MPPT of PV Systems Under Partial Shaded Conditions Through a Colony of Flashing Fireflies

Kinattingal Sundareswaran, Sankar Peddapati, and Sankaran Palani

***Abstract*—This paper reports the development of a maximum power-point tracking (MPPT) method for photovoltaic (PV) systems under partially shaded conditions using firefly algorithm. The major advantages of the proposed method are simple computational steps, faster convergence, and its implementation on a low-cost microcontroller. The proposed scheme is studied for two different configurations of PV arrays under partial shaded conditions and its tracking performance is compared with traditional perturb and observe (P&O) method and particle swarm optimization (PSO) method under identical conditions. The improved performance of the algorithm in terms of tracking efficiency and tracking speed is validated through simulation and experimental studies.**

***Index Terms*—Firefly algorithm (FA), maximum power-point tracking (MPPT), partial shaded conditions (PSCs), particle swarm optimization (PSO), perturb and observe (P&O) method, photovoltaic (PV) systems.**

I. Introduction

With growing world energy demand and soaring prices of fossil fuels together with concern about environmental issues have generated enormous interest in the utilization of renewable energy sources. The photovoltaic (PV) power generation has seen a rapid growth in the last few years leading to extensive use of solar energy; a PV system has the advantages of low maintenance cost, absence of moving or rotating parts and freedom from environmental pollution [1], [2]. Many countries provide generous financial schemes such as feed-in tariff [3], subsidized policies [4], etc., leading to rapid growth of PV power generation systems.

Due to high initial cost of PV power generation systems and its low energy conversion efficiency, a PV system is generally operated to extract maximum power from the PV source. In order to optimize the utilization of PV systems, maximum power-point tracking (MPPT) is generally employed, which requires power electronic interfaces such as dc–dc converter and/or inverter. The objective of MPPT is to extract maximum power generated by the PV systems under varying condition of temperature and solar insolation. A major challenge in PV systems is to tackle its nonlinear current–voltage $(I-V)$ characteristics, leading to a unique maximum power point (MPP) on its power–voltage $(P-V)$ characteristic curve. The process of MPPT is complicated by the fact that the $P-V$ curves vary largely with solar insolation and temperature.

Generally, the PV panels are connected in series and parallel so as to meet the load power demand. When climatic conditions vary, the MPP of the PV system also changes its position and several methods have been presented for tracking the MPP and are available in [5]–[11]. These methods include perturb and observe (P&O) [5], incremental conductance [6], short circuit current [7], open circuit voltage [8], load current/load voltage maximization technique [9], fuzzy control [10], neural-network-based schemes [11], etc. A detailed comparison of various methods for tracking MPP in PV systems is extensively discussed in [12]–[15]. The tracking methods discussed in these papers are effective and time tested under uniform solar insolation, where there is only one MPP in the $P-V$ curve of the PV system for a given temperature and insolation. In large PV systems, partially shaded condition (PSC) occurs wherein PV modules receive different solar insolation due to shadow of building, moving clouds, and other neighboring objects. The output power of the PV array decreases largely due to PSC and the quantum of power lost depend on system configuration, shading pattern and the bypass diodes incorporated in the PV modules. The effect of PSC on PV system has been investigated in several publications [16]–[18]. The immediate effect of PSC is that the resulting PV characteristic curve becomes complex with multiple peaks. Conventional methods of tracking MPP are based on "hill climbing" technique and these methods are not effective in reaching the global optima, when the PV system under PSC exhibits multiple peaks; rather most of the conventional methods may converge to local MPP leading to power loss.

Extracting maximum power from partially shaded PV arrays can be categorized into four groups [19]. In the first group, modified MPP techniques which are capable of converging to global maximum power point (GMPP) are employed and the second category utilizes different array reconfigurations. The third group describes different PV system architectures and the fourth category involves different converter topologies such as multilevel inverters. Though not highlighted, a closer examination of the work in [19] clearly indicates that the last three categories are costlier, require more components, and involve complex control and higher switching loss in comparison with modified MPPT techniques that fall under first category. In general, modified MPP algorithms always guarantee convergence to GMPP, system independence, and higher tracking efficiency.

Manuscript received July 10, 2013; revised November 6, 2013; accepted December 30, 2013. Date of publication January 17, 2014; date of current version May 15, 2014. Paper no. TEC-00393-2013.

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Digital Object Identifier 10.1109/TEC.2014.2298237

