JAYA Algorithm Based on Lévy Flight for Global MPPT Under Partial Shading in Photovoltaic System

Rambabu Motamarri and Nagu Bhookya

***Abstract*— Recent technologies associated with solar photovoltaic (PV) systems tend to depend mostly on irradiance. In a PV array, the distribution of irradiance is unequal varying from module to module under partial shading (PS) conditions. Because of the PS of the PV array; the number of peaks in power–voltage (P–V) characteristics increases. In such cases, it would be difficult to track the highest peak or global peak (GP) point of P–V curve using traditional maximum power point tracking (MPPT) algorithms, such as perturb and observe (P&O), hill climbing (HC), and incremental conductance (INC). However, these work effectively only under constant irradiance conditions, i.e., to track single peak P–V curves. However, in order to track the GP point of P–V curves, the conventional JAYA algorithm is used, but it takes more tracking oscillations and convergence time due to fewer control parameters. To overcome the drawbacks of the JAYA algorithm, this article proposes a JAYA algorithm based on the Lévy flight (JAYA-LF) under static and dynamic conditions of PV array. The performance of the proposed algorithm is examined through MATLAB/SIMULINK and from experiments with the designed prototype. The results observed by the proposed algorithm are then compared with conventional JAYA and particle swarm optimization (PSO) algorithm to show the superiority and better performance of the algorithm that combines JAYA with Levy flight.**

***Index Terms*— JAYA Lévy flight (JAYA-LF), maximum power point tracking (MPPT), partial shading (PS), particle swarm optimization (PSO), photovoltaic (PV).**

I. Introduction

AT PRESENT, the increased reliance on the generation of power from photovoltaic (PV) systems and supply to the power grid has been becoming popular as an encouraging sign for the future development of sources in renewable energy sources. PV systems offer quite a few benefits, such as being less maintenance compared with rotating machine interfaced power generating systems, offering quick installation time, and with the flexibility of placing PV panels on rooftops of homes and buildings, while the initial investment on solar power plants is reducing due to rapid advances in PV development technology and use [1] in comparison with other nonconventional sources of energy. However, the PV system offers lower efficiency due to nonlinearly varying characteristic of power–voltage (P–V), and fluctuating climatic conditions also pose a major challenge. Therefore, it becomes necessary to operate the PV system at its maximum power point (MPP). Efficiency is greatly influenced by moving clouds, dust, neighboring buildings, trees, and prevailing weather conditions.

Due to these obstacles, the PV system delivers low power. The low performance of the PV system, when the irradiance falling on the PV array plane is not distributed uniformly, is called partial shading (PS) occurrence [2]. Then, multiple local peaks and one global peak (GP) are available on P–V characteristics of a PV system. It is a great challenge to ensure global optimization for the PV system, in order to operate a global point rather than a local point [3], [4]. In the last few years, with the help of power electronic devices, many maximum power point tracking (MPPT) techniques have been implemented to provide global power from the PV array. The parameters considered in the methods vary according to their own performance. From these techniques, hill climbing (HC) [5] and perturb and observe (P&O) [6] are commonly used algorithms for their simplicity. Both algorithms work on a similar principle to attain the MPP. Periodically, the HC method provides power by perturbing the duty cycle to the converter, whereas the P&O method performs with a PV system voltage by perturbation. Based on the power levels, control parameters (duty cycle or voltage) can be increased or decreased to reach MPP. Due to the elegant performance of HC and P&O algorithms, it is easy to detect oscillations present around the steady-state point (MPP) and also power loss during tracking. If the perturbation step size is small, it can show better oscillation performance, while it reduces the speed response, and vice versa. To show superior performance to the P&O method, some improvements have been proposed by varying perturbation step size [7], [8]. The main weakness of these methods is that they are unable to capture GP under PS conditions. Incremental conductance (IC) works in the same manner as the P&O method [9], [10] and reaches MPP when P–V curve slope is zero, and it has drawbacks, vis-à-vis, accuracy, speed response, and incapable of tracking GP during the shading of PV array. The DIRECT search

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algorithm [11] is implemented along with the P&O algorithm. During the shading of the PV array, the main algorithm activates to reach GP, following which P&O holds the GP when the stop condition arrives. This process is complex, and oscillations observed at steady state are not applicable for reinitialization under dynamic cases. The GMPPT method was proposed in work [12] based on the information curves of *I-V* and *P–V* under PS. This approach first tracks all local peaks and then determines actual GP from all observation of local peaks under certain shading of PV patterns. This method uses 80% of the *I–V* curve, shows more tracking time, and is not applicable for reinitialization under dynamic cases. A new MPPT method [13] for GP introduces an analytic condition under partially shaded conditions and is also used the HC method to track GP with the help of $0.8\,V_{\rm oc}$ model, but oscillations are, nevertheless, present at steady state. From GMPPT methods, Nguyen and Low [11], Patel and Agarwal [12], and Alireza *et al.* [13] have each proposed one MPPT algorithm for searching GMPP, but the initialization of particles is dependent on the PV system. Furthermore, even GMPPT is found using these techniques, and Salam and Ahmed [14] report that a system-dependent method is not always suitable, particularly in extended PV systems. These algorithms may locate Local MPP instead of global MPP.

Bioinspired algorithms have been extensively used for solving nonlinear multimodel optimization problems effectively with quick response for a wide range of exploration to reach the global MPP under shading of PV array [16]. Optimization techniques during PS, such as PSO [16], are executed with three parameters, such as two acceleration factors and weight factors, which are to tuned to the maximum iteration, providing higher efficiency by taking more (30) iterations for global MPP. Deterministic PSO [17] has the limitation of velocity though it removes random generation values to get better performance of PSO, but the initial particles are dependent on the PV system, and oscillations around MPP show up in experimental results; according to the Lipschitz optimization (LIPO) [18], the importance of randomly generating numbers will provide better search process for GMPP without getting struck at LMPP, but LIPO tracks GP with more iterations, while modified PSO [19] yields optimum values of PSO (i.e. w, C_1, and C_2) without reinitialization. Under dynamic cases, PSO based on velocity [20] discards the weight factor tuning of PSO, has deterministic behavior, and adapts and regulates acceleration parameters, while the initial particles and acceleration parameters are dependent on the PV system, with reinitialization not considered during the change of the PV pattern. The natural cubic spline-guided Jaya algorithm (S-JAYA) [21] searches for global MPP with five initial particles, which depends on the PV system and takes more tracking time. Other algorithms, such as ant colony optimization (ACO) [22], require five initial parameters and complex computations; the artificial bee colony (ABC) [23] algorithm was proposed under PS; and its convergence speed is superior to PSO. However, when the initial particles are few, ABC is struck at a local peak, the firefly algorithm (FA) [24] uses six fireflies, and then the complexity of the system increases. Gray wolf optimization (GWO) [25] improves tracking performance over PSO and P&O under static variation with one tuning parameter but not performed with reinitialization under dynamic. GWO with fuzzy logic controller [26] proposed different kinds of reinitialization methods under shading of PV array with a minimum of five particles, which increases the burden on the system. Recent GMPPT technologies to increase the performance include a novel chaotic flower pollination algorithm (CFPA) [27] that improves the FPA performance with the help of chaos maps and shows higher efficiency compared with FPA, taking time is more even five initial particles and overall distribution of PSO [28], and also having five initial particles then increases complexity and burden on the system. Adaptive radial movement optimization (ARMO) [29] tracks location(s) of GMPP faster, but it is implemented by considering dependent initial particle, and the particles are more than five with three tuning parameters, thereby increasing complexity. Hybrid enhanced leader PSO-P&O [30] was proposed with many parameters along with tuning parameters though the designers had not reckoned with determining efficiency.

This article proposes an improvement of the JAYA algorithm based on Lévy flight (JAYA-LF) for a faster convergence process in GMPPT. In the JAYA algorithm, fewer control parameters lead to poor exploitation process and delay in convergence. The proposed technique tracks GMPP with fewer iterations, without tuning parameters, leading to a reduction of transient and steady-state oscillations, and minimum tracking period under the static condition and with reinitialization parameters under dynamic shading condition of PV arrays. To validate the performance of the JAYA-LF method, simulation and experimental comparisons are presented under six cases. The remaining sections of this article discuss the description of the PV system, implementation of GMPPT algorithms, performance results, and comparison of GMPPT methods, followed by conclusions.

