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Improved Global Maximum Power Point Tracking for Photovoltaic System via Cuckoo Search under Partial Shaded Conditions

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Abstract

Conventional maximum power point tracking (MPPT) methods are ineffective under partially shaded conditions because multiple local maximum can be exhibited on power–voltage characteristic curve. This study proposes an improved cuckoo search (ICS) MPPT method after investigating the cuckoo search (CS) algorithm applied in solving multiple MPPT. The algorithm eliminates the random step in the original CS algorithm, and the conception of low-power, high-power, normal and marked zones are introduced. The adaptive step adjustment is also realized according to the different stages of the nest position. This algorithm adopts the large step in low-power and marked zones to reduce search time, and a small step in high-power zone is used to improve search accuracy. Finally, simulation and experiment results indicate that the promoted ICS algorithm can immediately and accurately track the global maximum under partially shaded conditions, and the array output efficiency can be improved.

Key words: Improved cuckoo search, Maximum power point tracking, Multiple local maximum, Partially shaded conditions, Photovoltaic array

I. INTRODUCTION

Solar energy is currently experiencing rapid growth around the world with the continuous fall in the price of photovoltaic (PV) modules and increasing concern about environment protection. Solar energy is environment friendly, and relevant equipment is easy to install and has low maintenance cost. Improving not only the efficiency of PV cells but also that of maximum power point tracking (MPPT) ability is important to continue the development of solar energy [1]-[5].

The output characteristics of solar arrays are nonlinear. They also vary with solar irradiance and temperature. To address these issues, many conventional MPPT methods were proposed, such as perturb and observe (P&O) [6]–[9], incremental conduction (INC) [10], [11], hill climbing [12], [13], fuzzy logic control search method [14], and sliding control [15]. These conventional methods promote efficiency, and optimization of the mature and widely used output of PV systems under uniform condition is implemented.

In addition, power–voltage (P–V) characteristics have multiple peaks under partially shaded condition, and finding the global maximum power point (GMPP) is difficult. Traditional methods become invalid. They may also find a local maximum power point, which may decrease the output of solar array power [16]-[18]. To alleviate these problems, several MPPTs based on soft computing are proposed. These methods include particle swarm optimization (PSO) [19]-[21], genetic algorithm, artificial neural network [22], artificial bee colony [23], firefly algorithm [24], [25] and cuckoo search (CS) [26]. Despite their global search ability, these soft computing methods are generally more complex and slower than conventional methods.

CS algorithm has become the most popular soft computing algorithm recently. CS has been proven to be robust, have good convergence, and exhibits high efficiency. CS is currently the best method to optimize the MPPT of a PV system under partial shading condition. Despite these advantages, random steps cost considerable time, which is the common drawback of random algorithm. This study proposed an improved CS

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(ICS) algorithm, which introduces the conception of low-power, high-power, normal, and marked zones to overcome shortcomings. The adaptive step adjustment is also realized according to the different stages of the nest position. This algorithm adopts a large step in low-power and marked zones to reduce search time, whereas a small step is used in high-power zone to improve search accuracy. This scheme is an efficient solution to the coordination problem between global and local searching during MPPT.

This study is organized as follows: P&O, PSO, and CS algorithms are reviewed in Section II. The ICS algorithm is presented in Section III. Section IV presents the simulation results and analysis. Section V presents the experimental results.

II. Basics of P&O, PSO, and CS

The performance of ICS is evaluated in comparison with those of P&O, PSO, and CS MPPT methods. Brief overviews of these methods are presented in this paper to facilitate the following discussion.

A. P&O

P&O, the most widely used MPPT, is regarded as the standard benchmark for any new MPPT algorithm for comparison because of its effectiveness. This algorithm first calculates power (P) by sensing the voltage and current. Then, a perturbation in the duty (D) of the DC–DC converter is provided based on the change of power by following this basic rule.

$$\begin{aligned} D_{new} &= D_{old} + \Delta D \quad (if\ P > P_{old}) \\ D_{new} &= D_{old} - \Delta D \quad (if\ P < P_{old}) \end{aligned} \tag{1}$$

In Equ. (1), ΔD is known as the perturbed duty. The most important aspect of this algorithm is to determine the size of ΔD. If ΔD is large, then the convergence is fast, but a large fluctuation occurs in the steady-state power.

B. PSO

PSO, a swarm intelligence optimization algorithm, was first proposed by Kennedy and Eberhart in 1995 [27]. The algorithm is modeled according to bird flocks. It also iteratively tries to improve a candidate solution with regard to a given measure of quality. In this algorithm, several cooperative particles are used in an n-dimensional space. Each particle moves around in the search space according to mathematical formulae to exploit its position and velocity. The position of a particle is influenced by its own best position and the best known position of all particles. The velocity and position of particles are calculated with

$$v_i^t = wv_i^{t-1} + c_1 r_1 (x_{pbi} - x_i^{t-1}) + c_2 r_2 (x_{cgb} - x_i^{t-1}), \tag{2}$$

$$x_i^t = x_i^{t-1} + v_i^t. \tag{3}$$

In Equ. (2), w is the inertia weight; c_1 and c_2 are the acceleration constants; x_{pbi} is the personal best position of the i-th particle; x_{cgb} is the current global best position among all the positions searched; r_1 and r_2 are random variables that are distributed uniformly within [0,1]; and t is the iteration number.

