best}}^{(t)} \end{pmatrix}, & \text{if } P_i^{(t+1)} > P_{\text{best}}^{(t)} \\ \begin{pmatrix} D_{\text{best}}^{(t)} \\ D_i^{(t+1)} \end{pmatrix}, & \text{otherwise} \end{cases} \\
 \begin{pmatrix} P_1 \\ P_2 \end{pmatrix} &= \begin{cases} \begin{pmatrix} P_{\text{sbest}}^{(t+1)} \\ P_{\text{best}}^{(t+1)} \end{pmatrix}, & \text{if } P_i^{(t+1)} > P_{\text{best}}^{(t)} \\ \begin{pmatrix} P_{\text{best}}^{(t+1)} \\ P_{\text{sbest}}^{(t+1)} \end{pmatrix}, & \text{otherwise} \end{cases}
 \end{aligned}$$

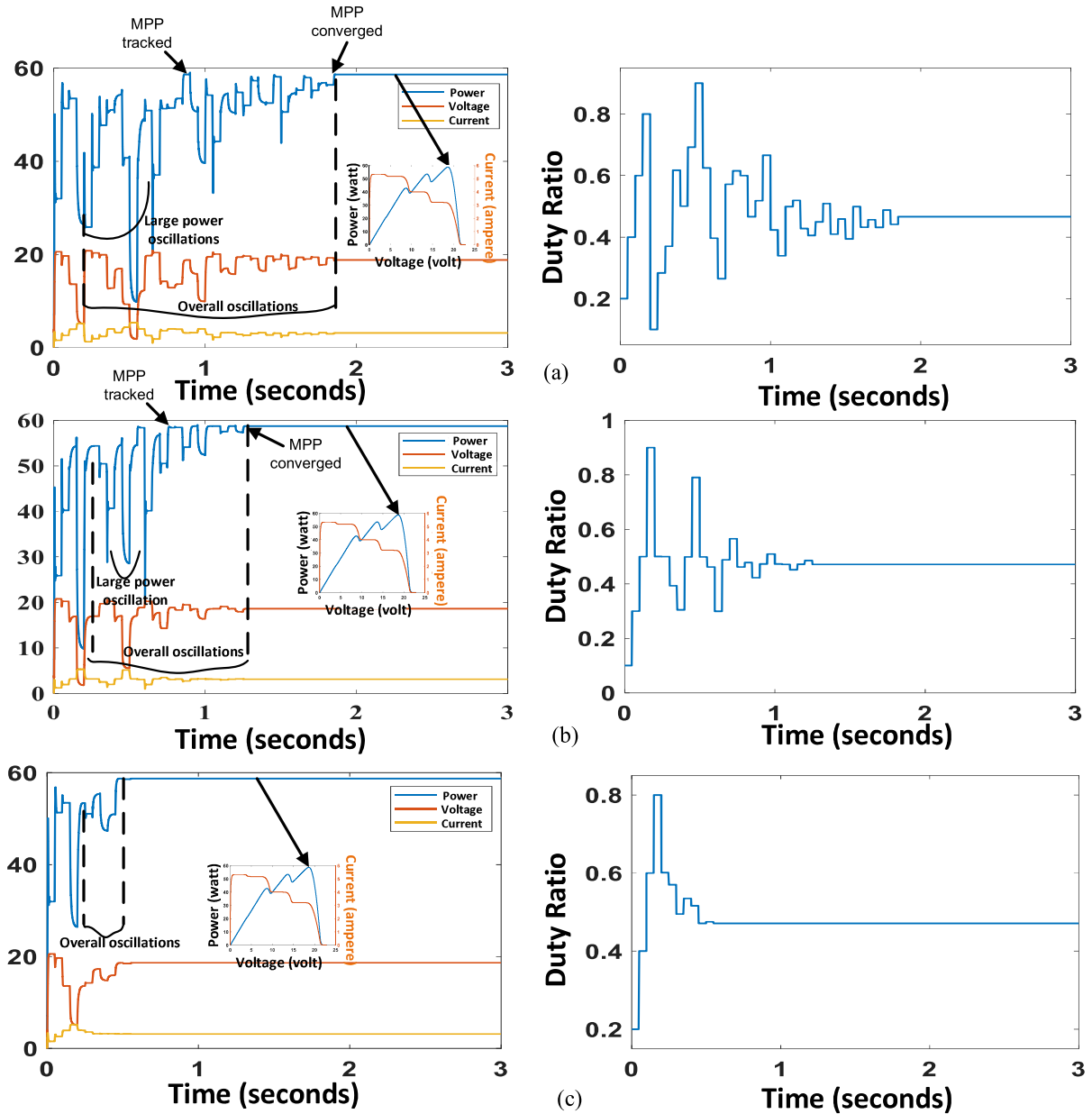
where  $D_i^{(t+1)}$  is the solution in the next iteration,  $D_i^{(t)}$  is the solution at the current iteration,  $D_{\text{best}}$  is the best solution (larger power value),  $D_{\text{sbest}}$  is the second-best solution,  $r$  is a random number between 0 and 0.25,  $P_i$  is the power value that corresponds to  $D_i$ ,  $P_{\text{best}}$  is the power value that corresponds to  $D_{\text{best}}$  and  $P_{\text{sbest}}$  is the power value that corresponds to  $D_{\text{sbest}}$ . The two best solutions resulting from the MLSS step initialize (7) as  $D_{\text{best}}$  with the best duty ratio,  $D_{\text{sbest}}$  with the second-best duty ratio,  $P_1$  with  $P_{\text{sbest}}$  and  $P_2$  with  $P_{\text{best}}$ . There are three possible relative positions of  $D_{\text{best}}$  and  $D_{\text{sbest}}$  with respect to the power peak. They may be both at the left side or the right side or one at the left, and the other at the right side of the power peak. Depending on the case, the update equation is adjusted automatically (taking the appropriate branch) to find the optimal duty ratio (approaching the power peak).