II. Description of PV System

A. Modeling of PV Module

A PV module can be modeled as a single-diode model [31] and its PV module parameters are shown in Table I. The output current ($I_{\rm pv}$) of the module is given by

$$I_{\rm pv} = I_{\rm ph} - I_{\rm ao}\left[e^{\left(\frac{(V_{\rm pv}+R_s I_{\rm pv})\times q}{N_{\rm cs}kT_c a_{\rm fd}}\right)} - 1\right] - \frac{V_{\rm pv}+R_s I_{\rm pv}}{R_p} \tag{1}$$

where $I_{\rm ph}$ is the light generated current, $I_{\rm ao}$ is the reverse saturation current, $V_{\rm pv}$ is the module output voltage, $R_s(0.221\ \Omega)$ is the series resistance, $R_p(415.5\ \Omega)$ is the parallel resistance, $N_{\rm cs}$ is series-connected cells in the module, q is the electron charge [1.6×10^{-19} C], Boltzmann's constant is $k[1.38\times10^{-23}$ J/K], the temperature in kelvin is T_c, and $a_{\rm fd}$ is the diode ideality factor ($1 \le a \le 1.5$) [33].

The mathematical details of $I_{\rm ph}$ and $I_{\rm ao}$ are described as

$$I_{\rm ph} = \left(\frac{R_p+R_s}{R_p} I_{\rm sc} + K_i(T_C - T_{\rm ref})\right)\frac{S}{S_{\rm ref}} \tag{2}$$

$$I_{\rm ao} = \frac{I_{\rm sc} + K_i(T_c - T_{\rm ref})}{e^{\left(\frac{V_{\rm oc}+K_v(T_c-T_{\rm ref})}{N_{\rm cs}kT_c a_{\rm fd}}\times q\right)} - 1} \tag{3}$$

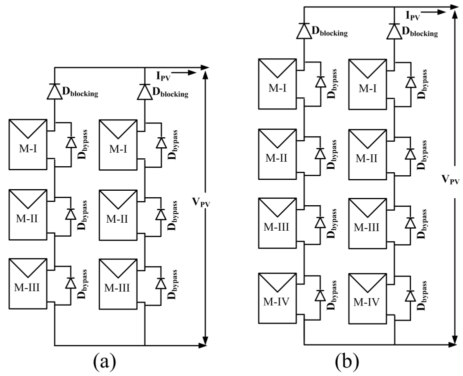


Fig. 1. PV array configurations. (a) Three PV modules in series and two path such modules in parallel (3S2P). (b) Four PV modules in series and two path such modules in parallel (4S2P).

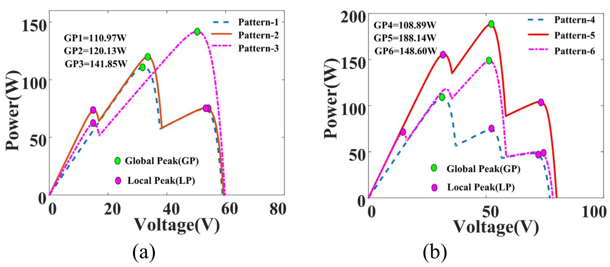


Fig. 2. PV array characteristics. (a) 3S2P. (b) 4S2P.

where I_{sc} and V_{oc} are the short-circuit current and the open-circuit voltage, respectively. K_i and K_v are coefficient of current (0.0032 A/K) and voltage (−0.123 V/K). T_c and T_{ref} are cell's working and reference temperature (25 °C). S and S_{ref} are the working and reference irradiance (1000 W/m^2) [33], respectively.

The performance of the proposed JAYA-LF algorithm can be established with two kinds of PV arrays under PS. The first one involves three PV modules in series such that two combinations are in parallel and labeled 3S2P, as shown in Fig. 1(a). The second one is implemented with a four series-connected PV module such that two combinations are in parallel and labeled 4S2P, as shown in Fig. 1(b). The corresponding P–V characteristics under different shaded PV array scenarios or patterns are shown in Fig. 2, and in each scenario, the multiple peaks are different due to shading where the irradiance level pertaining to each case is presented in Table II.

III. Implementation of GMPPT Algorithms

A. GMPPT Through PSO Algorithm

The most powerful algorithm that was considered ideal for GMPPT was the particle swarm optimization (PSO) algorithm. The PSO algorithm was proposed by Eberhart and James [32] in 1995. This optimization method has been used for the purpose of control to locate GP where it was first applied for MPPT [33]. PSO is a population-based algorithm and is modeled based on the behavior of bird flocks. It has to maintain an individual swarm, i.e., particles, where each particle is selected to take action as a solution of a candidate. The position of particles is affected by the best particle in the neighborhood, i.e., P_{besti}. In the overall population, the best particle is known as G_{best}.

The position of particle X_i is computed as

$$X_i^{k+1} = X_i^k + \theta_i^{k+1} \tag{4}$$

where θ_i stands for the step size. The velocity is updated based on global best and the best particle as follows:

$$\theta_i^{k+1} = w\theta_i^k + C_1 R_1 \left[P_{besti} - X_i^K\right] + C_2 R_2 \left[G_{best} - X_i^k\right] \tag{5}$$

where w is the inertia weight, C_1 and C_2 are the acceleration coefficients, and $R_1 \& R_2 \in U(0, 1)$. The position X_i^{k+1} is denoted as an updated duty cycle, and the velocity stands for the step size.

B. JAYA Algorithm

The JAYA algorithm [34] has recently come up with a metaheuristic method for solving optimization problems. It is very simple and efficient and does not have many specific parameters for convergence. Power "P_{pv}" is assumed to be an objective function for the maximization problem. The idea is to find the best particle X_{best} and worst particle X_{worst} among all solutions after initializing the particle positions called duty cycles of the boost converter. Based on the best and worst particle updated, the new particle position is determined as follows:

$$X_i^{k+1} = X_i^k + R_1\left(X_{best} - X_i^k\right) - R_2\left(X_{worst} - X_i^k\right) \tag{6}$$

where X_i^k and X_i^{k+1} are present and updated duty cycles, and R_1 and R_2 are random generation from uniform distribution $U[0, 1]$. The term $R_1(X_{best} - X_i^k)$ brings the particle closer to the best position, while the $R_2(X_{worst} - X_i^k)$ term brings out the worst condition solution. The objective functions for each updated particle position are calculated according to (6).

C. JAYA Algorithm Based on Lévy Flight

The JAYA algorithm that can be implemented to GMPPT is a very simple and efficient algorithm with a few specific parameters. The JAYA algorithm equation (6) has two random numbers because of which random nature exploration is good enough for initial tracking, but its exploitation process is poor. However, due to the minimum number of control parameters, its tracking oscillations and convergence time are more in the JAYA algorithm. Thus, in order to improve the exploration and exploitation process, the JAYA algorithm is implemented based on Lévy flights (LFs) called JAYA-LF. The proposed JAYA-LF algorithm flowchart is shown in Fig. 3, and its procedure is explained in the following.

The LFs [35]–[37] imply random nature, which can be implemented along with the JAYA algorithm for rapid convergence. Its nature is to search in small steps for the exploitation process; otherwise, it takes a long jump from one area to another area for the purpose of exploration purpose [38]. Based on the LF concept support to the JAYA algorithm, the tracking time to reach global power is low, and also it uses minimum iteration. The proposed JAYA-LF algorithm population is updated based on the condition given in the flowchart and is rand <0.25 [39] for the proper search operation to achieve global MPPT.

Two steps are required for the creation of random numbers with the help of Lévy flight [37] and [38], i.e., the choice of random direction and the production of steps that obey the selected Lévy distribution. Random walks are captured from Lévy stable distribution. The simple formula for the power law $L(s) \sim |s|^{-1-\beta}$, where $0 < \beta < 2$ is an index [40]. Mathematically, the Lévy distribution can be defined as

$$L(s, \gamma, \mu) = \begin{cases} \sqrt{\frac{\gamma}{2\pi}} \exp\left[-\frac{\gamma}{2(s-\mu)}\right] \frac{1}{(s-\mu)^{3/2}}, & 0 < \mu < s < \infty \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

where μ parameter is location or shift parameter and γ is a scale parameter.