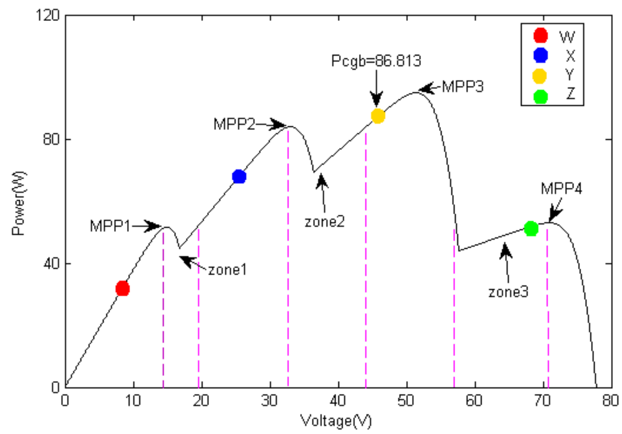


Fig. 1. Sketch map of PSO.

PSO spends time in every peak even if this peak has been searched by other particles with a small step. MPP3 is the global MPP, and Y is the current global optimal position around these initial positions, as shown in Fig. 1. Particles W, X, and Z search the curve that tends to Y. Equ. (2) indicates that when x_i is between x_{pbi} and x_{cgb} and x_i is not x_{pbi}, the search step v_i becomes small. In the search process, zones 1, 2, and 3 meet the conditions mentioned, and these zones are searched with a small step. Z searches zone 3 with a small step, whereas X searches zone 2 with a small step. W adopts a small step to search zones 1 and 2 even if zone 2 has been searched by X before. The power value in zones 1 and 3 is obviously small. In these low-power zones, searching with a small step is not needed. The low-power zone is searched with a small step, and the zone searched by other particles with a small step is searched before a huge time is taken and a significant energy loss occurs.

C. CS

CS, a global optimization algorithm inspired by the parasitic reproduction strategy of cuckoo birds, was proposed by Yang Xinshe and Deb Suash [28],[29]. This algorithm is simple and easy to install; thus, it has gradually become popular among the intelligent algorithms [30]–[33].

In nature, the search for a suitable nest of a host bird is similar to the search for food, which occurs in a random or a quasi-random form. Yang and Deb used three idealized rules for CS based on the brood parasitic behavior of a cuckoo: (1) Each cuckoo lays one egg at a time, and this egg is placed in randomly chosen nests. (2) The best nest with the highest-quality eggs will carry over to the next generation. (3) The number of available nests is fixed, and the number of available nests (laid by a cuckoo) discovered by the host bird maintains a probability P_a, where $P_a \in [0,1]$.

On the basis of these three rules, the strategy of CS for a nest is as follows:

$$x_i^{(t+1)} = x_i^t + \alpha \oplus Levy(\lambda) \ , \tag{4}$$

where x_i^t refers to samples/eggs, i is the sample number, and t is the number of iterations. The product $\oplus$ indicates entry-wise multiplication, where $\alpha = \alpha_0 (x_{cgb} - x_i^{t-1})$. A simplified scheme of levy distribution is presented in [23] as

$$Levy(\lambda) \approx \frac{u}{(|v|)^{1/\beta}} , \tag{5}$$

where β=1.5 , α_0 is the levy multiplying coefficient (chosen by designer), whereas u and v are determined from the normal distribution curves, namely,

$$\begin{aligned} u &\approx N(0, \sigma_u^2) \\ v &\approx N(0, \sigma_v^2) \end{aligned} . \tag{6}$$

If Γ denotes integral gamma function, then the variables σ_u and σ_v are defined as

$$\begin{aligned} \sigma_u &= \left(\frac{\Gamma(1+\beta) \times \sin(\pi \times \beta / 2)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times (2)^{\left(\frac{\beta-1}{2}\right)}} \right)^{1/\beta} \\ \sigma_v &= 1 \end{aligned} . \tag{7}$$

Given the virtue of Levy distribution, the step consists of several small steps and occasionally large steps and long-distance jumps. The random step may obviously produce excessively small steps in a low-power zone, and the zone searched by other cuckoos before with small steps may be searched again, thereby prolonging the tracking time.

III. Principle of ICS

In CS algorithm, Lévy flight is used to produce a random step length. However, this step is sometimes large and sometimes small. In the search process, a large step length can search the global optimal value easily. However, the search accuracy is reduced at the same time, thereby causing a large fluctuation in the steady state power at certain times. A small step size corresponds to a low search speed. However, the optimization precision is improved. Lévy flight can generate random step length but without adaptability. The ICS algorithm addresses this problem by handling the relationship between the global optimization ability and the optimization precision according to the different stages of the search results with adaptive dynamic adjustment of step size. In this study, we first introduce the conception of low-power, high-power, normal, and marked zones to overcome the defect of PSO and CS. Each zone is defined as follows:

Low-power zone: If the output power at i-th nest position is small, then the position is recognized as a low-power position.