**4) RUNNING EXAMPLE**

For a more thorough understanding of our algorithm, several of its steps, given the Power versus Voltage (P-V), the Power versus time (P-t), and the Duty Ratio versus time (D-t) curves, are illustrated through a running example in Fig. 6. The red sliding window shows the position of P-t and D-t curves in every step. Let the four duty ratios  $D_1, D_2, D_3$  and  $D_4$  be initialized as 0.2, 0.4, 0.6 and 0.8 respectively. The  $D_1$  duty ratio highlighted with a green circle corresponds to the highest power and, thus it is selected as the initial best duty ratio.



**FIGURE 6.** In (a) the four duty ratios are assigned initial values evenly distributed between 0 and 1. D1 is the best initial solution because it corresponds to the highest power. In (b) after identifying that larger duty ratios than the best initial solution (D1) lead to higher power values, the candidate solutions are redistributed between the best initial solution i.e.  $D1 = 0.2$ , and a duty ratio that is slightly above the middle duty ratio between D1 and the next larger duty ratio from initialization i.e.,  $D2 = 0.4$ . So, the lower bound is 0.2 and the upper bound is 0.305. Finally in (c) the metaheuristic best-solution update equation based on the two best solutions from the solution redistribution step takes place.



**FIGURE 7.** Transient power analysis while executing (a) JayaLF, (b) AJaya, and (c) LBNS algorithm for a given PS condition. The proposed algorithm exhibits fewer and smaller in magnitude power fluctuations that lead to less power losses.

After that, according to Algorithm 1 in lines 6-8, we have to make a tiny increment to  $D_1$  (initial best solution) and compute the corresponding finite difference. From the P-V plot in Fig. 6a, yellow it can be seen that such an increment leads to larger power due to the inverse relation of voltage and duty ratio with power (we obtain higher power values while increasing duty ratios or equivalently decreasing the voltage)<sup>1</sup> and thus the finite difference results to be positive. As a result, the maximum power has to be towards higher duty ratios. Then, in Fig. 6b, the solutions are redistributed

<sup>1</sup>In equation 4 given that  $V_o$  is constant, the voltage has to be decreased when the duty ratio is increased.

evenly between  $D_1$  (the initial best solution as lower bound) and the duty ratio (upper bound) located slightly above the middle of  $D_1$  and the next larger duty ratio that was initialized as  $D_2 = 0.4$ . Finally, the duty ratios  $D_4$  and  $D_3$ , which correspond to the two highest power values in Fig. 6b, initialize our metaheuristic update equation 7, which updates a single candidate solution until two consecutive updates converge, in Fig. 6c.