In general, the Lévy distribution should be defined in terms of the Fourier transform

$$F(k) = \exp\left[-\alpha |k|^{\beta}\right], \quad 0 < \beta \leq 2 \tag{8}$$

where α is a scale factor between $[-1, 1]$. β is the Lévy index. The small value of β allows the variable to jump long distances in a search area and keeps away from local optima; the large value of β continues to obtain new values around the variable. As a result, by employing LFs on updating the population, variables are able to take short jumps together with occasionally long-distance jumps toward the best value, thereby enhancing the population diversity and facilitating the algorithm to achieve stronger global exploration throughout the search area. In this study, apply LFs to each variable of the current iteration using the following equation:

$$X_i^{k+1} = \text{Levy walk}\left(X_i^k\right) + R_1 \times \left(X_{\text{best}} - X_i^k\right) - R_2 \times \left(X_{\text{worst}} - X_i^k\right) \tag{9}$$

where

$$\text{Levy walk}\left(X_i^k\right) = X_i^k + \text{stepsize} \tag{10}$$

where

$$\text{stepsize} = 0.01 \times \text{step} \times \left(X_i^k - X_{\text{best}}\right). \tag{11}$$

This factor 0.01 comes from the fact that step/100 should be the typical step size of walks, where a step is a typical length scale; otherwise, LFs may become so aggressive, which makes new solutions jump outside of the domain and, thus, waste evaluations. X_i^k and X_{best} are variables from (6).

For a random walk, the value of the step can be calculated by Mantegna's algorithm as

$$\text{step} = \frac{u}{|\upsilon|^{1/\beta}}. \tag{12}$$

Here, β plays an important role in distributions, by assigning different values for β, and the distribution is changed differently. In this study, 1.5 is chosen as a constant value for β [40].

TABLE I

PV MODULE PARAMETERS

P_{max}	V_{OC}	I_{SC}	V_{max}	I_{max}
$60W$	$21V$	$3.8A$	$17.1V$	$3.5A$

The other two parameters u and υ are drawn from normal distributions with a standard deviation σ_u and σ_υ given by

$$u \sim N\left(0, \sigma_u^2\right), \quad \upsilon \sim N\left(0, \sigma_\upsilon^2\right)$$

where

$$\sigma_u = \left(\frac{\Gamma(1+\beta) \times \sin(\pi \times \beta/2)}{\Gamma\left(\left(\frac{1+\beta}{2}\right)\right) \times \beta \times (2)^{\left(\frac{\beta-1}{2}\right)}}\right)^{\frac{1}{\beta}} \quad \text{and } \sigma_\upsilon = 1 \tag{13}$$

where $\Gamma(\cdot)$ is the standard Gamma function.

If shading occurs suddenly when executing the present scenario of PV array, it will be recognized based on present and next power comparisons by the following equation:

$$\frac{|P_{n+1} - P_n|}{P_n} \geq \delta. \tag{14}$$

The terms P_n and P_{n+1} are present and future power output of the PV system, respectively, while δ is considered as 2% according to [41].

D. Step-by-Step Procedure for Proposed Algorithm

The proposed algorithm has to follow the steps outlined in the following.

Step 1: Initialize the particles at fixed positions between 0.1 and 0.9 of the duty cycle and specific parameters.

Step 2: Measure the power P_{pv} from each particle of duty cycle by sensing V_{pv} and I_{pv} and corresponding duty cycle to boost converter

$$P_{\text{pv}} = V_{\text{pv}} \times I_{\text{pv}}.$$

Step 3: Obtain particle best and worst values from the population.

Step 4: Update the position of each particle by using (6) and (9) as per the condition given in the flowchart.

Step 5: Repeat procedure from steps 2 to 4 till one reaches global MPPT of P–V array characteristics.

Step 6: If shading occurs, the JAYA-LF algorithm detects it by sensing the power comparison equation (14) and then reinitializes the initial parameters.

IV. SIMULATION RESULTS

The simulation work is implemented in MATLAB/SIMULINK according to the schematic circuit diagram of boost converter along with PV array, as shown in Fig. 4. The proposed algorithm generates duty by sensing voltage and current from the PV array output. The proposed algorithm is modeled in Simulink using an s-function as per the flowchart shown in Fig. 3. The modeling of the PV array is implemented based on the parameters of the PV module, as shown in Table I. The PV modules are connected in series

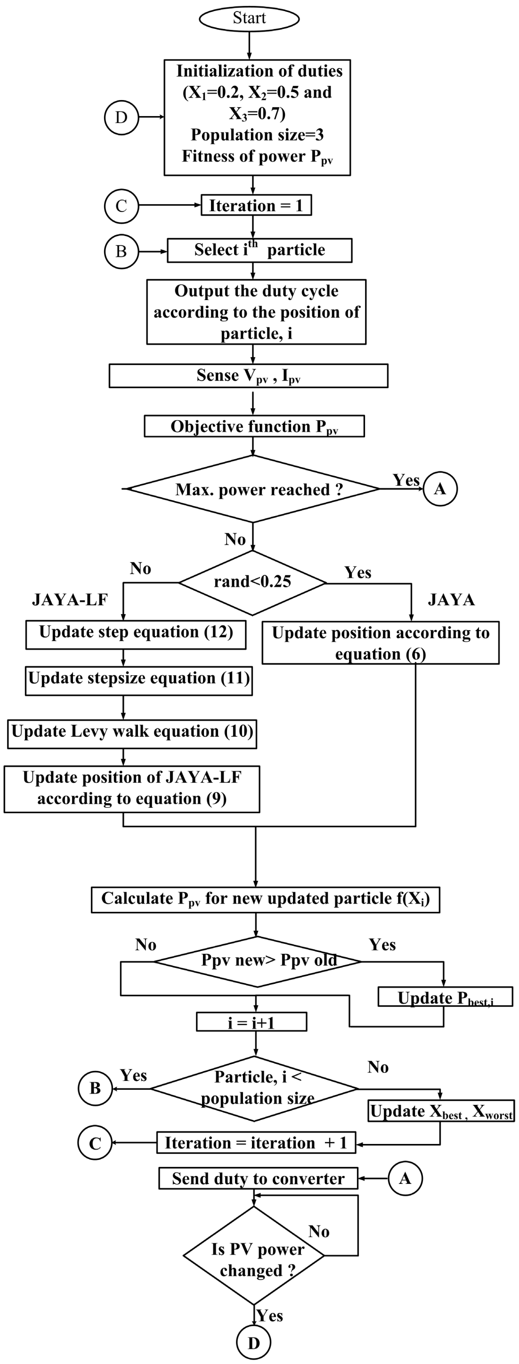


Fig. 3. Flowchart of the proposed algorithm.

and parallel with blocking and bypass diodes, as shown in Fig. 1. The proposed JAYA-LF algorithm is verified under six cases of PV array scenarios in order to show the superiority over conventional JAYA and PSO algorithms during the PS effect. In the first three scenarios, the global MPP of 3S2P with left peak, middle peak, and right peak is considered in P–V characteristics. The next three scenarios of global MPPs involve first peak, second peak, and third peak from the left of the P–V curve at 4S2P. The initial particles of three algorithms termed duty cycle to boost converter with points are $x_1 = 0.2, x_2 = 0.5$, and $x_3 = 0.7$ considered without depending on the PV system. The