In the case of a shaded PV system, the PV curve possesses multiple peaks and convergence to global MPP is mandatory for extracting maximum power from the PV system. The optimization algorithm selected for MPPT should ideally possess the properties of simple computational steps, faster convergence, and guaranteed convergence to GMPP together with the feasibility of implementation in a low-cost digital controller. Biologically inspired optimization algorithms such as genetic algorithms (GAs), ant colony systems (ACS), artificial immune systems (AIS), particle swarm optimization (PSO) techniques, etc., have been extensively used for various engineering applications. Among these methods, PSO is simple in structure, computationally less expensive, and easy to incorporate for online applications. Capitalizing the inherent properties of PSO, a few researchers have recently employed PSO for GMPP tracking under partial shaded conditions [20]–[24]. These works employ conventional PSO and/or improved versions of PSO for enhanced tracking efficiency. It is shown that the proposed methods based on PSO guarantee convergence to GMPP and is far superior to conventional P&O method. While conventional PSO yields promising results [23], it causes oscillations in output power before reaching GMPP. An improved PSO where the duty cycles are initialized in two phases is reported in [22] which results in reduced steady state oscillations; however, the work in [22] does not compare the performance of the system with conventional PSO and its improved version. Furthermore, the two-stage initialization process may lead to increased computational burden and reduced tracking speed which are not deliberated in [22]. It is important to mention that while most of the works [23], [24] claim that the PSO-based approach is superior to conventional methods of tracking, a comparison between PSO and conventional methods in terms of tracking speed through simulated and/or measured results is not available under identical conditions of partial shading; such a comparison of MPPT tracking could have highlighted the superiority of PSO.

The PSO method for MPPT in PV systems under PSC is preferred by the researchers over other evolutionary algorithms because of its simple computation steps, easy of experimental implementation and increased tracking speed. The application of other evolutionary algorithms for MPPT under PSC is not available in the reported literature. Recently, Yang has developed a metaheuristic algorithm known as firefly algorithm (FA) and is available in [25], [26]. This algorithm is inspired by the flashing behavior of fireflies to attract other fireflies for mating purpose. It is shown in [26] that PSO is a special category of FA. The work in [26] compares PSO with FA by employing several multimodal optimization test functions. The statistical analysis of the comparison clearly indicates that FA is potentially more powerful in finding global optima with least computing time. A closer examination of the results presented in [26] highlights the superiority of FA over PSO in terms of convergence rate and computational burden. This aspect has been further verified in [27]. Recent works [28], [29] also confirmed the superiority of FA in solving complex optimization problems.

The objective of this paper is to develop an FA-based scheme for tracking GMPP under PSC in a PV system. The proposed method is shown to be accurate, converges faster to GMPP, and is system independent. Several case studies under different PSC conditions are considered, and the proposed scheme is developed to track the GMPP. This paper also reports the application of conventional P&O and PSO methods for MPPT under identical conditions, and through simulation and experimental studies, it is shown that the FA-based tracking is superior to the existing methods in terms of reduced computational complexity and tracking speed. The transients in power, voltage and current before reaching GMPP are shown to be very least with the proposed method in comparison with P&O and PSO methods. The computed results are validated with experiments carried out on two different configurations of PV arrays. Examination of extensive simulation results together with measurements carried out on the two prototypes show that FA-based MPPT always converge to GMPP irrespective of the location of GMPP. The tracking efficiency in all test cases is shown to be higher than 99.5%. The new MPPT scheme is simple, fast converging, does not require *priory* knowledge of the system. Further, the scheme is easily realized using a low-cost PIC16F876 A microcontroller. One major highlight of this paper is that comparative evaluation of P&O, PSO, and FA methods have been experimentally carried out and presented, which is not available in the earlier publications.

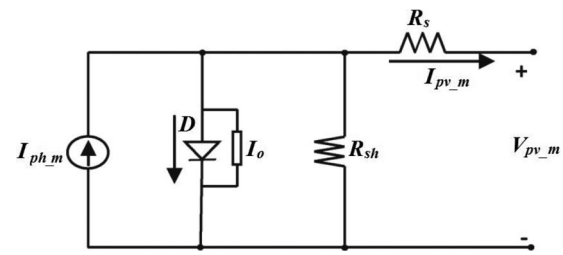

Fig. 1. Single diode model of PV module.

II. Characteristics of PV Array Under PSCs

A. PV Model

From the electrical equivalent of single diode model of PV module shown in Fig. 1, the output current, I_{pv_m} by neglecting shunt resistance R_{sh} can be written as [2],

$$I_{pv\_m} = I_{ph\_m} - I_o \left[\exp\left(\frac{V_{pv\_m} + R_s I_{pv\_m}}{V_t}\right) - 1\right]. \quad (1)$$

The photo current, I_{ph_m} of a solar module is determined using the following equation:

$$I_{ph\_m} = (I_{sc\_N} + k_i \Delta T)\lambda. \quad (2)$$

PV modules output voltage, V_{pv_m} from (1) when I_{ph_m} is greater than I_{pv_m} can be written as [30]

$$V_{pv\_m} = V_t \left[\ln\left(\frac{I_{ph\_m} - I_{pv\_m}}{I_o}\right) + 1\right] - R_s.I_{pv\_m}. \quad (3)$$

PV modules output voltage, V_{pv_m} from (1) when I_{ph_m} is less than I_{pv_m} can be written as [30]

$$V_{pv\_m} = 0 \quad (4)$$

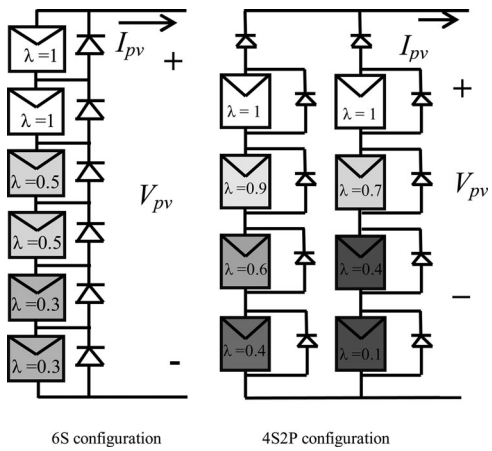

Fig. 2. Two PV configurations under study with PSC.