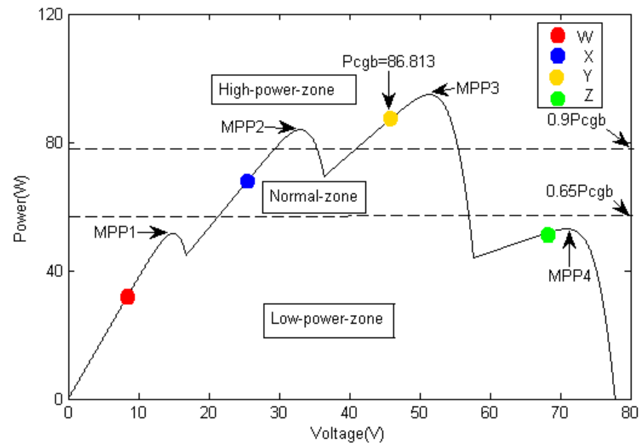


Fig. 2. Sketch map of ICS

The zone that includes all these low-power positions is called low-power zone. A low-power position is judged with the following formula:

$$(P_{cgb} - P_i) / P_{cgb} > 0.35 , \tag{8}$$

where P_{cgb} is the output power of the current global best point, and P_i is the output power of the i-th nest position.

High-power zone: If the output power at i-th nest position is close to the output power at the current global best duty position, then the position is recognized as a high-power position. The zone that includes all these high-power positions is called high-power zone. A high-power position is judged with the following formula:

$$(P_{cgb} - P_i) / P_{cgb} < 0.1 . \tag{9}$$

Normal zone: If the position is neither low-power position nor high-power position, then the position is regarded as normal position. The zone that includes all normal positions is called normal zone. A normal position is judged with the following formula:

$$0.1 \le (P_{cgb} - P_i) / P_{cgb} \le 0.35 . \tag{10}$$

Marked zone: If the zone that is not around the global nest position at present (the distance between this zone and current global best position is larger than $step_{max}$) is searched by other nests, then it is marked. This zone is regarded as the marked zone.

W, X, Y, and Z are the initial positions of the four nests, which are evenly dispersed, as shown in Fig. 2. After initialization, the power value that corresponds to four nests positions is obtained. The current global best power P_{cgb} is also obtained based on the comparison. The zone where the power value is less than 0.65 P_{cgb} is a low-power zone. The zone where the power value is more than 0.9 P_{cgb} is a high-power zone. The zone where the power value is between 0.65 and 0.9 P_{cgb} is a normal zone. The iterative changes of the nest positions result in the gradual increase of the output power (P_{cgb}), and these zones are updated. Fig. 2 indicates that W and Z in low-power zone are far from the current global best

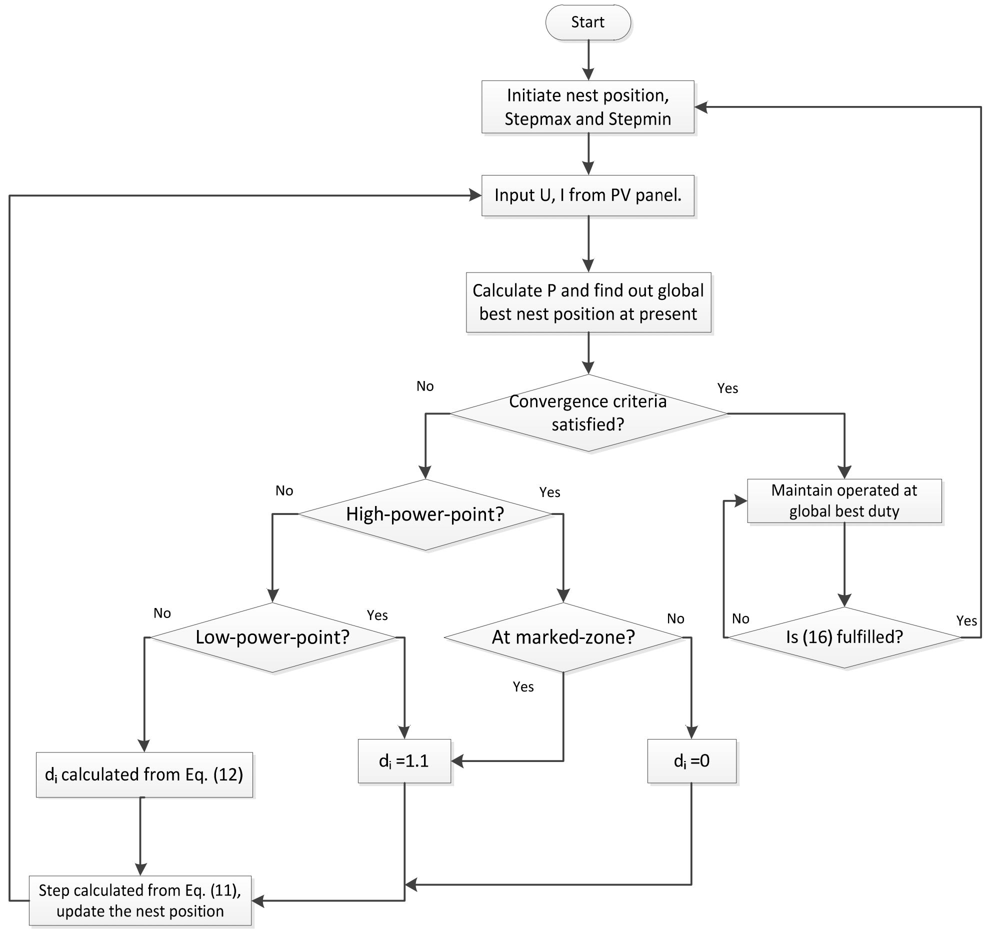


Fig. 3. Flowchart of ICS

position. Taking a large step causes them to move to the current global best position direction as soon as possible and move out of the low-power zone as quickly as possible. Y is the current global best position among the initial positions. Searching this zone with a small step not only determines GMPP but also improves accuracy. X is in the normal zone. The step in this zone realizes the adaptive step adjustment according to the fitness of the last generation nest and the distance between the nest and current global best nest.