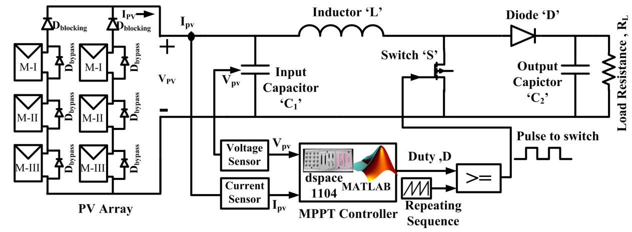


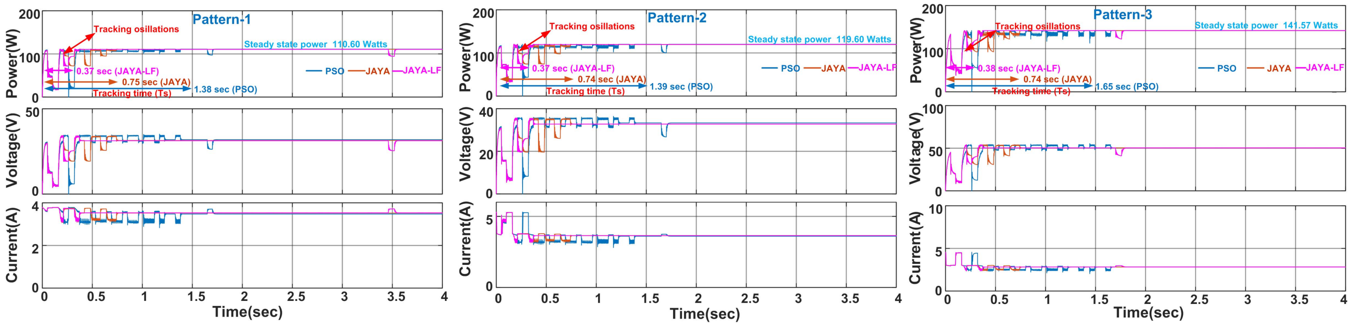
Fig. 4. Application of the PV array to the boost converter.

remaining parameters of the boost converter and algorithms are represented in Table III.

A. Simulation Results of 3S2P PV Array

In the PV array configuration, six PV modules are used to form 3S2P, as shown in Fig. 1(a); in pattern-1, the irradiances of the first, second, and third rows are 500, 500, and 200 W/m^2. Out of that, two irradiances are the same, while one is different. Therefore, the corresponding P–V curve has two peaks where the first peak (left peak) is GP, as shown in Fig. 2(a). Consider 3S2P as PV source to boost converter and operate the switch (MOSFET) of the converter by providing pulse from the proposed algorithm; the JAYA-LF will execute based on V_{pv} and I_{pv} of the PV array output voltage and current. The PSO algorithm is applied to the proposed system, and the tracking time to reach global MPP (110.60 W) is 1.38 s with ten iterations. The time required is substantial for PSO due to three tuning parameters, with these being weight and acceleration parameters (i.e., w, C_1, and C_2), which are unable to find optimum values during tracking. In order to reach the global MPP (110.60 W) of the JAYA algorithm, the time required is 0.75 s with five iterations and many transient oscillations. The proposed JAYA-LF only takes 0.37 s along with three iterations for GMPP (110.60 W) of pattern-1. The JAYA-LF yields better results compared with conventional JAYA and PSO algorithms in terms of tracking time and number of iterations for GMPPT.

The proposed algorithm gives better results compared with PSO and JAYA algorithms because the PSO has more control parameters to get global optima, whereas, with PSO, the random numbers help to jump from one location to another location for initial searching, implying that the exploration process is good. In order to converge to GP, it takes time due to three tuning factors (w, C_1, and C_2); because the algorithm is unable to arrive at the exact value through iterations, it takes more time to converge, making the exploitation process poor. The JAYA algorithm is highly easy to work and efficient in this aspect and does not have many specific parameters for convergence. It exploration process is good with the presence of random numbers, but the exploitation process is poor due to fewer control parameters. The variation at steady-state power is not constant but oscillating, and so the exploitation is poor. In order to improve the exploration and exploitation process, LFs are added to the JAYA algorithm. The LFs imply random nature, which can be implemented along with the JAYA algorithm for rapid convergence. By employing LFs on updating the population, variables are able to take short jumps and long-distance jumps [38] to improve the process



(a) (b) (c)

Fig. 5. Simulation results of 3S2P. (a) Pattern-1. (b) Pattern-2. (c) Pattern-3.

TABLE II

IRRADIANCE (W/M^2) OF MODULES IN PV ARRAY

Module (M)	Pattern -1	Pattern -2	Pattern -3	Pattern -4	Pattern -5	Pattern -6
M-I	500	700	600	500	700	700
M-II	500	500	400	500	700	500
M-III	200	200	400	200	500	400
M-IV	-	-	-	100	200	100

TABLE III

DESIGNED PARAMETERS

Particulars	**Specifications**
Proposed	$\beta = 1.5$
PSO	$C_{1,min} = 1$, $C_{1,max} = 2$, $C_{2,min} = 1$, $C_{2,max} = 2$, $w_{min} = 0.1$, $w_{max} = 1$,
Boost coverter	$L = 1.5mH$, $C_1 = C_2 = 100\mu F$, $F_s = 10kHz$, Diode − MUR860, MOSFET − IRFP460, 100Ω 10A Variable Rheostat load
Sampling period (T_s)	Population size = 3 For simulation $T_s = 50ms$, For experimental $T_s = 200ms$.

TABLE IV

SIMULATION PERFORMANCE ANALYSIS OF 3S2P AND 4S2P CONFIGURATIONS

Technique	Rated Power of PV array (Watt)	Extracted Output Power of PV (Watt)	Tracking time(sec)	Iterations	Efficiency of PV (%)
Proposed	110.97	110.60	0.37	03	99.66
JAYA	Pattern-1	110.60	0.75	05	99.66
PSO		110.60	1.38	10	99.66
Proposed	120.13	119.60	0.37	03	99.55
JAYA	Pattern-2	119.60	0.74	05	99.55
PSO		119.60	1.39	10	99.55
Proposed	141.85	141.57	0.38	03	99.80
JAYA	Pattern-3	141.57	0.74	05	99.80
PSO		141.57	1.65	11	99.80
Proposed	108.89	108.30	0.37	03	99.45
JAYA	Pattern-4	108.30	0.75	05	99.45
PSO		108.30	1.50	10	99.45
Proposed	188.14	188.10	0.37	03	99.97
JAYA	Pattern-5	188.10	0.75	05	99.97
PSO		188.10	1.93	11	99.97
Proposed	148.60	148.40	0.37	03	99.86
JAYA	Pattern-6	146.30	1.14	08	98.45
PSO		146.30	1.55	11	98.45

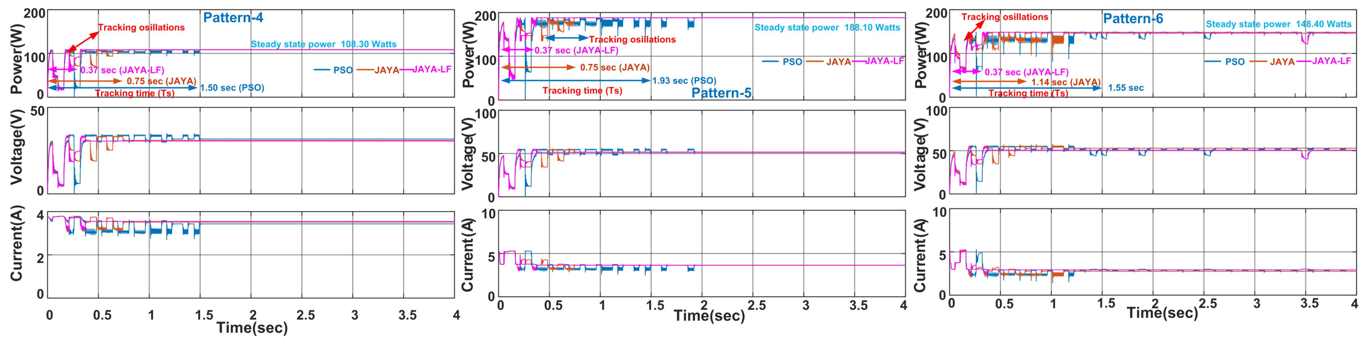
of exploitation and exploration. The simulation results of pattern-1 are shown in Fig. 5(a), and performance details are presented in Table IV. Similar to pattern-1, the other two patterns of middle peak and right peak called patten-2 and pattern-3 of the 3S2P configuration have also been applied as PV source to converter, and its irradiance levels and performance results are shown in Tables II and IV, respectively. The P–V curves and simulation results are shown in Figs. 2(a) and 5(b) and (c). In these cases also, JAYA-LF overcomes the disadvantages of PSO and JAYA algorithms. Furthermore, the tracking performances of these three MPPT algorithms can be described by MPPT efficiency η, which can be calculated as follows:

$$\eta = \frac{P_1}{P_2} \times 100\%. \tag{15}$$

The term P_1 means that the output power is in the stable mode of the PV system under the JAYA-LF MPPT algorithm. P_2 is the maximum output power of the PV system under certain (PS) conditions.