**V. EXPERIMENTAL RESULTS**

The proposed algorithm (LBNS) was evaluated by comparing it with the recently proposed JayaLF [16], and AJaya [17]

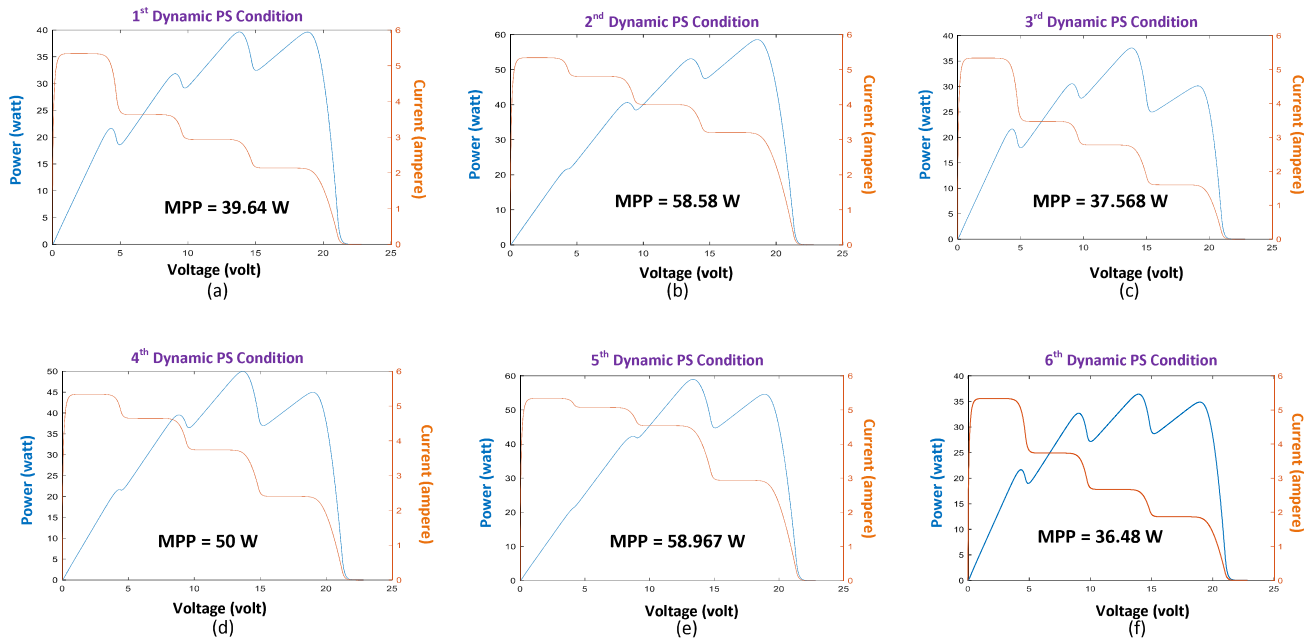


FIGURE 8. P-V curves of the (a) 1<sup>st</sup>, (b) 2<sup>nd</sup>, (c) 3<sup>rd</sup>, (d) 4<sup>th</sup>, (e) 5<sup>th</sup>, and (f) 6<sup>th</sup> dynamic PS condition.

TABLE 2. Resulting energy loss ( $E_{Loss}$ ), convergence time ( $T_{Cnv g}$ ), and converged MPP ( $MPP_{Cnv g}$ ) of the algorithms under test in the dynamic PS scenario.

