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A Prediction Model Guided Jaya Algorithm for the PV System Maximum Power Point Tracking

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***Abstract*—This paper proposes a novel model-free solution algorithm, the natural cubic spline guided Jaya algorithm (S-Jaya), for efficiently solving the maximum power point tracking (MPPT) problem of PV systems under partial shading conditions. A PV system which controls the power generation with its operating voltage is considered. As the same as the generic Jaya algorithm, the S-Jaya is free of algorithm-specific parameters. A natural cubic spline based prediction model is incorporated into the iterative search process to guide the update of candidate solutions (operating voltage settings) in the S-Jaya and such extension is capable of improving the tracking performance. Simulation studies and experiments are conducted to validate the effectiveness of the proposed S-Jaya algorithm for better addressing PV MPPT problems considering a variety of partial shading conditions. The performance of the proposed algorithm is benchmarked against the generic Jaya and the particle swarm optimization (PSO), which has been widely considered in the model-free MPPT, to demonstrate its advantages. Results of simulation studies and experiments demonstrate that the S-Jaya algorithm converges faster and provides a higher overall tracking efficiency.**

***Index Terms*—Heuristic search, Jaya algorithm, maximum power point tracking, partial shading conditions, photovoltaic system.**

I. Introduction

THE increasing penetration of photovoltaic (PV) power draws a high research attention in developing the maximum power point tracking (MPPT) techniques of PV systems [1, 2]. The power generation performance of a PV system is typically described by an electrical characteristic curve, such as the power-voltage (*P-V*) curve, and in such curve, a point indicating that the PV system produces the maximal power output is identified as the maximum power point (MPP). Ideally, the PV system can be controlled to achieve the MPP over its life-span if the characteristic curve is fixed. However, in practice, the characteristic curve varies nonlinearly with the variation of environmental conditions, such as the solar irradiance and PV cell temperature [3, 4], so that it is challenging to obtain the MPP. To address the optimization of the PV power production, MPPT algorithms have been developed to control PV systems to approach MPPs [5, 6].

Classical MPPT methods including the perturb and observation (P&O) [7], the incremental conductance (INC) [8], as well as the fractional open-circuit voltage/short-circuit current [9] have been developed. Both P&O and INC methods track the MPP by perturbing the voltage reference. Hence, the operating point always oscillates around the MPP with a steady state error proportional to the perturbation size. A small perturbation size can yield a higher accuracy but diminish the tracking speed. The attempts of overcoming the speed-accuracy tradeoff due to the fixed step size motivate the research of developing adaptive methods [10, 11]. The principle of the fractional open-circuit voltage/short-circuit current method simply updates the operating point with a fraction of the open-circuit voltage/short-circuit current. Yet, the accuracy of the MPPT method based on the fractional open-circuit voltage/short circuit current is not sufficient.

All previously mentioned MPPT methods [7-11] cannot handle PV systems exposed to the non-uniform irradiance caused by the partial shading as there will be multiple local peaks on the *P-V* curve. P&O and INC methods will be trapped into the local maxima. The partial shading commonly occurs on PV arrays occupying large regions due to the movement of clouds. Therefore, it is essential to study an MPPT method which is capable of handling the partial shading conditions.

MPPT methods with the capability of tracking the global MPP (GMPP) and improving the tracking efficiency under partial shading conditions have been vigorously discussed. A comprehensive review [12] categorized developed methods into two groups, extensions of classical MPPT methods [13, 14] and computational intelligence based methods [15, 16]. The first group of studies focused on upgrading classical MPPT methods by a more sophisticated control approach. Femia *et al.* [17] proposed a distributed MPPT method to improve the efficiency of PV systems; however, its