B. Simulation Results of 4S2P PV Array

In the setup, the PV array is implemented with eight PV modules to form 4S2P, as shown in Fig. 1(b). System complexity is increased compared with 3S2P. The 4S2P array is taken into consideration in order to prove that the proposed method works well for complex configurations also. The three patterns are first, second, and third peaks from left of the P–V curve, as shown in Fig. 2(b), and its irradiance (W/m^2) levels shown in Table II. In pattern-4, the PSO algorithm takes time to locate GP power (108.30 W) in 1.5 s with ten iterations. The JAYA algorithm tracks GP power (108.30 W) in 0.75 s with five iterations, while the proposed JAYA-LF algorithm takes 0.37 s to track GP (108.30 W) with three iterations. Thus, with a 4S2P array, the proposed algorithm gives the best performance compared with JAYA and PSO in terms of tracking oscillation, tracking time with fewer iterations, and without tuning parameters. The advantages of pattern-5 and patten-6 are the same as those of pattern-4. The simulation results of voltage, current, and power 4S2P waveforms are



(a) (b) (c)

Fig. 6. Simulation results of 4S2P. (a) Pattern-4. (b) Pattern-5. (c) Pattern-6.

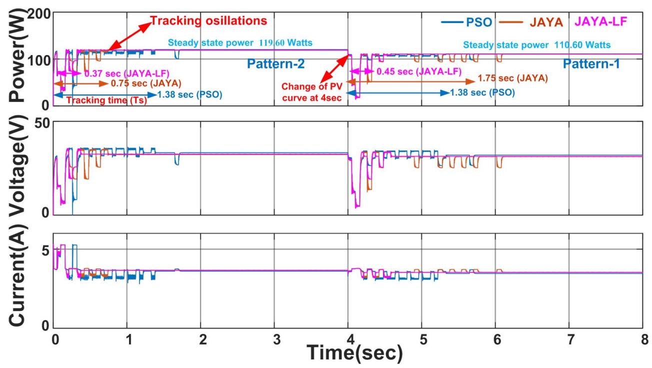


Fig. 7. Dynamic simulation results of pattern-2 to pattern-1.

shown in Fig. 6, while the simulation performance of 4S2P PV array results is presented in Table IV.

C. Simulation Dynamics of Pattern-1 and Pattern-2

The dynamics in the simulation are observed from pattern-2 to pattern-1 in comparison with PSO, JAYA, and the proposed algorithms. In fact, when one of the shading pattern-2 is considered, it will track GP power (119.60 W) with the proposed method and maintain constant power up to 4 s. After that, pattern-1 is applied to the system, and then, the proposed algorithm recognizes the system as per the power equation given in (14). If it is confirmed by the proposed algorithm that there has been a change of pattern, the algorithm has to reinitialize the initial parameters and then start tracking new GP power (110.60 W) according to pattern-1. Finally, the JAYA-LF method proves advantageous under dynamic conditions compared with JAYA and PSO algorithms as shown in the results in Fig. 7 in terms of tracking time and tracking oscillations with a reduced number of iterations.

V. Experimental Results

An experimental prototype of the PV system designed is shown in Fig. 8; it consists of a programmable PV simulator followed by a boost converter. In real time, the proposed algorithm can be implemented by DSPACE 1104 controller installed using MATLAB software. Here, the PV array configurations were replaced by a programmable PV simulator (Magna power electronics XR600-9.9/415+PPPE+HS). The

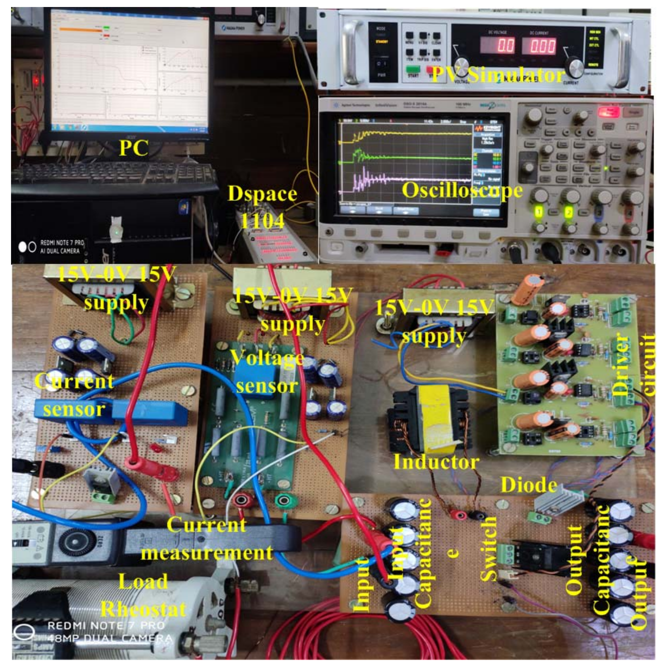


Fig. 8. Prototype of the designed PV system.

pulse generation to switch OFF boost converter has emerged from the control algorithm provided by sensing voltage (LV25-p) and current sensor (LA55-p) from the output of the PV simulator. The parameters considered for experiments were the same as those for simulation, and the advantages of the proposed JAYA-LF algorithm were verified to be the same as that was observed during simulation work compared with JAYA and PSO algorithms, with six cases of PV patterns under PS for GMPPT.

A. Results of 3S2P PV Array Configuration

The PV array patterns were applied through the PV simulator. In the 3S2P configuration, three PV patterns of left, middle, and right peaks were considered in this case. In order to verify maximum voltage and maximum current with respect to the global power of a particular PV array pattern, the screenshot of P–V curve operating point and I–P curve was taken from PV simulator software by operating the point on GP on each curve and placing that in each experimental result

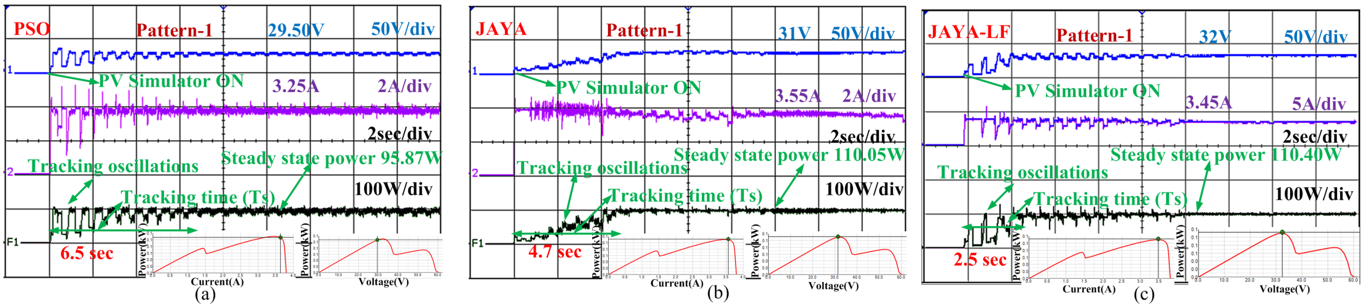


Fig. 9. Experimental waveforms of pattern-1. (a) PSO. (b) JAYA. (c) Proposed.