Dynamic PS condition	Algorithm								
	JayaLF			AJaya			LBNS		
	$E_{Loss}$ (J)	$T_{Cnv g}$ (sec)	$MPP_{Cnv g}$ (W)	$E_{Loss}$ (J)	$T_{Cnv g}$ (sec)	$MPP_{Cnv g}$ (W)	$E_{Loss}$ (J)	$T_{Cnv g}$ (sec)	$MPP_{Cnv g}$ (W)
1 <sup>st</sup>	80	0.66	39.6	99.745	1.12	39.28	52.287	0.38	39.418
2 <sup>nd</sup>	412.7	2.21	58.55	247.44	1.26	58.55	147.44	0.47	58.55
3 <sup>rd</sup>	287.3	2.06	37.575	78.167	0.968	37.5	38.997	0.47	37.54
4 <sup>th</sup>	352.77	1.8	49.97	132.5	1.27	44.89	88.35	0.46	49.967
5 <sup>th</sup>	412.27	1.33	58.64	232.416	1.22	53.99	107.25	0.5	58.959
6 <sup>th</sup>	28.36	0.56	32.9	69.66	1.02	36.472	24.825	0.42	34.87

algorithms. Moreover, JayaLF was initialized like our proposed algorithm because its initialization, as it is proposed in [16], led to inferior performance. Also, the JayaLF was sticking to local peaks due to weak exploration. To solve this, we have modified the random number ranges in its equation to increase its exploration and avoid local MPP (0 to 0.95 for the random number with best enhancing component, and 0 to 1.2 for the random number with worst avoiding component). The abbreviation for the improved version is kept to be same (JayaLF). To show the proposed algorithm’s practical use, we also provide results for dynamic partial shading conditions that emulate better a real situation. Our experimental setup consists of four PV modules in series with open-circuit voltage ( $V_{ov}$ ) = 5.425V, short circuit current ( $I_{sc}$ ) = 5.34A, MPP Voltage ( $V_{MPP}$ ) = 4.35V, and MPP current ( $I_{MPP}$ ) = 5.02A. The DC-DC boost converter was designed with inductance ( $L$ ) = 1.15mH, input capacitance ( $C_i$ ) = 47uF, output capacitance ( $C_o$ ) = 470uF, and load resistance ( $R_o$ ) = 20Ω. Finally, the results were obtained using the Typhoon Hardware-In-Loop (HIL) software interface [27]. To quantify the power oscillations until the convergence of each algorithm to their

respective MPP, we evaluated the energy loss ( $E_{Loss}$ ), i.e.,

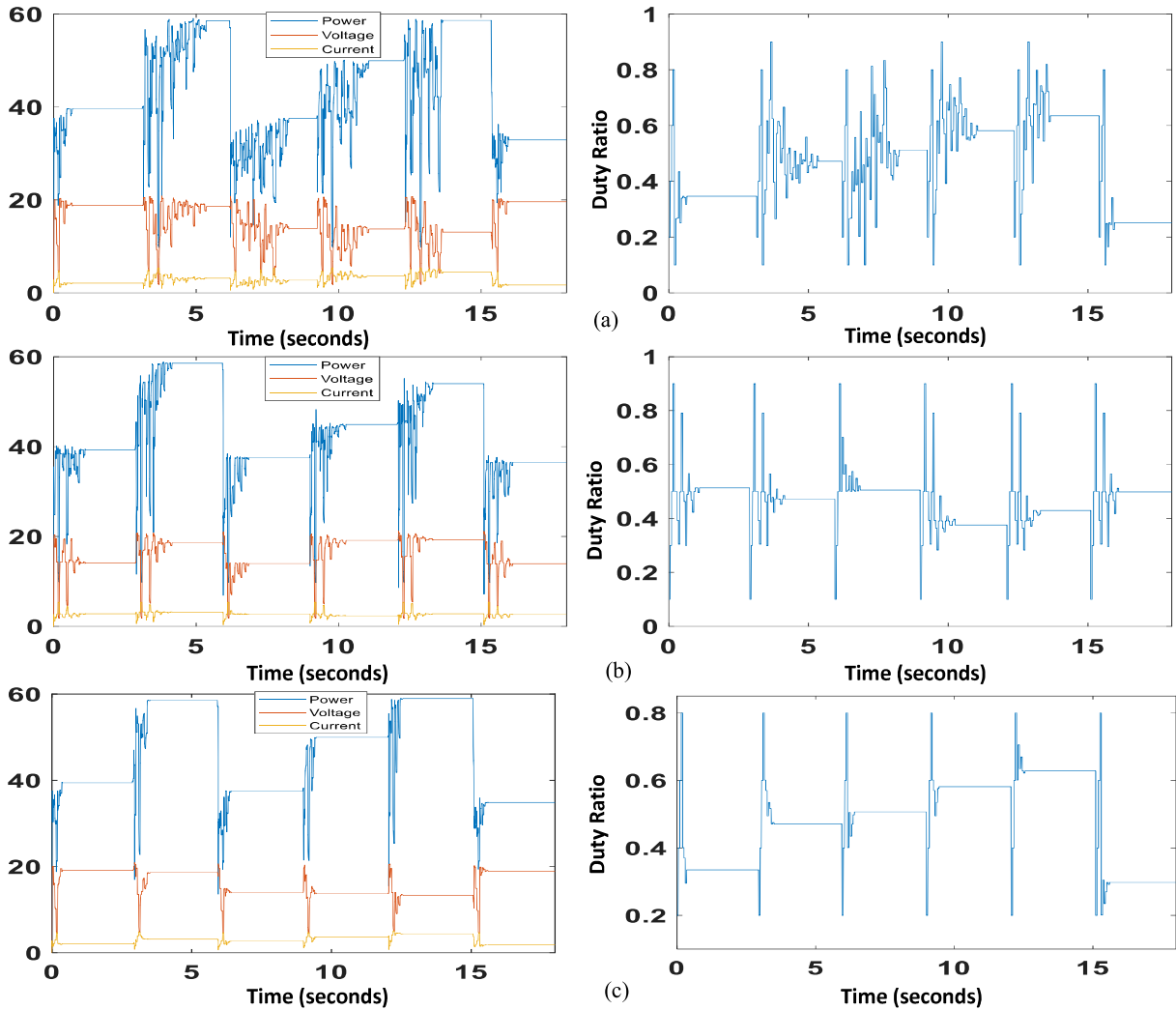
$$E_{Loss} = \int_0^{T_{Cnv g}} (MPP_{Cnv g} - Power(t)) dt$$