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implementation led to an increase of the PV system complexity and required the installation of the extra hardware. Kobayashi *et al.* [18] developed a two-stage method which firstly moved the operating point to the vicinity of the GMPP by estimating the equivalent load line and next employed the INC method to drive the convergence of the operating point to the GMPP. In [18], the MPPT efficiency is impaired due to the estimation of the equivalent load at the first stage, which requires frequent suspensions of the supply to loads to obtain the short-circuit current and open-circuit voltage. More importantly, the method cannot guarantee to track the GMPP if it lies on the left side of the load line. The second category of studies of MPPT for PV systems targeted on developing model-free control approaches that were solved by computational intelligence methods. In [19], a neural network (NN) based INC method was developed to track the GMPP under partial shading conditions. Applications of heuristic search algorithms including the genetic algorithm (GA) [20], particle swarm optimization (PSO) [21], differential evolution (DE) [22], and firefly algorithm (FA) [1] in estimating the optimal operating point to track the GMPP for PV systems have also been reported. In [16], the PSO algorithm outperformed classical MPPT methods based on P&O and INC. However, the performance of heuristic search algorithms can be significantly affected by settings of the algorithm-specific parameters. The inappropriate tuning of algorithm-specific parameters will increase iterations required for reaching the algorithm convergence and produce local optimal solutions. Thus, it is meaningful to develop a solution algorithm with fewer or free of algorithm-specific parameters while maintain or even improve the optimization performance.

This study proposes a novel method to track the GMPP for PV systems considering partial shading conditions based on a natural cubic spline guided Jaya algorithm (S-Jaya). The generic Jaya algorithm is a variant of the swarm intelligence proposed by Rao [23] in 2016. The fundamental principle of the algorithm is to iteratively update candidate solutions for a given problem by moving them towards the best solution and away from the worst solution. Compared with the GA, PSO, DE, and FA, Jaya does not require algorithm-specific parameters and such advantage naturally makes Jaya an attractive solution algorithm for the MPPT of PV systems. In Jaya algorithm, the update of candidate solutions is controlled by two random numbers generated from a uniform distribution $U[0, 1]$ to ensure a good exploration of the solution space. However, such stochastic process does not guarantee a better MPPT for PV systems. To enhance the MPPT performance of PV systems in terms of the faster convergence, lower oscillation, and higher efficiency, a natural cubic spline based prediction model is incorporated into the iterative solution update of the Jaya algorithm. The utilization of the natural cubic spline model in the iterative process of the S-Jaya algorithm can avoid worse updates and thereby improves the MPPT performance. Simultaneously, the natural cubic spline model can be renewed online to maintain its prediction accuracy and produce correct decisions of updating solutions. The performance of S-Jaya algorithm including its convergence speed and efficiency in tracking GMPP for PV systems under various partial shading conditions is examined through simulation studies as well as experiments. In addition, advantages of S-Jaya algorithm are validated by benchmarking against the generic Jaya algorithm and PSO for the MPPT of PV systems.

II. The Problem Formulation

In this section, the considered PV system and its power generation process are firstly described. Next, a model-free MPPT problem based on such PV system is formulated.

A. The PV module model

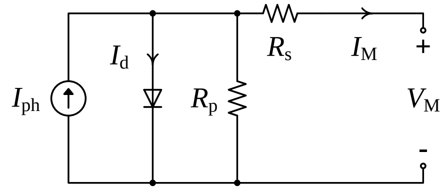

Fig. 1. The equivalent circuit of a PV module [3].

A PV cell is an elementary device of the PV system for converting the solar energy into the electricity and a PV module is composed of multiple cells. The equivalent circuit of a PV module illustrated in Fig. 1 has been introduced in [3]. Based on Fig. 1, electrical characteristics of PV modules under different environmental conditions have been mathematically described by (1) – (4) [24].

$$I_{\mathrm{M}} = I_{\mathrm{ph}} - I_0\left(\exp\left(\frac{V_{\mathrm{M}} + R_{\mathrm{S}} I_{\mathrm{M}}}{V_t}\right) - 1\right) - \frac{V_{\mathrm{M}} + R_{\mathrm{S}} I_{\mathrm{M}}}{R_{\mathrm{P}}} \tag{1}$$

$$V_t = \frac{akTN}{q} \tag{2}$$

$$I_{\mathrm{ph}} = \left(I_{\mathrm{ph\_STC}} + k_{\mathrm{I}}\left(T - T_{\mathrm{STC}}\right)\right)\frac{G}{G_{\mathrm{STC}}} \tag{3}$$

$$I_0 = \frac{I_{\mathrm{MSC\_STC}} + k_{\mathrm{I}}\left(T - T_{\mathrm{STC}}\right)}{\exp\left(\dfrac{V_{\mathrm{MOC\_STC}} + k_{\mathrm{V}}\left(T - T_{\mathrm{STC}}\right)}{V_t}\right) - 1} \tag{4}$$