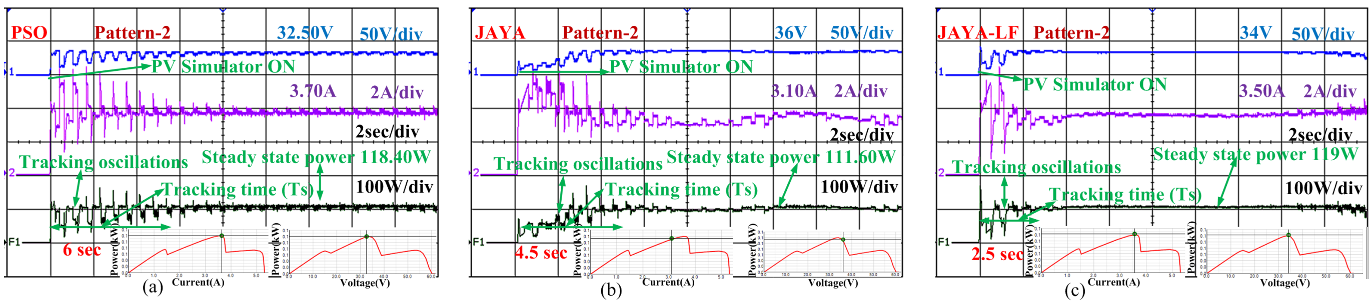


Fig. 10. Experimental waveforms of pattern-2. (a) PSO. (b) JAYA. (c) Proposed.

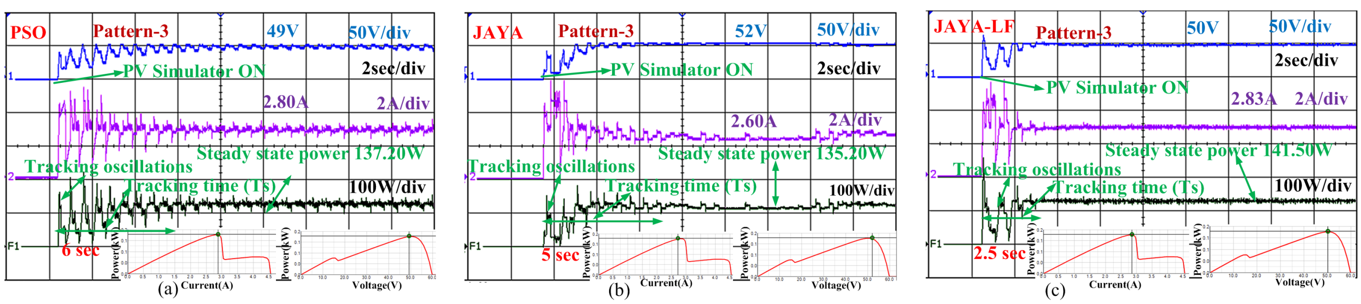


Fig. 11. Experimental waveforms of pattern-3. (a) PSO. (b) JAYA. (c) Proposed.

below the right-hand side corner. The performance results of the 3S2P are presented in Table V.

In pattern-1, the PSO algorithm tracks global power of 95.87 W with a tracking time of 6.5 s in 11 iterations; from the results shown in Fig. 9, both tracking and steady-state oscillations were observed. The tracking time was more in PSO due to three tuning parameters (w, C_1, and C_2). The power obtained by the JAYA algorithm was 110.05 W with a tracking time of 4.75 s to reach GP of P–V curve in eight iterations; the observations from using the JAYA algorithm are oscillations and power loss during initial tracking due to fewer specific parameters. The proposed JAYA-LF algorithm consumes the power of 110.40 W with a time of 2.5 s and takes fewer iterations (4), while showing fewer oscillations during tracking compared with the JAYA and PSO algorithms. Thus, during the experiment phase too, JAYA-LF outperformed both JAYA and PSO algorithms in terms of minimum tracking time, fewer iterations, and without using tuning parameters. Similar advantages were obtained for pattern-2 of PSO, JAYA, and the proposed algorithm, with the tracking time of (6, 4.5, and 2.5 s) and iterations of (ten, eight, and four), respectively. In pattern-3, the tracking time was (6, 5, and 4) s with (ten, nine, and four) iterations for the PSO, JAYA, and proposed algorithms. The results are shown in Figs. 10 and 11 for pattern-2 and pattern-3, respectively, and the corresponding results are presented in Table V.

B. Results of 4S2P Array Configuration

The first, second, and third peaks from the left-hand side of the P–V curve of the 4S2P configuration were considered. In pattern-4, the power generated by PSO is 106.75 W in 5 s along with nine iterations to reach GMPPT and JAYA tracked the power of 104 W in 4 s and seven iterations for GMPPT, while the proposed algorithm tracks the global power of 107.10 W in 2 s and three iterations. The proposed algorithm overcomes the problems connected with JAYA and PSO. Its experimental results are shown in Fig. 12, and the details are presented in Table V.

In a similar way, in pattern-5, the JAYA, PSO, and proposed algorithms track GMPP with a time of (6, 5, and 3) s and iterations of (ten, nine, and five), respectively. In pattern-6,

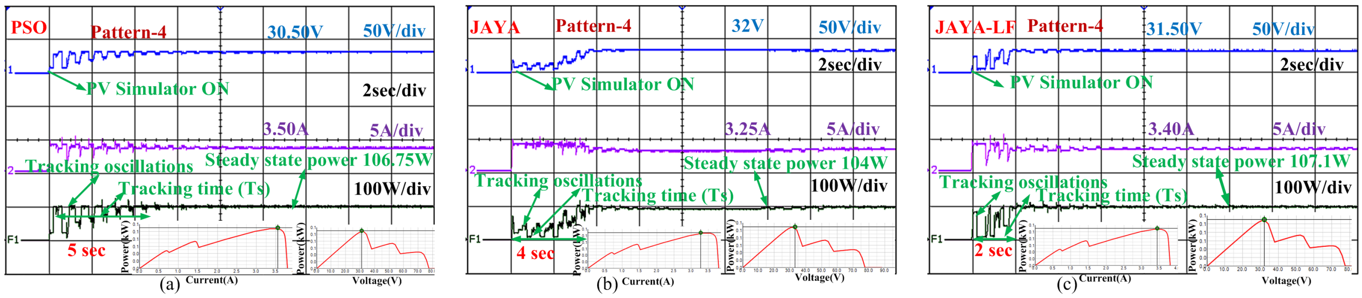


Fig. 12. Experimental waveforms of pattern-4. (a) PSO. (b) JAYA. (c) Proposed.

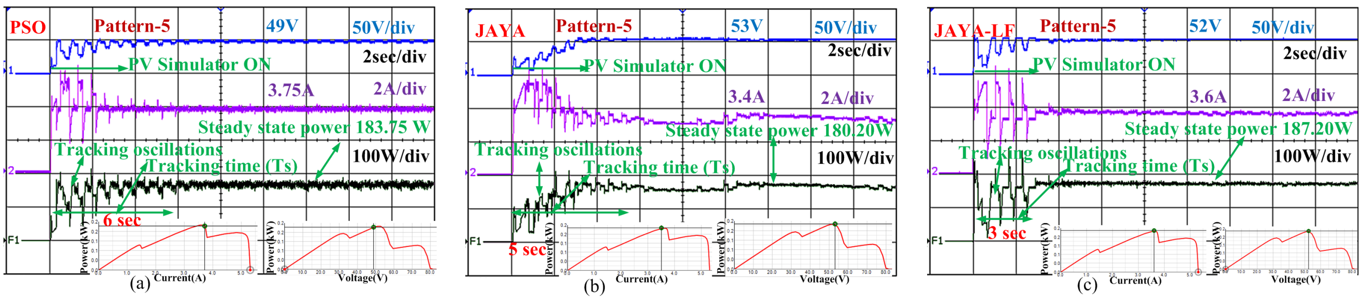


Fig. 13. Experimental waveforms of pattern-5. (a) PSO. (b) JAYA. (c) Proposed.