$$step_{i} = step_{min} + \left(step_{max} - step_{min}\right) d_{i} \tag{11}$$

where $step_{max}$ and $step_{min}$ represent the maximum and minimum steps, respectively. Parameter d_i is used to achieve adaptive step. In the normal zone, d_i follows Equ. (10). In the low-power and marked zones, d_i follows Equ. (11). In the high-power zone, d_i follows Equ. (12).

$$d_{i} = \frac{\| x_{i} - x_{cgb} \|}{d_{max}} \quad \left(normal - zone\right), \tag{12}$$

$$d_{i} = 1.1 \quad \left(marked - zone \cup low - power - zone\right), \tag{13}$$

$$d_{i} = 0 \left(high - power - zone\right), \tag{14}$$

where x_i is the i-th nest position, and x_{cgb} represents the current global best nest position. d_{max} is the maximum distance between the best position and the rest of the nest locations.

This study proposed the following termination strategy to avoid power oscillation when the system reaches the steady state. The nests in the initial positions are dispersed evenly. GMMP is considered found when all the nests are concentrated, that is, when the standard deviation of all nest positions is less than a certain threshold. The following is the judging condition:

$$\sigma < \varepsilon \tag{15}$$

In the formula, σ is the standard deviation of the current position of all the particles, and **ε** is a set threshold, where $\varepsilon = 0.005$.

The output characteristics of the PV array change when the external environment changes. The maximum power point also changes. Therefore, the ICS algorithm should be restarted when the following conditions are met:

$$\left|\frac{P' - P}{P}\right| \geq \Delta P \tag{16}$$

where P is a sampled power value after the termination of iteration, P' is the sampled power value in the next sampling period, and ΔP is the power change tolerance. The ICS algorithm flowchart is shown in Fig. 3.

IV. Simulation and Analysis

A. Simulation Model and Parameters

A PV system includes the following to investigate the accuracy and performance of the proposed method: three PV modules connected in series, a DC/DC boost converter, a resistant load, and a control system, which are considered and simulated in MATLAB/Simulink software. The simulation model is shown in Fig. 4. The parameters of this PV system are shown in Table I.

B. Simulation Result and Analysis

The following three cases are simulated and analyzed to compare the performance of the proposed ICS MPPT method with that of P&O, PSO, and CS:

Case1: Normal operating conditions

Case 2: Partial shading conditions

Case 3: Fast variation of the solar irradiance

The parameters of the four MPPT methods are shown in Table II. N is the particle number in PSO and cuckoo number in CS and ICS.

1) Normal Operating Conditions: Fig. 5 shows the P–V characteristic of solar array under a normal operating condition, and the GMPP value is 239.235 W. In this condition, the temperature is 25 °C, and the isolation is 1000 W/m^2. The MPPT trajectories of P&O, PSO, CS, and ICS are presented in Fig. 6. PSO, CS, P&O, and ICS take approximately 0.96, 0.8, 0.8, and 0.72 s, respectively, to reach the MPP. The time responses of P&O and ICS are better than those of the two other methods. The accuracy of ICS is higher than that of P&O.

2) Partial Shading Conditions: This investigation is implemented to assess and compare the performances of PSO, CS, P&O, and ICS algorithms under partial shading condition. In this condition, the irradiance levels of the four PV modules are set as 1000, 700, 500, and 200 W/m^2. The temperature of the modules is 25 °C. Fig. 7 shows the P–V characteristic of solar array under partial shading condition. Four peaks exist in the curve, and MPP3 is GMPP whose value is 94.864 W. The MPPT trajectories of P&O, PSO, CS, and ICS algorithm are shown in Fig. 8. PSO, CS, and ICS algorithms can find the global MPP, which is approximately 94.811 W in this condition, whereas the P&O converges to a local MPP and fluctuates at approximately 50.019 W. The output power with P&O is only approximately 52.7569% of the global MPP. This finding indicates that power losses are considerable. To reach the global MPP, PSO, CS, and ICS take 1.36, 1.20, and only approximately 0.88 s, respectively. The ICS algorithm is obviously better than the PSO and CS algorithms because the adaptive step size can shorten the convergence time.

3) Fast Variation of Solar Irradiance: A step change is applied to the solar irradiance, which is presented in Fig. 9, to investigate and verify the performance and accuracy of ICS under rapidly changing solar irradiance.