where

$$\Delta T = T - T_N \tag{5}$$

$$V_t = \frac{\eta k T N_s}{q} \tag{6}$$

$$R_s = -\frac{dV_{pv\_m}}{dI_{pv\_m}}\Big|_{\mathrm{Voc\_N}} - \frac{1}{X_V} \tag{7}$$

$$X_V = \frac{I_o \exp\left(V_{oc\_m}/V_t\right)}{V_t} \tag{8}$$

$$V_{oc\_m} = V_{oc\_N} + V_t \ln(\lambda) + k_v \Delta T. \tag{9}$$

Equations (2)–(9) are used in developing simulation model. Now, depending on the type of the PV array configuration, the total current and voltage across the PV array is computed based on the number of series and parallel modules. For detailed explanation, one may refer to [30]. In these equations, I_o is the saturation current in amperes, V_t is the thermal voltage in volts, I_{sc_N} and V_{oc_N} are, respectively, the PV modules short circuit current and open circuit voltage at standard temperature, λ is the solar insolation in kW/m^2, q is the electronic charge in coulombs, k is the Boltzmann's constant in joules per kelvin, T is the surface temperature of the panel in kelvin, T_N is the standard temperature, i.e., $273 + 25$ K, R_s is the series resistance in ohms, N_s the number of series cells, k_i is the current temperature coefficient, and k_v is the voltage temperature coefficient, and η is the ideality factor.

B. System Description

To get the desired output voltage and current, PV modules are connected in series and/or parallel to form a PV array. Here, bypass diodes and blocking diodes are used to protect PV modules from the hot spot problems. With bypass diode, $P-V$ Characteristic curve has multiple peaks, i.e., local and global maxima are introduced in the characteristic curves under PSC. Two different types of PV configurations are considered in this paper and are given in Fig. 2. The first configuration has six series-connected partially shaded PV modules named as 6 S configuration and is shown in Fig. 2. The corresponding PV curve for 6 S configuration is now computed using (2)–(9) and is depicted in Fig. 3. This curve has three peaks with the GMPP of 41.59 W located in the middle. The next configuration, as shown in Fig. 2, consists of eight PV modules connected in four series two parallel manner with typical partial shading is named as 4S2P configuration. Its $P-V$ curve, as computed through (2)–(9), is also included in Fig. 3 and this curve has got four peaks with its GMPP of 66.56 W. The specifications of single PV module used in this study are given in Table I.

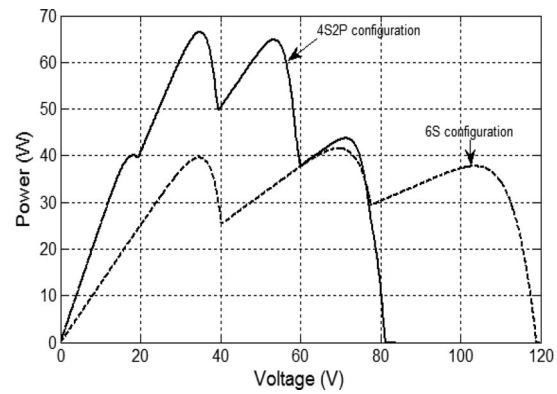

Fig. 3. $P-V$ Characteristics under different shading conditions.

TABLE I
PARAMETERS FOR SINGLE PV MODULE

Maximum Power (P_{max})	20W
Open Circuit Voltage (V_{oc})	21V
Maximum Power Voltage (V_{mp})	17.2V
Short Circuit Current (I_{sc})	1.28A
Maximum Power Current (I_{mp})	1.2A

III. INTRODUCTION OF FA AND ITS APPLICATION TO GMPP TRACKING

The FA is a population-based optimization and is introduced by Yang [25], [26]. This optimization algorithm is inspired by the movement of lightning bugs-commonly known as fireflies. The flashing light of fireflies is an amazing sight in the summer sky in the tropical and temperate regions. Two fundamental functions of such flashes are to attract mating partners and to attract potential prey. In addition, flashing may also serve as a protective warning mechanism. The rhythmic flash, the rate of flashing and the amount of time form part of the signal system that brings both sexes together. For simplicity in describing Firefly Algorithm, the following three assumptions are made: 1) all fireflies are unisex so that one firefly will be attracted to other fireflies regardless of their sex; 2) the attractiveness between two fireflies is proportional to relative brightness and the less brighter one will move toward the more brighter one. If there is no brighter one in a firefly colony, each one will move randomly and 3) the brightness of a firefly is affected or determined by the landscape of the objective function. For a maximization

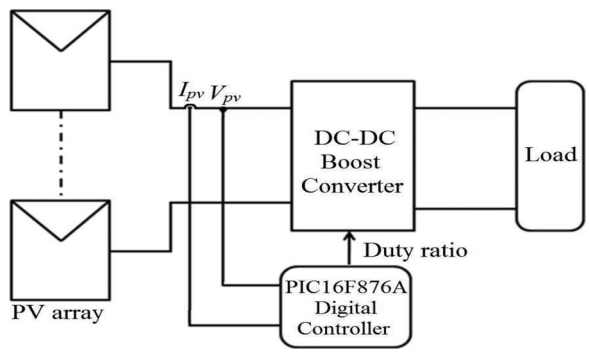

Fig. 4. Block diagram of FA-based MPPT scheme.

problem, the brightness can simply be proportional to the value of the objective function.