In (1), I_{M} and V_{M} are the terminal current and voltage of the PV module respectively, R_{S} is the series resistance, R_{P} is the shunt resistance, I_{ph} is the light-generated current, I_0 is the diode reverse saturation current, as well as V_t is the thermal voltage. In (2), a represents the diode ideality factor, k is the Boltzmann constant, q is the electron charge, and N is the number of cells in series. In (3) and (4), k_{I} and k_{V} are temperature coefficients of short-circuit current (I_{MSC}) and open-circuit voltage (V_{MOC}) respectively while G and T are the solar irradiance and the cell temperature respectively. Note that the subscript STC refers to the measurements under standard test conditions G_{STC} = 1000 W/m^2, T_{STC} = 25 °C, and spectrum air mass (AM) 1.5. Values of a, $I_{\mathrm{ph\_STC}}$, R_{S}, and R_{P} in (1)-(4) can be derived by using the specification data provided by PV module manufacturers.

Based on (1) - (4), the relationship between PV module current-voltage (*I-V*) characteristics and environmental conditions of G and T can be simplified into (5).

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$$g\left(I_{\mathrm{M}},V_{\mathrm{M}},G,T\right)=0 \tag{5}$$

B. The PV power generation

A common configuration of a PV array composed of $N_{\mathrm{S}}\times N_{\mathrm{P}}$ modules is depicted in Fig. 2, where N_S and N_P separately describe the number of PV modules in one string and the number of strings. The power generation of the PV array is determined by (6).

$$P=V\cdot\sum_{i=1}^{N_{\mathrm{P}}}I\left(i\right) \tag{6}$$

where V is the terminal voltage of the PV array and $I(i)$ is the current of the string i.

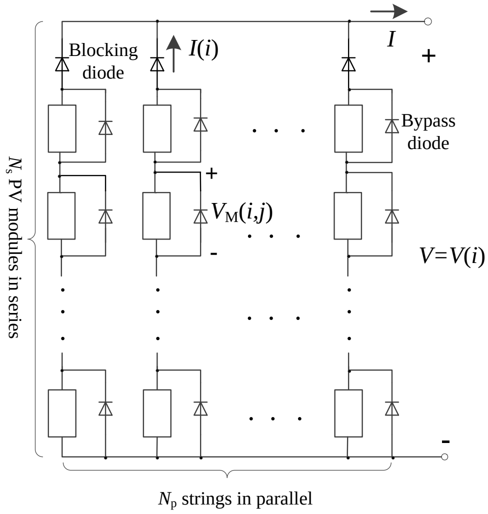

Fig. 2. The common configuration of a PV array.

In (6), V can be operated to control P. As strings in Fig. 2 are connected in parallel, V is exactly the string voltage, $V(i)$, which is equivalent across N_P strings. The $V(i)$ can be adjusted through (7) and (8).

$$V=V\left(i\right)=\sum_{j=1}^{N_{\mathrm{S}}}V_{\mathrm{M}}\left(i,j\right)-V_{\mathrm{Dblocking}} \tag{7}$$

$$\begin{cases} V_{\mathrm{M}}\left(i,j\right)=-V_{\mathrm{Dbypass}}, & \text{if } I_{\mathrm{ph}}\left(i,j\right)<I\left(i\right) \\ g\left(I\left(i\right),V_{\mathrm{M}}\left(i,j\right),G\left(i,j\right),T\left(i,j\right)\right)=0, & \text{if } I_{\mathrm{ph}}\left(i,j\right)\geq I\left(i\right) \end{cases} \tag{8}$$

In (7) and (8), $V_{\mathrm{Dblocking}}$ and V_{Dbypass} are forward voltages of the blocking diode and bypass diode respectively while (i, j) indicates the index of the PV module.