TABLE V
EXPERIMENTAL PERFORMANCE OF 3S2P AND 4S2P CONFIGURATIONS

Technique/ Parameter	Rated Power of PV array (Watt)	Extracted Output Power of PV (Watt)	Tracking time(sec)	Iterations	Efficiency of PV (%)
Proposed	110.97	110.40	2.5	04	99.48
JAYA	Pattern-1	110.05	4.7	08	99.17
PSO		95.87	6.5	11	86.39
Proposed	120.13	119.00	2.5	04	99.05
JAYA	Pattern-2	111.60	4.5	08	92.89
PSO		118.40	6.0	10	98.55
Proposed	141.85	141.50	2.5	04	99.75
JAYA	Pattern-3	135.20	5.0	09	95.31
PSO		137.20	6.0	10	96.72
Proposed	108.89	107.10	2.0	03	98.35
JAYA	Pattern-4	104.00	4.0	07	95.50
PSO		106.75	5.0	09	98.03
Proposed	188.14	187.20	3.0	05	99.50
JAYA	Pattern-5	180.20	5.0	09	95.77
PSO		183.75	6.0	10	97.66
Proposed	148.60	147.90	2.0	03	99.52
JAYA	Pattern-6	143.10	5.5	09	96.29
PSO		144.37	6.0	11	97.15

GMPP is located with (6.5, 5.5, and 2) s and in (11, nine, and three) iterations for the PSO, JAYA, and proposed JAYA-LF algorithms, respectively. The results of pattern-5 and pattern-6 are shown in Figs. 13 and 14, while a detailed explanation is provided in Table V. The operating points on GP of the P–V curve and the I–P curve are shown in the respective results below the right-hand side corner for the sake of convenience.

C. Dynamic of Pattern-1 and Pattern-2

Verification of the proposed JAYA-LF algorithm for the sudden change of shading occurs on the PV system. According to Fig. 15, pattern-2 was applied tracks global power of (118.80, 112.20, and 119) W with a tracking time (7, 5.5, and 3) s of the PSO, JAYA, and proposed JAYA-LF algorithms and continues up to (15, 12, and 16) s; then, suddenly, pattern-1 was initiated immediately the algorithm recognizes newly updated PV array based on power equation (14), and the algorithm has to reinitialize the initial parameters and track the GMMP of pattern-1 (110.40, 105.60, and 110.40) W with a time of (9, 6, and 3) s. From this, the proposed algorithm performs well even in dynamic conditions also.

D. Experimental Results' Comparisons of Proposed JAYA-LF Method and [39]

The experimental results' comparisons of the proposed JAYA-LF and [39] under six shading patterns are shown in Figs. 16 and 17. From these results, the proposed algorithm shows better performance than [39]. The proposed JAYA-LF algorithm tracks a power of 110.40 W within 2.50 s and takes four iterations to reach GP power for pattern-1, as shown in Fig. 16. [39] takes the tracking time of 3.30 s with six iterations in order to get the global power of 110.40 W. The performance evaluations of the proposed and [39] algorithms with six shaded conditions of PV arrays are mentioned in Table VI.

E. Proposed Method Verified for Pattern-7 to Pattern-10

The proposed algorithm is verified for four different patterns of PV array 3S2P and 4S2P in real time with similar

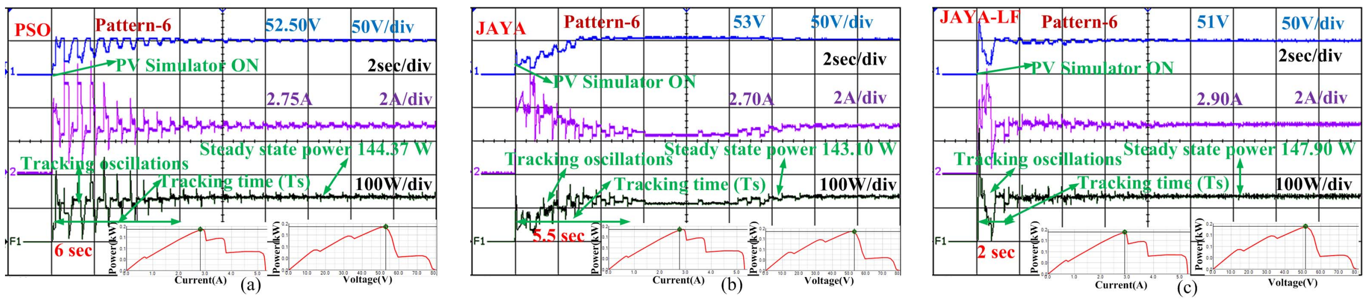


Fig. 14. Experimental waveforms of pattern-6. (a) PSO. (b) JAYA. (c) Proposed.

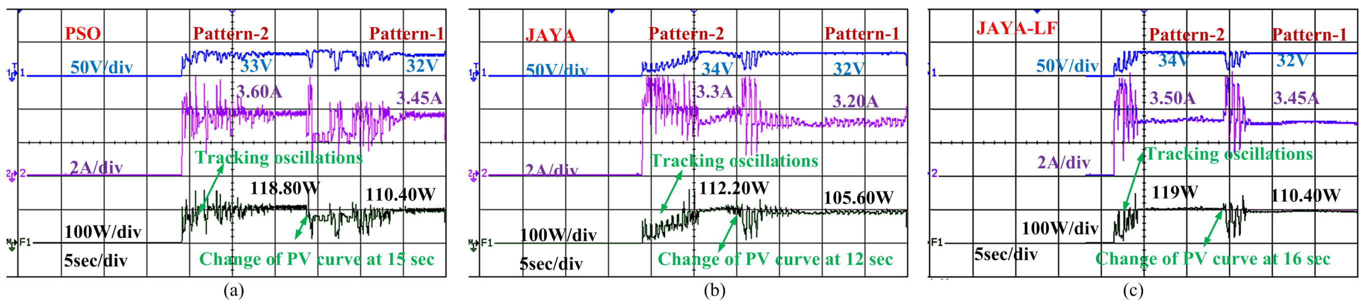


Fig. 15. Experimental waveforms changing from pattern-2 to pattern-1. (a) PSO. (b) JAYA. (c) Proposed.

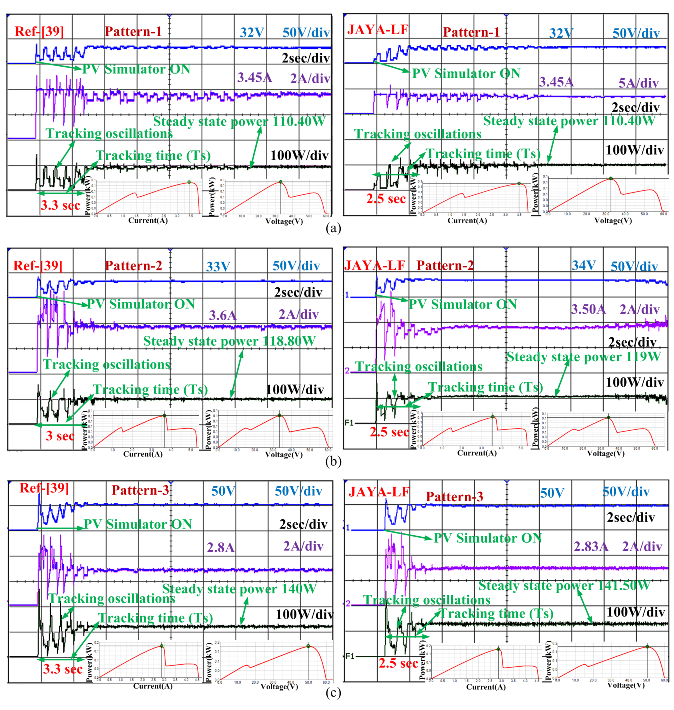


Fig. 16. Experimental results' comparison of and proposed JAYA-LF algorithm and [39] of 3S2P PV array. (a) Pattern-1. (b) Pattern-2. (c) Pattern-3.

advantages of previous patterns. Pattern-7 and pattern-8 belong to 3S2P with a global power rating of 95.24 and 121.77 W; pattern-9 and pattern-10 belong to 4S2P with a global power rating of 140.21 and 149.69 W. Its P–V curves are shown in Fig. 18, and the related experimental results are shown in Fig. 19.