where  $T_{Cnv g}$  is the convergence time,  $MPP_{Cnv g}$  is the convergent MPP of each algorithm and  $Power(t)$  is the tracking power at time  $t$ .

### A. STATIC PARTIAL SHADING CONDITION

First, a static PS scenario with shaded three out of four modules was considered. The insolation configuration of the four panels was 1000, 970, 750, and 600  $W/m^2$  respectively with the MPP of 58.74 W. Fig. 7a shows the results for the JayaLF. As observed, because the algorithm considers several candidate solutions at each iteration, the power evaluation corresponding to each one results in different power values that lead to multiple power fluctuations and eventually to power losses. Also, as shown in the figure, the JayaLF does not have a good decision-making capability for final convergence to MPP and generates fluctuations between the start-tracking and the convergent time instant that again leads





**FIGURE 9.** Transient power analysis while executing (a) JayaLF, (b) AJaya, and (c) LBNS algorithm when PS conditions change dynamically. The proposed algorithm exhibits again fewer and smaller in magnitude power fluctuations that lead to less power losses.

to power losses. The convergence time, MPP tracked, and energy loss of JayaLF were approximately 1.86 seconds, 58.62 Watt, and 374.33 respectively.

Fig. 7b illustrates the performance of the AJaya. After the initialization phase, like JayaLF, the algorithm produces many large power fluctuations. However, the magnitude of these fluctuations is milder, and they are fewer than those in JayaLF. Also, unlike JayaLF, the algorithm converged to MPP with lesser power fluctuations between the start-tracking and the convergent time instants. Though AJaya demonstrates better results than the JayaLF, the power fluctuations are still high and lead to power losses. The convergence time, MPP tracked, and energy loss of AJaya were approximately 1.26 seconds, 58.72 Watt, and 225.79 respectively.