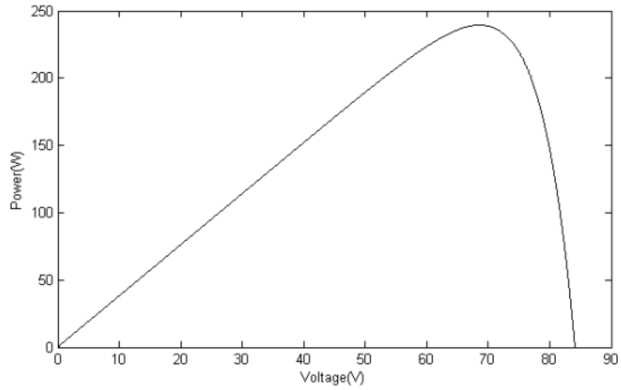


Fig. 4. Boost-based MPPT system.

TABLE I
PARAMETERS OF PV SYSTEMS

Parameters	Value
Short-circuit current	4.02 A
Open-circuit voltage	21 V
Current at P_{max}	3.5 A
Voltage at P_{max}	17 V
Maximum power	60 W
C_1	200 μF
C_2	90 μF
L	0.15 mH
R_{load}	40 Ω
Frequency of MOSFET	50 kHz

TABLE II
PARAMETERS OF THE FOUR MPPT METHODS

PSO	CS	P&O	ICS
$w = 0.1$	$\alpha_0 = 0.2$	$\Delta D = -0.02$	$step_{min}$ = 0.01
$c_1 = 0.2$	$P_a = 0.8$		$step_{max}$ = 0.06
$c_2 = 0.3$	$N = 4$		$N = 4$
$N = 4$			

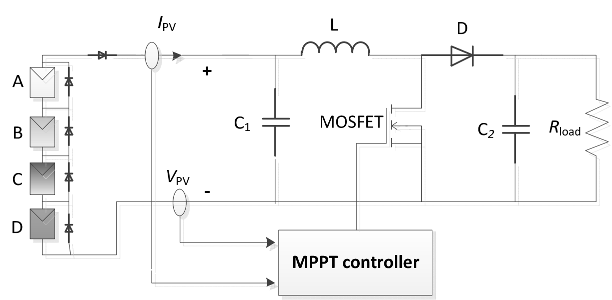
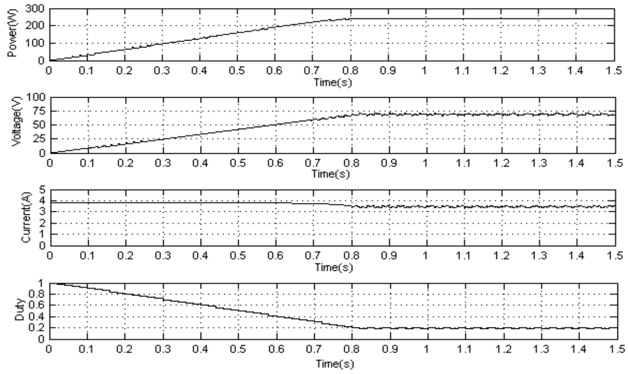


Fig. 5. P–V curve under a uniform condition

The trajectories of the solar array for PSO, CS, P&O, and ICS algorithms are plotted in Fig. 10. PSO, CS, and ICS can find the global MPP in this condition, whereas P&O converges to a local MPP.



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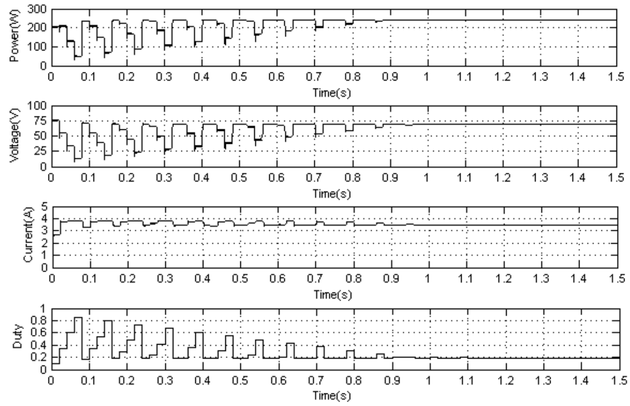

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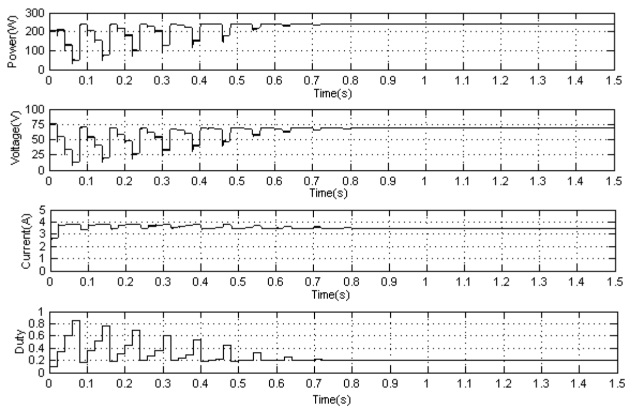

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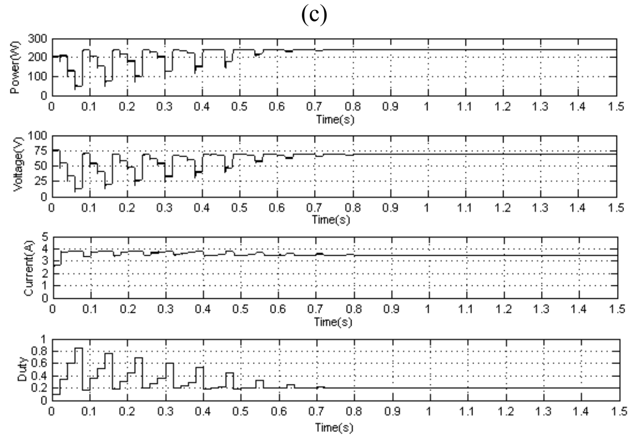


(d)

Fig. 6. Tracking trajectories of (a) P&O, (b) PSO, (c) CS, and (d) ICS under uniform condition.