TABLE VI
EXPERIMENTAL PERFORMANCE OF THE PROPOSED JAYA-LF ALGORITHM AND [39]

Technique	Rated Power of PV array (Watt)	Extracted Output Power of PV (Watt)	Tracking time(sec)	Iterations	Efficiency of PV (%)
Proposed	110.97	110.40	2.50	04	99.48
[39]	Pattern-1	110.40	3.30	06	99.48
Proposed	120.13	119.00	2.50	04	99.05
[39]	Pattern-2	118.80	3.00	05	98.90
Proposed	141.85	141.50	2.50	04	99.75
[39]	Pattern-3	140.00	3.30	06	98.69
Proposed	108.89	107.10	2.00	02	98.35
[39]	Pattern-4	107.10	3.00	05	98.35
Proposed	188.14	187.20	3.00	05	99.50
[39]	Pattern-5	188.10	3.50	06	99.50
Proposed	148.60	147.90	2.00	03	99.52
[39]	Pattern-6	146.45	3.00	05	98.55

VI. COMPARATIVE STUDY

The PSO [16] algorithm takes more time to capture GP of multiple peaks on a P–V curve due to (w, C_1, and C_2) factors as these factors contribute to the inability of tuning optimum value during the course of iterations to attain GP location faster. ARMO [29] tracks location(s) of GMPP faster, but it is implemented by considering the dependent initial particle, and the particles are more than five. The GWO [25] algorithm is applied for GMPP with one tuning parameter over the course of iterations, but the parameters are not reinitialized when the change of PV pattern occurs, and there is a delay in convergence as well due to the linear

TABLE VII
COMPARISON OF THE PROPOSED WITH EXISTING GMPPT ALGORITHMS

Parameters/ Method	PSO[16]	ARMO[29]	GWO[25]	HAPO & PSO[42]	S-Jaya[21]	MPV-PSO[20]	GWO-FLC[26]	Proposed
Tracking speed	Moderate	Fast	Moderate	Fast	Fast	Fast	Fast	Fast
Iterations	More	Less	Moderate	Less	Less	Less	Less	Less
Tuning parameters	3	3	1	Nil	Nil	2	1	Nil
Initial particles	Independent	Dependent	Independent	Dependent	Dependent	Dependent	Independent	Independent
Population	5	> 5	3	3	5	3	> 5	3
Efficiency	High	High	High	High	High	High	High	Very High
Re-initialization	Considered	Considered	Not considered	Considered	Considered	Considered	Considered	Considered

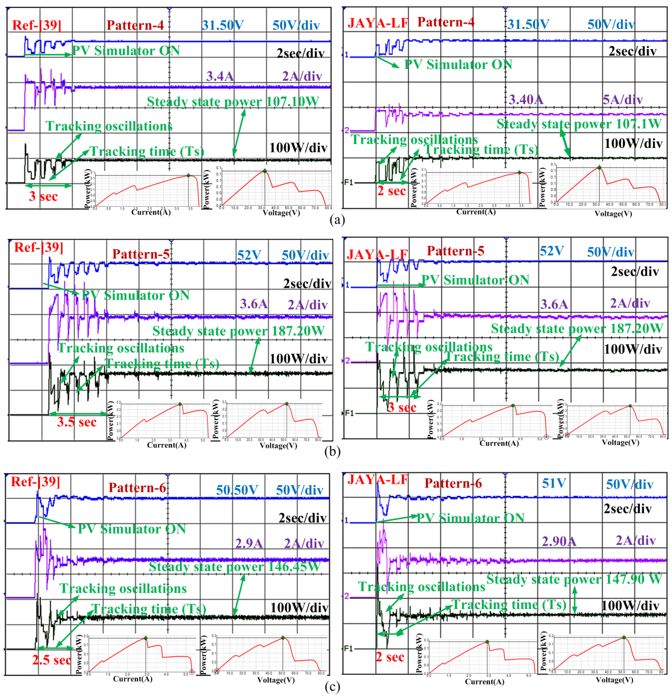


Fig. 17. Experimental results' comparison of proposed JAYA-LF algorithm and [39] of 4S2P PV array. (a) Pattern-4. (b) Pattern-5. (c) Pattern-6.

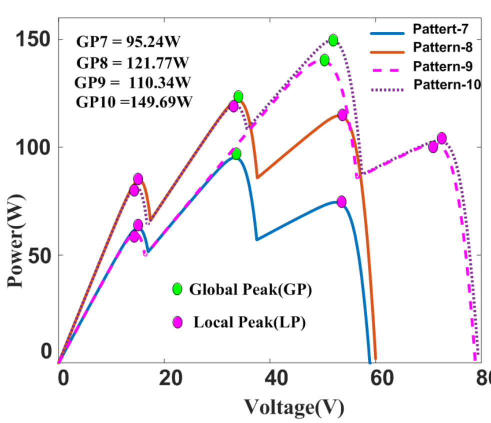


Fig. 18. P–V curves of pattern-7 to pattern-10.

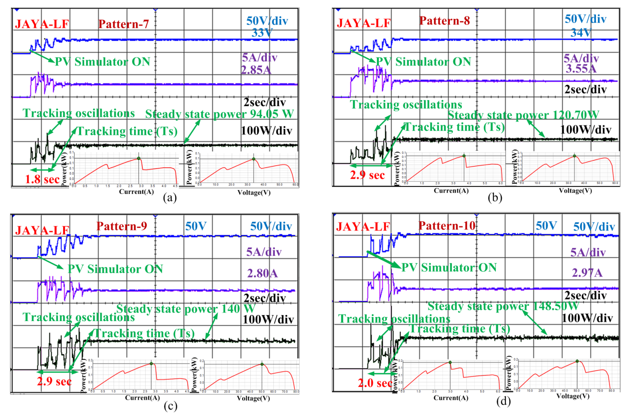


Fig. 19. Experimental results of the proposed algorithm. (a) Pattern-7. (b) Pattern-8. (c) Pattern-9. (d) Pattern-10.

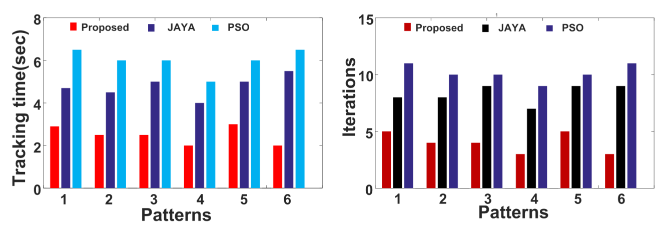


Fig. 20. Comparison of the proposed, JAYA, and PSO of (a) tracking time (s) and (d) iterations with the respective patterns.

control tuning parameter. The recent HAPO & PSO [42] algorithms have rapid convergence, but the initial parameters are dependent. S-Jaya [21] promises improved performance compared with the JAYA algorithm, but it is implemented with five dependent parameters. MPV-PSO [20] performs better compared with PSO, the reason being MPV-PSO is achieved by removing weight factor, while cognitive factors are updated with current particle by tuning them with the system voltage. The GWO-FLC [26] is considered for higher power levels with an average of the five-to-ten-member initial population. Due to more particles' initialization, there is a burden on the system. In this article, the proposed JAYA-LF algorithm enables faster convergence compared with JAYA and PSO methods. The JAYA algorithm response is slow for the GMPPT application because of fewer specific parameters. In order to improve the performance of JAYA, JAYA is represented by a combination of LF for fast convergence. The LFs imply random nature, which can be implemented along with the JAYA algorithm for rapid convergence. By employing LFs on updating the population, variables are able to take short jumps and long-distance jumps [38] to improve the process of exploitation and exploration. The concept behind LF is searching in small steps for the exploitation process while taking a long jump for the exploration process from one place to another before commencing searching; this improves the overall performance of the JAYA-LF algorithm. The comparison of the proposed JAYA-LF technique with seven recent GMPPT techniques was made, details of which figure in Table VII and are also shown in Fig. 20 using the experiment-based tracking time and iteration with respect to each PV pattern of three algorithms.

VII. Conclusion

In this article, a novel JAYA algorithm based on the Levy flight was proposed, simulated, and implemented for tracking GP power during PS of PV arrays. The JAYA-LF algorithm tracks GP power with fewer iterations and lower convergence time. The oscillations at steady and transient states are reduced without any tuning parameter; the three initial particles are independent of the PV system. To highlight the benefits of the proposed algorithm, a detailed verification with conventional JAYA and PSO algorithms is presented. The proposed algorithm performed far better than JAYA and PSO methods and could track GP under all shaded conditions of PV array with superior performance even under dynamic shaded conditions, with higher and more reliable efficiency.

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