Let p and q be two fireflies positioned at X_p and X_q, respectively. Let the distance between these two fireflies is denoted as r_{pq}. In a single dimensional space, we can write

$$r_{pq} = \|X_p - X_q\|. \tag{10}$$

The degree of attractiveness, β is a function of distance between two fireflies and is given by

$$\beta(r) = \beta_0 e^{-\gamma(r_{pq})^n}, \quad n \geq 1. \tag{11}$$

In the aforementioned equation, γ, which controls the decrease of light intensity, is termed as absorption coefficient and is between 0 and 10 and $n = 2$ [26]. The symbol β_0 is initial attractiveness and is chosen as 1, such that the brightest firefly strongly determines the position of other fireflies in its neighborhood [25], [26].

Assuming that the brightness of firefly p is less than that of q, the new position of firefly p is given by the following equation:

$$X_p^{t+1} = X_p^t + \beta(r)(X_p - X_q) + \alpha\left(\text{rand} - \frac{1}{2}\right). \tag{12}$$

Here, random movement factor α is constant throughout the program and falls in the range [0, 1] and rand is a random number uniformly distributed between 0 and 1 for each movement of firefly. A large amount of α makes the movement to explore the solution through the distant search space and the smaller α tends to facilitate local search [28].

A. Application of FA Toward MPPT

The block diagram of the FA-based MPPT scheme is given in Fig. 4. Here, the PV array is interfaced to the load through the boost converter. For a population of fireflies, i.e., duty ratios, the digital controller measures V_{pv} and I_{pv} and computes the output power. The steps of FA algorithm toward MPPT are described below:

1) Step 1: Parameter Setting: Fix the constants of the FA, namely, βo, γ, n, α, population size N, and the termination criterion. In this algorithm, the position of the firefly is taken as a duty cycle d of the dc–dc converter. The brightness of each firefly is taken as generated power P_{pv} of the PV system, corresponding to the position of this firefly.

TABLE II
PARAMETERS OF BOOST CONVERTER

Switching frequency, f_s	50 kHz
Capacitor, C	470 μH
Inductor, L	1.812 mH
Internal resistance of Inductor, r_L	0.394 Ω

2) Step 2: Initialization of Fireflies: In this step, the fireflies are positioned in the allowable solution space between $d_{\min}$ to $d_{\max}$ where $d_{\min}$ and $d_{\max}$ represent the minimum and maximum values of the duty ratio of the dc–dc converter. In this paper, $d_{\min}$ is taken as 2% and $d_{\max}$ is set at 98%.

Thus, position of each firefly represents the duty ratio of the dc–dc converter.

It may be noted that increased number of fireflies results in higher computing time while, a lesser number of fireflies will result in a local maximum. Hence, in this paper, the number of fireflies is chosen as 6.

3) Step 3: Brightness Evaluation: In this step, the dc–dc converter is operated corresponding to the position of each firefly (i.e., duty ratio) sequentially. For each duty ratio, the corresponding PV output power, P_{pv} is taken as the brightness or light intensity of the respective firefly.

This step is repeated for position of all fireflies in the population.

4) Step 4: Update the Position of Fireflies: The firefly with maximum brightness remains in its position and the remaining fireflies update their position based on (12).

5) Step 5: Terminate the program if the termination criterion is reached; else go to step 3. The optimization algorithm is terminated once the displacement of all fireflies in consecutive steps reaches a set minimum value. Once the program is terminated, the dc–dc converter operates at the optimum duty cycle corresponding to GMPP.

6) Step 6: Reinitiate the FA if the solar insolation changes, which is detected by the digital controller by sensing the change in the power output.

IV. SIMULATION STUDIES

In order to evaluate the performance of firefly-based MPPT, extensive simulation studies were carried out. The block diagram for tracking GMPP under PSC is shown in Fig. 4. The simulation studies are now carried out for the partially shaded conditions demonstrated in Fig. 2 for the 6 S and 4S2P configurations. The specifications of boost converter employed in Fig. 4 are given in Table II. A dedicated computer program is developed in MATLAB for FA-based MPPT in both cases. The simulation results are discussed now.

The MPPT curves for the 6 S configuration with partially shaded condition shown in Fig. 2 employing P&O, PSO, and FA are delineated in Fig. 5(a). The computed variation of PV voltage and current are also shown separately in this figure. This figure shows that both FA and PSO converge to the global optima of 41.59 W. The convergence time for FA is 2.1 s, while it is 13.6 s for PSO. The P&O-based method reaches the local peak of 39.1 W with 12.7 s.