Based on (6) - (8), the model of estimating the PV power output based on the controllable parameter V and non-controllable parameters, $\mathbf{G}$ and $\mathbf{T}$, can be further simplified into a form presented in (9).

$$P=f\left(V,\mathbf{G},\mathbf{T}\right) \tag{9}$$

where $f(\cdot)$ represents the implicit P-V relationship while $\mathbf{G}=\{G(i,j)\}$ and $\mathbf{T}=\{T(i,j)\}$ describe the matrices of the solar irradiance and the cell temperature of the PV array.

C. The model-free maximum PV power tracking

The model $f(\cdot)$ in (9) is multimodal and its form varies with **G** and **T** whose values are challenging to obtain in practice. Fig. 3 demonstrates the P-V curve of a PV array including three modules connected in series under various partial shading conditions. It is observable that there are multiple modes. Simultaneously, the magnitude of the GMPP and its location are different according to partial shading conditions. The multiple local maxima on the P-V curve prevent classical P&O and INC methods from obtaining the GMPP. It is highly valuable to develop approaches for tracking the GMPP of PV systems under partial shading conditions without knowing the form of the PV power generation and the information of environmental conditions. As P can be observed through the PV system by modifying settings of V, it is possible to realize a model-free maximum PV power tracking if there exists an approach which is capable to rapidly discover the optimal V by learning knowledge from a limited number of modifications of V in a PV system. Let $f(\cdot)$ denote a real process providing values of P based on settings of V, the model-free MPPT problem of a PV system can be formulated as (10) by assuming that **G** and **T** are constant during the tracking cycle.

$$\begin{aligned} &\max P_{\mathbf{G,T}} \\ &\text{s.t.}\quad P_{\mathbf{G,T}}=f\left(V\right) \\ &\qquad 0\leq V\leq V_{\mathrm{OC}} \end{aligned} \tag{10}$$

where $P_{\mathbf{G,T}}$ is the power output conditioned on **G** and **T** while V_{OC} is the open-circuit voltage of the PV array.

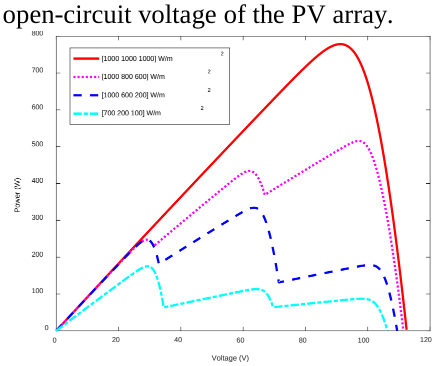

Fig. 3. P-V curve depending on **G** at **T** = 25 °C.

III. SOLUTION ALGORITHMS

The optimization model (10) cannot be solved with classical optimization tools due to its implicit form. Heuristic search algorithms have been widely applied to address model-free problems [25] and are suitable to serve as the solution algorithm of the model (10) in this study. To provide more efficient and effective MPPT of a PV system under partial shading conditions, a novel S-Jaya algorithm is proposed. The generic Jaya algorithm [23] is a variant of swarm intelligence which deploys the similar iterative search principle to obtain the optimal solution. However, in this study, the regular principle of updating candidate solutions can lead to either an improvement or a degradation of the PV power generation as the PV power generation model is implicit and the observation of the effectiveness of updated solutions relies on the PV system. Such uncertainty will make the MPPT performance inefficient or even less effective. To overcome this challenge, we extend the Jaya algorithm by integrating a natural cubic spline model for predicting the PV power output based on updated solutions to reduce negative solution updates in the iterative search. Through such advancement, the S-Jaya

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algorithm can offer better MPPT performance than ordinary heuristic search algorithms.