Fig. 7c demonstrates the performance of the proposed algorithm LBNS. After the initialization phase, there is an insignificant power fluctuation due to the redistribution of the candidate duty ratios (see subsection IV-A2) in the region of duty ratios where it is more probable to find the best

duty ratio. Also, only one solution with a shallow exploration requirement was updated. As a result, the convergence to the MPP is very fast, with negligible power fluctuations between the start-tracking and the convergent time instant. Moreover, like the conventional algorithms, a single updating solution makes it more computational-friendly. All these benefits contribute to faster convergence with fewer and smaller in magnitude power fluctuations than AJaya and JayaLF, which leads to reduced power losses. The convergence time, MPP tracked, and energy loss were approximately 0.46 seconds, 58.72 Watt, and 107.71 Joule respectively.

**B. DYNAMIC PARTIAL SHADING CONDITIONS**

In addition to the static partial shading condition, a scenario where the shading of PV modules changes randomly with time is provided to demonstrate how fast the proposed algorithm can adapt to dynamically changing conditions. The simulation was executed for eighteen seconds, assuming six different PS conditions, each lasting for three seconds. The

scheduling of the insolation conditions of the four panels in this experiment is given in Table 1. The power versus voltage (P-V) and current versus voltage (I-V) curves are also shown in Fig. 8 for all six dynamic partial shading conditions along with their MPP values.

Fig. 9a shows the results for the JayaLF algorithm. The JayaLF produced several large power oscillations in almost all PS conditions. Moreover, there are tiny fluctuations after the MPP is tracked and until the convergence to MPP. However, the overall power losses remain high. More specifically, the times to converge to MPP were approximately 0.66, 2.21, 2.06, 1.8, 1.33, and 0.56 seconds, the MPPs tracked were approximately 39.6, 58.55, 37.575, 49.97, 58.64, and 32.9 Watt, and finally, the energy losses were 80, 412.7, 287.3, 352.77, 412.27, and 28.36 Joule, for all six timeslots, respectively.

Fig. 9b shows the results for the AJaya algorithm. Again, AJaya presents fewer and weaker power fluctuations than JayaLF. On the other hand, the JayaLF presents fewer power fluctuations than AJaya, after tracking MPP and until the final convergence. More specifically, the times taken to converge to MPP were approximately 1.12, 1.26, 0.968, 1.27, 1.22, and 1.02 seconds, the MPPs tracked were approximately 39.28, 58.55, 37.5, 44.89, 53.99, and 36.472 Watt, and finally, the energy losses were 99.745, 247.44, 78.167, 132.5, 232.416, and 69.66 Joule, for all six timeslots, respectively.

Fig. 9c shows the results for the LBNS algorithm. It is clear that for all timeslots, the LBNS exhibits the least and the smallest in magnitude power fluctuations after its initialization and between the start-tracking and the convergent time instant. More specifically, the times taken to converge to MPP were approximately 0.38, 0.47, 0.47, 0.46, 0.5, and 0.42 seconds, the MPPs tracked were approximately 39.418, 58.55, 37.54, 49.967, 58.959, and 34.87 Watt, and finally, the energy losses were 39.418, 58.55, 37.54, 49.967, 58.959, and 34.87 Joule, for all six timeslots, respectively.

Table 2 summarizes all the results from the last experiment. The average energy loss and convergence time for JayaLF were 262.23 Joule and 1.436 seconds, AJaya 143.32 Joule and 1.143 seconds, and LBNS 76.524 Joule and 0.45 seconds, respectively. Moreover, the proposed algorithm consumed  $3.42\times$  and  $1.87\times$  less energy and converged  $3.19\times$  and  $2.54\times$  faster than JayaLF and Ajaya, respectively. Finally, on top of the faster convergence and the reduced energy loss, the proposed algorithm also converged to similar MPP values with JayaLF and Ajaya.

## VI. CONCLUSION

In this work, we build upon metaheuristic algorithms to further reduce their computational complexity and mitigate the power losses for the problem of MPPT under partial shading conditions. First, our search space is confined around two duty ratios where it is most likely to find the maximum power, using a power versus duty ratio sensitivity criterion. Then, yellow a single candidate solution is updated based on the previous two duty ratios until the final convergence.

Our experimental results showed that the proposed algorithm, in addition to the low computational complexity, converges  $3.12\times$  faster and results in  $2.71\times$  less energy loss on average than two recently proposed algorithms for the same problem. In the future, we plan to reduce further the computational complexity, the convergence time, and the resulting energy loss of the proposed algorithm.

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