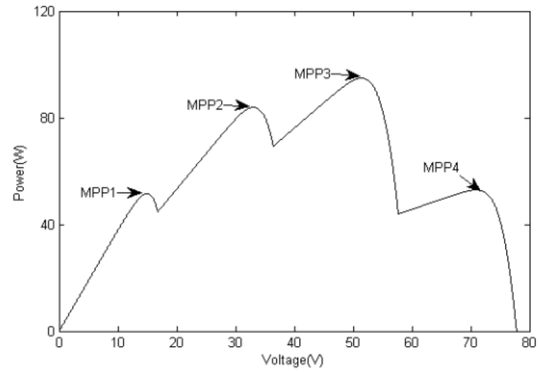
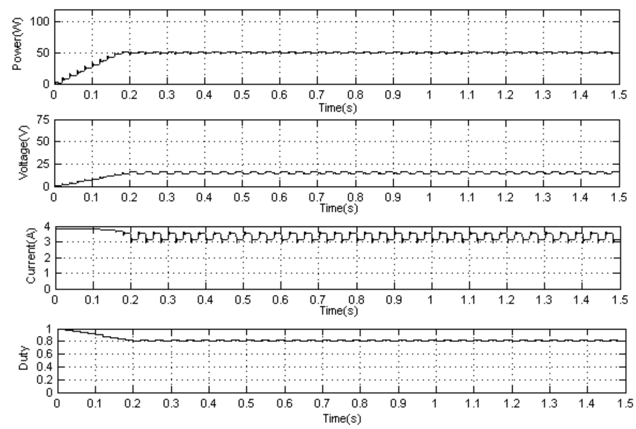


Fig. 7. P–V curve under partial shading condition.



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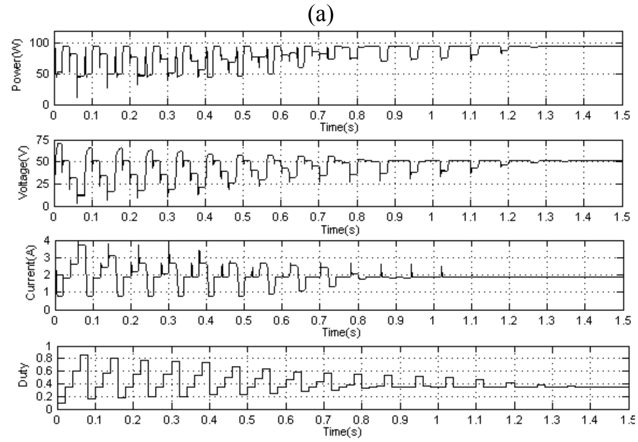

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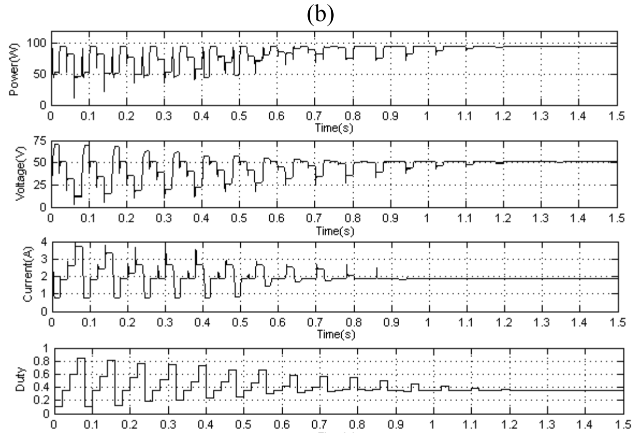

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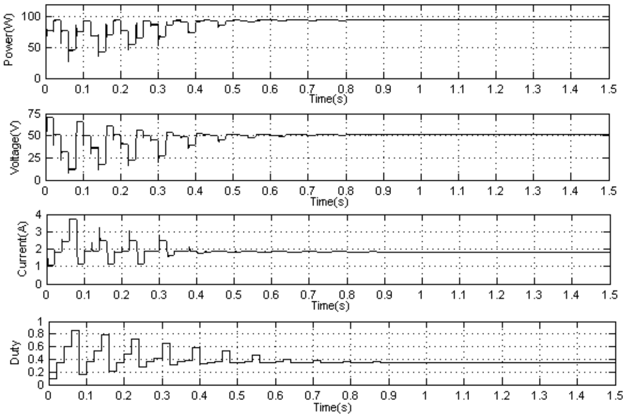

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Fig. 8. Tracking Trajectories of (a) P&O, (b) PSO, (c) CS, and (d) ICS under partial shading condition.