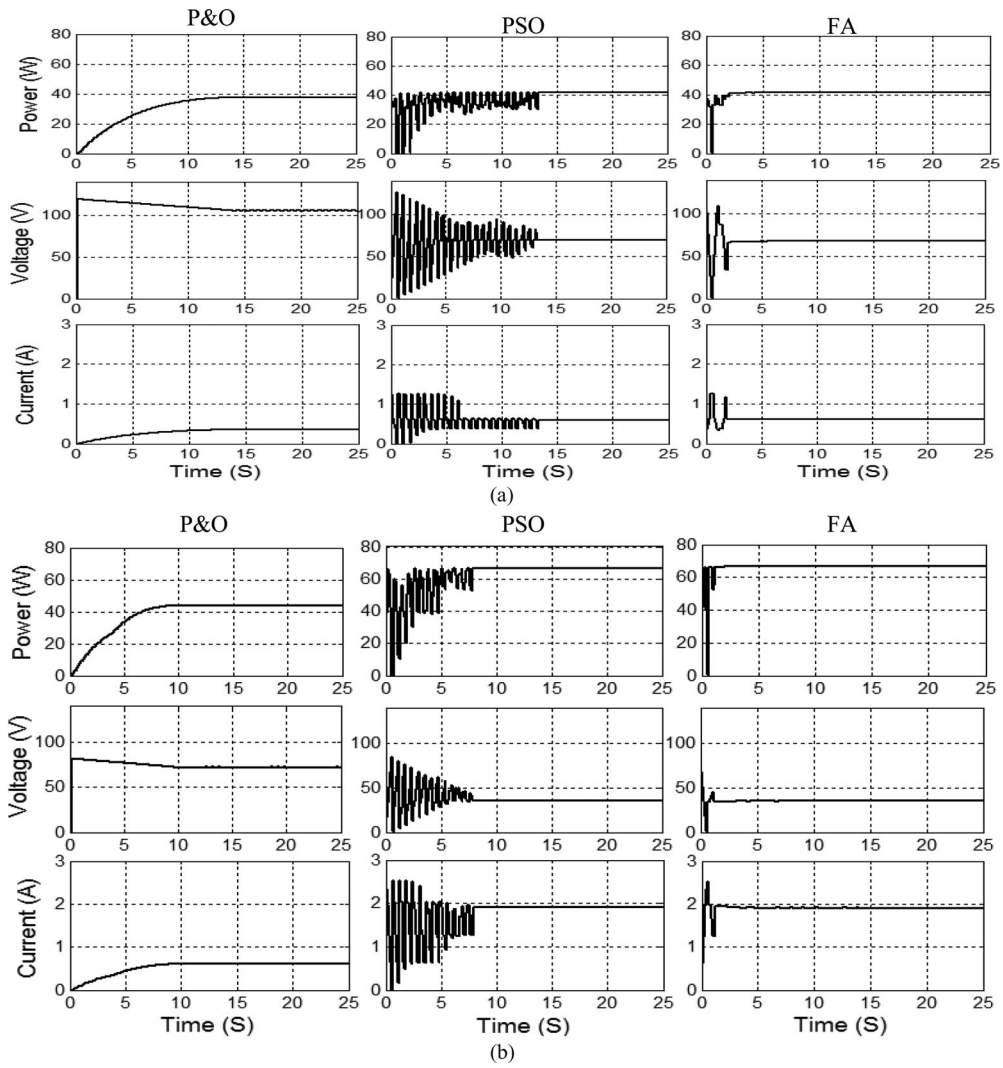

Fig. 5. Variation of power, voltage and current of the PV system during MPPT using P&O, PSO, and FA methods for (a) pattern-1 and (b) pattern-2.

The simulation results of MPPT-based on the three algorithms for the partially shaded condition of 4S2P configuration given in Fig. 2 is illustrated in Fig. 5(b). In this case also, FA converges to the GMPP of 66.56 W with 1.96 s; PSO also tracks GMPP but the tracking speed is 7.8 s. The P&O method, however, gets trapped into the local peak of 43.69 W with 8.8 s.

It may be noted that when PV power system is spread over large areas, partial shading is a very common feature and either the pattern of shading or the time at which the shading occurs cannot be predicted since partial shading is largely due to moving clouds. Thus, the partial shading can occur at any time during day time and the MPPT algorithm has to restart whenever shading pattern changes. Hence, the time required to find the MPP is a major factor. Further the P&O method cannot achieve faster response or global convergence.

The aforementioned simulation findings carried out for two different PV configurations strongly suggest that the FA-based algorithm is far superior to the existing methods in terms of tracking speed and convergence to global optima and possesses good tracking efficiency. The tracking efficiency is calculated by taking the ratio between averaged output power obtained under steady state and maximum available power of the PV array under certain shading pattern [23]. It is important to mention that the initial population is kept the same in PSO and FA methods in both cases for fairness of comparison. The characteristics of the simulation results presented in Fig. 5 are briefly summarized in Table III. Further a qualitative comparison between different methods is listed in Table IV. Tables III and IV show the superiority of FA-based MPPT over the other two methods.