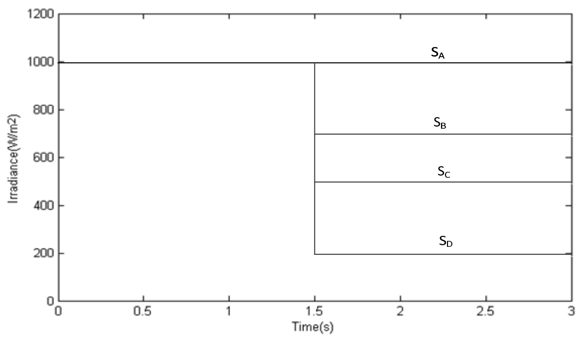
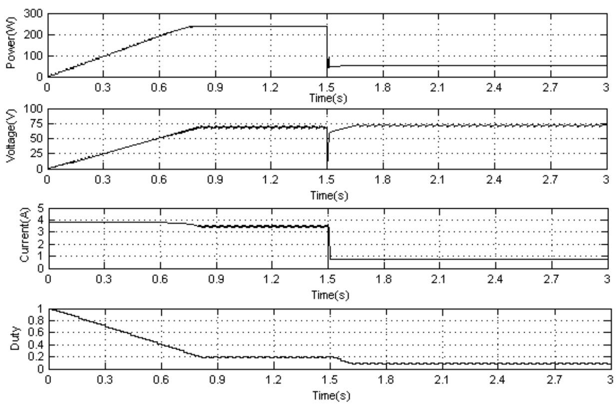


Fig. 9. Fast variation of the solar irradiance.



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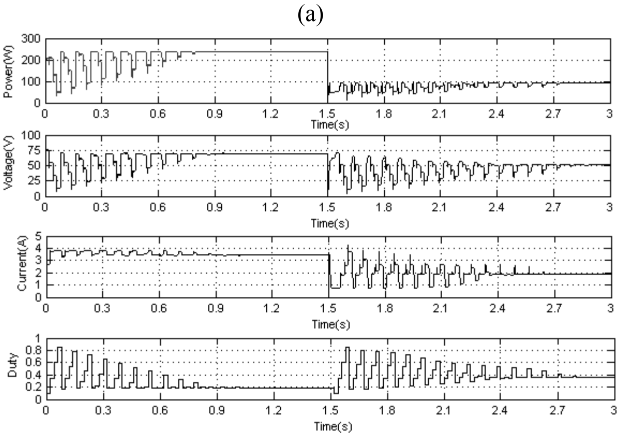

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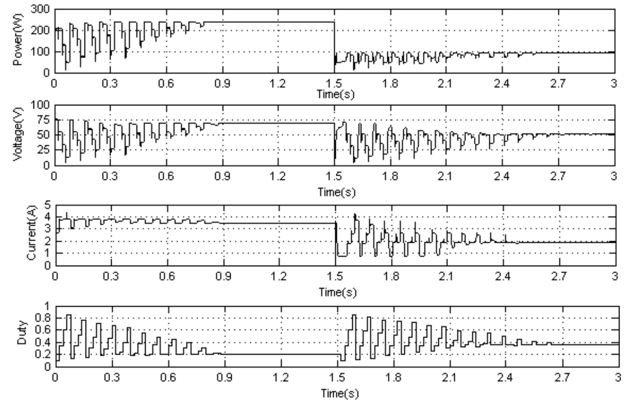

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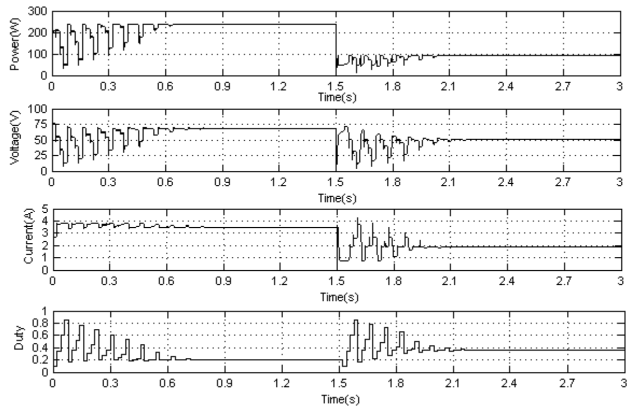


(d)

Fig. 10. Tracking trajectories of (a) P&O, (b) PSO, (c) CS, and (d) ICS under fast variation of solar irradiance condition.

V. Experimental Results and Analysis

The experiment with a DSP-controlled (DSP, TI TMS320F28335) DC/DC boost converter is implemented to verify the ICS algorithm. In the experiment, the four modules are connected in series, and three of them are covered with a translucence membrane to produce different irradiance levels. Another DSP is set as a tracer to obtain data, such as array power, voltage, and current. The RS485 serial ports and PC monitoring interface are used for communication and data storage, with the data transmitted every 2 ms. The data of duty are obtained from the controller DSP. The design specification of boost converter is the same as that of the converter in Simulink, whose parameters are shown in Table I.

P–V curve is scanned with the electrical load, and the curve is shown in Fig. 11. The four peaks in the curve can be determined easily, and the measured GMPP value is 87.598 W. P&O, PSO, CS, and ICS are used to track the maximum power point under partial shading condition. Fig. 12 proves that PSO, CS, and ICS can track global MPP, whereas P&O method falls into a local MPP. The performances of the four MPPT methods during the experiment are summarized in Table III. The convergence time of ICS is shorter than those

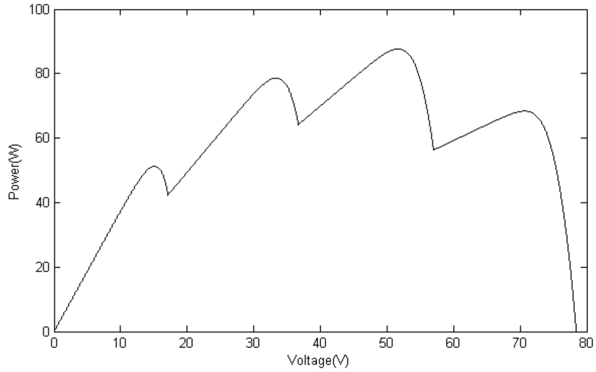
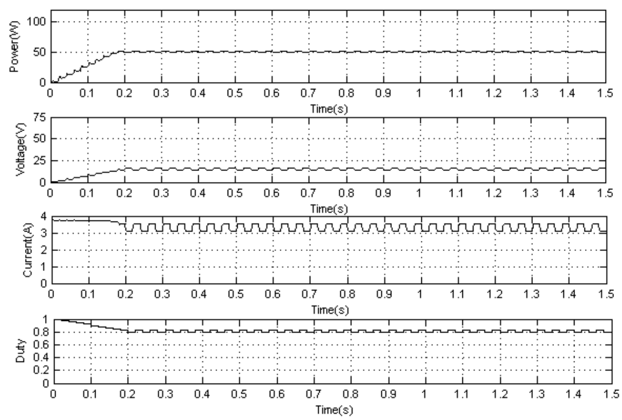


Fig. 11. Experimental curve of P–V.



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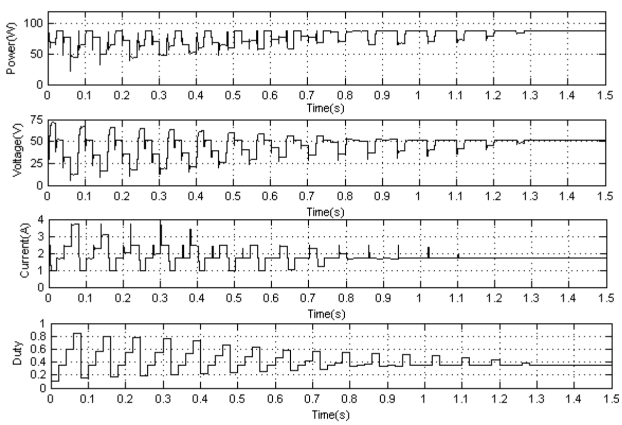

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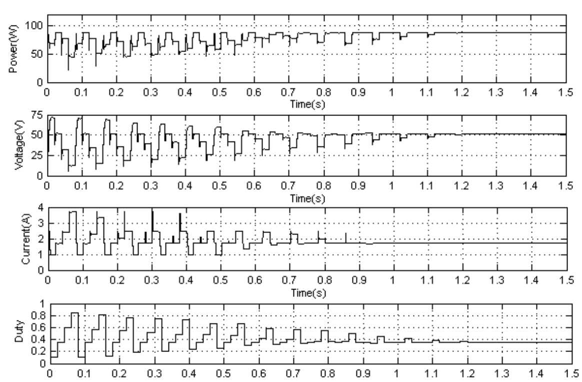

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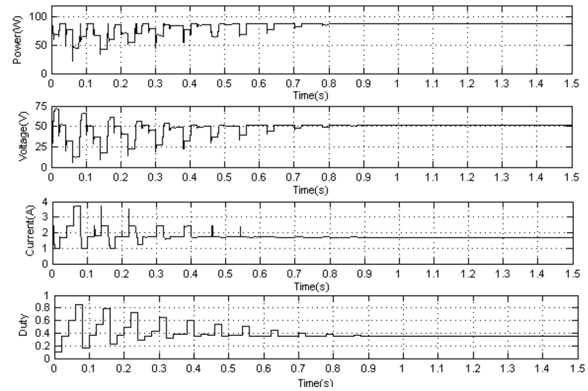

(d)

Fig. 12. Experimental tracking trajectory of (a) P&O, (b) PSO, (c) CS, and (d) ICS under partial shading condition.

TABLE III

SUMMARY OF MPPT PERFORMANCE IN THE EXPERIMENT

MPPT algorithms	Tracking time (s)	Tracked Power (W)	Tracking efficiency (%)
P&O	0.18	49.882–50.034	56.94–57.12
PSO	1.28	87.531	99.92
CS	1.20	87.534	99.93
ICS	0.88	87.547	99.94

of PSO and CS.

VI. CONCLUSION

In this study, ICS MPPT is presented, and its performance is compared with those of PSO, CS, and P&O. Random step is abandoned, and the conception of low-power, high-power, normal, and marked zones is introduced. Adaptive step adjustment is also realized according to the different stages of the nest position. Large step is adopted to save time in low-power and marked zones, whereas small step is used in high-power zone to ensure global tracking ability and to improve accuracy. The simulation and experiment confirm that ICS can track the global MPP with high accuracy under different conditions, including partial shading condition. Results also confirm the superior performance of ICS over the other three algorithms.

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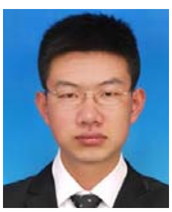

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