The successful convergence of any biologically inspired algorithm is largely influenced by the parameters of the algorithms and PSO and FA are no exceptions. The parameters of these algorithms are generally identified from the available literature and fine tune them if required. In the present work, PSO has six parameters, namely, $w_{\max}, w_{\min}, c_{1\max}, c_{1\min}, c_{2\max}$, and $c_{2\min}$ and α and γ are the two parameters of FA. In order to optimize these parameters in both the algorithms, a few shaded conditions for the 6 S and 4S2P configuration are considered

TABLE III
PERFORMANCE COMPARISON OF P&O, PSO, AND FA METHODS

Shading Pattern	Tracking Methods	Power (watts)	Voltage (volts)	Current (amperes)	Tracking Speed (seconds)	Maximum Power from P-V Curve (watts)	% Tracking Efficiency
1	P&O	37.4886	105.9000	0.3540	12.7	41.59	90.14
	PSO	41.4538	68.1806	0.6080	13.6		99.67
	FA	41.576	69.993	0.594	2.1		99.97
2	P&O	43.6957	71.7500	0.6090	8.8	66.56	65.65
	PSO	66.4869	34.9931	1.9000	7.8		99.89
	FA	66.5577	34.8637	1.9090	1.96		99.99

TABLE IV
QUALITATIVE COMPARISON BETWEEN DIFFERENT METHODS

Type	P&O	Standard PSO	Firefly
Periodic Tuning	Not required	Not required	Not required
Tracking Speed	Slow	Medium	Fast
Tracking Accuracy	Low(May locate local peak)	Accurate	Highly Accurate
Implementation Complexity	Low	Medium	Medium
Sensed Parameters	V_{pv}, I_{pv}	V_{pv}, I_{pv}	V_{pv}, I_{pv}
Necessary Conditions for convergence/Limitations	May trapped to local peak	Convergence to global peak is always guaranteed	Convergence to global peak is always guaranteed
Dynamic response	Poor	Oscillatory	Good
Steady state oscillations	Large	Zero	Zero
Execution time	Very fast	Fast	Fast

TABLE V
PARAMETERS OF ALGORITHMS

Parameters of PSO algorithm		Parameters of FA algorithm	
w_{max}	2	A	0.98
w_{min}	0.1	Γ	0.0012
$c_{1,max}$	2		
$c_{1,min}$	1		
$c_{2,max}$	2		
$c_{2,min}$	1		

then the parameters are iteratively optimized so as to reach GMPP in each PSC. The optimized parameters thus obtained are given in Table V.

V. EXPERIMENTAL EVALUATION

In order to substantiate the veracity of the simulation study, experiments were carried out on 6 S and 4S2P configurations. For the 6 S configuration, trasnparent materials of different thickness are placed on a few PV modules to create partially shaded condition. The measured $P-V$ curve is shown in Fig. 6 indicated as pattern-1. A closer examination of this curve indicates a local peak of 16.24 W and GMPP of 29.65 W. An experimental setup corresponding to Fig. 4 was fabricated in the laboratory. The digital controller employed was PIC 16F876 A microcontroller operating at 4 MHz. Dedicated computer programs for MPPT-based on P&O, PSO, and FA methods were developed in MPLAB and then downloaded to PIC microcontroller. Microcontroller was then used for online MPPT of 6 S PV configuration under partially shaded condition. The experimentally determined tracking curves employing P&O, PSO, and FA methods are given in Fig. 6(b), (c), and (d), respectively. The tracking curve of P&O gets trapped in a local optima of 16.24 W, whereas both PSO and FA reach the GMPP of 29.65W. As is evident from this figure, the tracking speed of FA is the highest since it takes 3.703 s to reach GMPP compared to PSO which takes 11.85 s for global convergence. The oscillations in the PV power are sustained for a longer duration with PSO-based MPPT, where as this oscillations vanish quickly with FA-based approach.

It is interesting to examine the characterstics of the three algorithms, when the shading pattern is changed from one to another. In such a case the algorithms need to jump out of the current MPPT point and research the new PV curve for the new GMPP. Toward this objective, all PV modules are covered with equally thick transperent materials and the new PV curve corresponing to changed shaded condition is given in Fig. 6(a) and is labeled as pattern-2. As is seen in this figure, the new $P-V$ curve is smooth and has got only one peak of 38.83W. The measured MPPT curves for each algorithm for pattern-2 are included in Fig. 6(b), (c), and (d). The tracking curves of PSO and FA research the new $P-V$ curve and track the new GMPP of 38.83W. It is worth mentioning that P&O also reaches GMPP in this case, since there is only one peak in the $P-V$ curve.

The experiment is now repeated with 4S2P configuration with two types of shading which result in two different $P-V$ curves as shown in Fig. 7(a). The first $P-V$ curve which is labeled as pattern-3 has three peaks with GMPP of 42.35 W. The experimentally determined tracking curves based on the three algorithms are given in Fig. 7(b), (c), and (d). The curves plotted in Fig. 7(c) and (d) show the global convergence ability of both FA and PSO method. As expected, the P&O settles to the local peak of 40.24 W.

After 25 s, when the shading pattern is changed a new $P-V$ curve marked as pattern-4 emerges. This curve also has three peaks with GMPP at 34.59 W. The three algorithms now research the PV curve and the tracking of MPP by the three

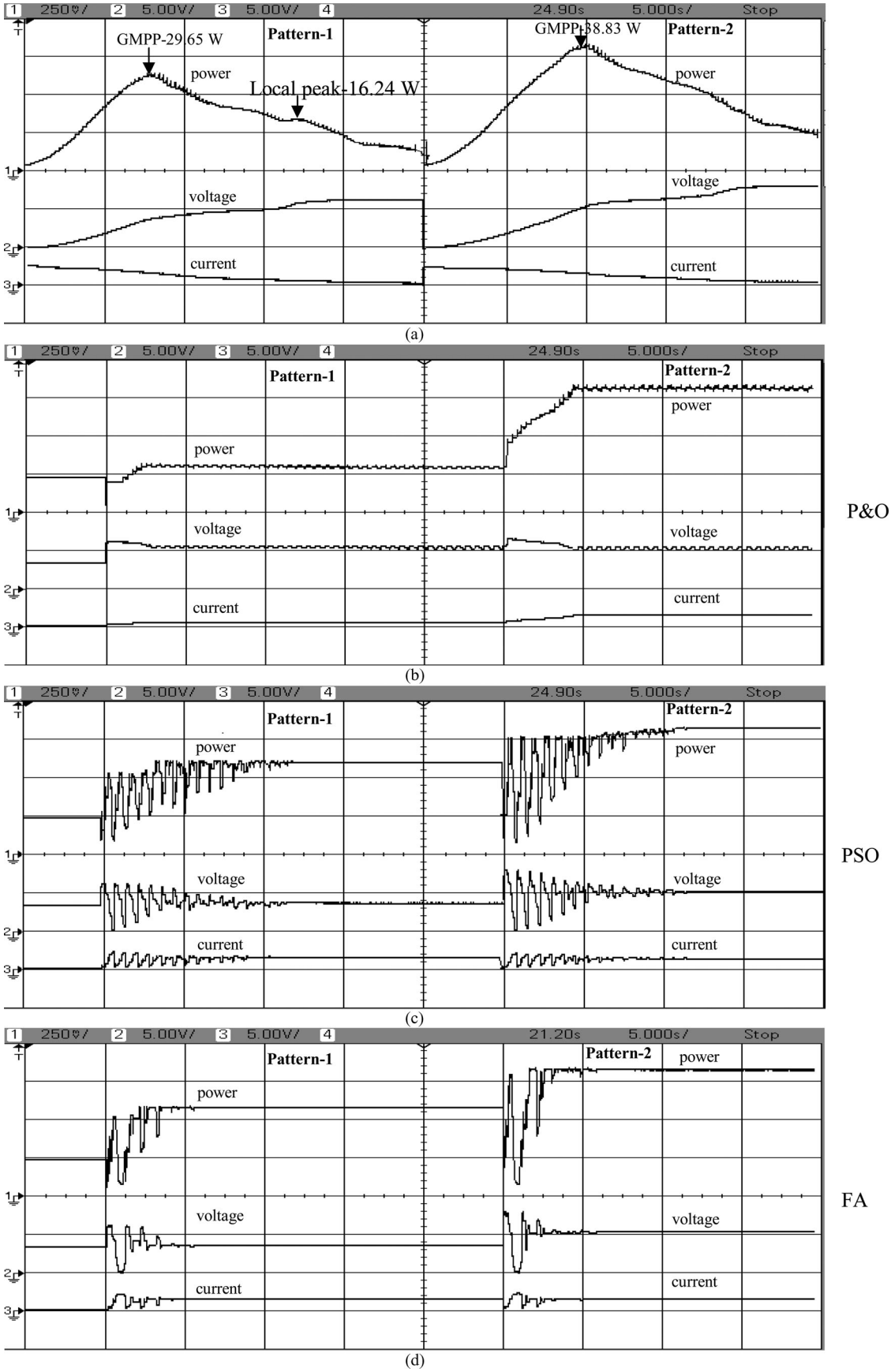

Fig. 6. Experimental results with 6 S configurations. (a) $P-V$ curve. Tracking curves using (b) P&O, (c) PSO, and (d) FA methods (scale: power—12 W/division, voltage—60 V/division, and current—2 A/division).

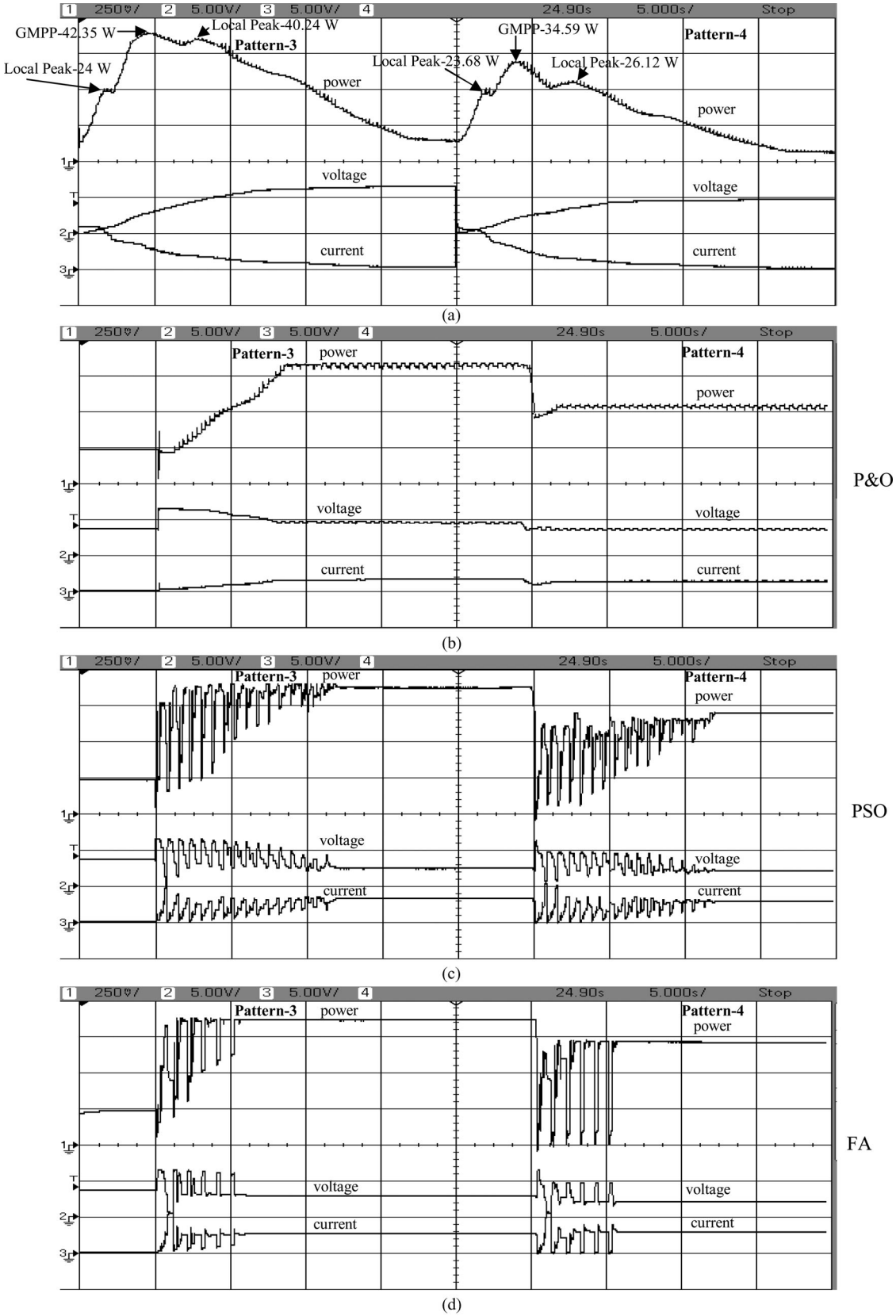

Fig. 7. Experimental results with 4S2P configurations. (a) $P-V$ curve. Tracking curves using (b) P&O, (c) PSO, and (d) FA methods (scale: power—12 W/division, voltage—60 V/division, and current—2 A/division).

algorithms are included in Fig. 7(b), (c), and (d). Both FA and PSO algorithms realign the search path towads the new GMPP of 34.59 W, whereas the P&O algorithm again gets trapped to local optima of 26.12 W.

It is important to note that both PSO and FA algorithms need to jump out of the current MPPT and research the operation area even with slight variation in insolation. While this is a disadvantage, the advantage of confirmed convergence to GMPP outweighs this demerit.

The experimental results depicted in Figs. 6 and 7 clearly demonstrate that FA is capable of reaching GMPP and reorient itself toward the new GMPP when the shading pattern changes resulting new $P-V$ curve. While PSO is also capable of jumping from existing MPP and relocate new MPP with change in solar insolation, FA method has the advantage of least turbulance in PV output power, P_{pv} before reaching GMPP. Thus, it is apparent from the measured results that FA-based approach is superior to the other two methods.

VI. Conclusion

This paper has presented a new MPPT algorithm based on a colony of fireflies for quickly tracking GMPP in partially shaded PV arrays. The tracking procedure consists of positioning the fireflies in the possible solution space and based on the PV power output, the flies move to promised regions. The development of this algorithm for MPPT is lucidly illustrated and the results are analysed. Computer simulations and experiments carried out on two different PV configurations have demonstrated that the new scheme is system independent, quickly converges to GMPP, and also outperforms the existing methods such as PSO in terms of tracking speed and oscillations in PV output power. The new algorithm is shown to capable of jump out of the current MPPT point and reorient towards new GMPP under rapidly changing partial shading conditions. The proposed method is computationally inexpensive and could be implemented on low-cost microcontroller.

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