A. Jaya algorithm

In (10), $P = f(V)$ is the objective function to be maximized and the terminal voltage V is its solution. To maximize P, the generic Jaya algorithm firstly initializes n candidate solutions and next iteratively updates them with (11) and (12) to obtain the optimal solution, V_{opt} [23].

$$V'_{i,j} = V_{i,j} + r_{i,1}\left(V_{i,best} - \left|V_{i,j}\right|\right) - r_{i,2}\left(V_{i,worst} - \left|V_{i,j}\right|\right) \quad (11)$$

$$V_{i+1,j} = \begin{cases} V'_{i,j}, & \text{if } f\left(V'_{i,j}\right) > f\left(V_{i,j}\right) \\ V_{i,j}, & \text{if } f\left(V'_{i,j}\right) \le f\left(V_{i,j}\right) \end{cases} \quad (12)$$

In (11) and (12), $V_{i,j}$ represents the j^{th} candidate solution at i^{th} iteration, $V'_{i,j}$ describes the updated $V_{i,j}$, while $r_{i,1}$ and $r_{i,2}$ are two independent random numbers generated from a uniform distribution, $U[0,1]$. The $V_{i,best}$ and $V_{i,worst}$ denote the best and the worst solutions among the entire pool of candidate solutions respectively. The term $r_{i,1}(V_{i,best} - |V_{i,j}|)$ is applied to move the candidate solution towards the best solution. The term $-r_{i,2}(V_{i,worst} - |V_{i,j}|)$ aims at assisting a candidate solution to escape from the worst solution. The $V'_{i,j}$ will be retained for the next iteration if it provides a better objective function value than the $V_{i,j}$ as shown in (12).

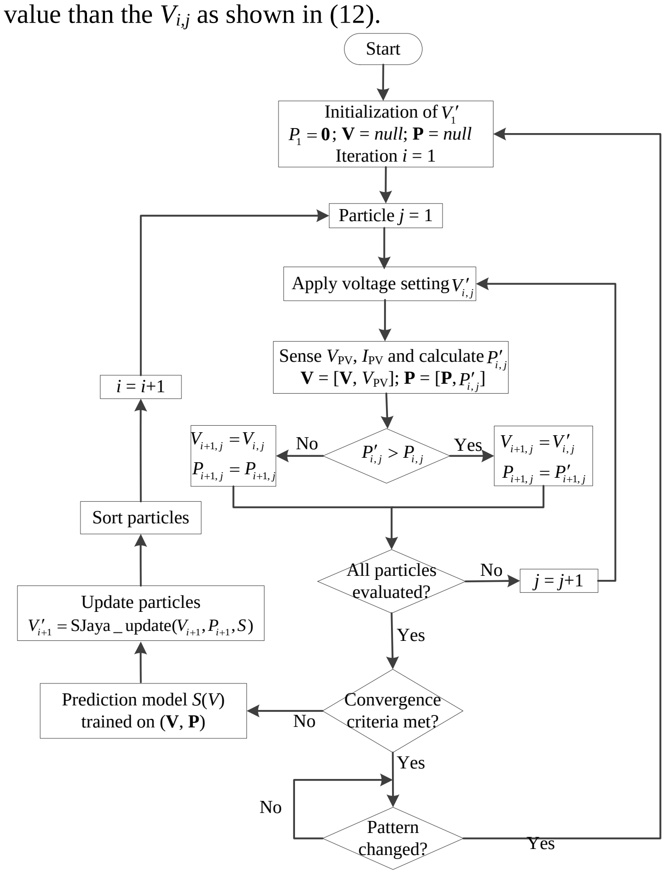

Fig. 4. Flow chart of the S-Jaya algorithm for the MPPT

B. S-Jaya Algorithm for MPPT

In the generic Jaya algorithm, two random numbers, $r_{i,1}$ and $r_{i,2}$, are applied to update candidate solutions. As the fitness evaluation in this study relies on the PV system, the stochastic process can lead to an improvement or a degradation of the PV power output. To reduce possible negative solution updates and thereby to enhance the MPPT performance, in this study, a natural cubic spline based PV power output prediction model is incorporated into the iterative update of candidate solutions. An updated solution $V'_{i,j}$ will be accepted as a setting of V for the PV system if a better PV power output is predicted by the natural cubic spline-based prediction model. Otherwise, the $V'_{i,j}$ will be discarded and a new updated solution will be generated.

The flow chart of S-Jaya algorithm for the MPPT is described in Fig. 4. In the flow chart, $V'_i = \{V'_{i,j}\}_{j=1}^{n}$, $V_i = \{V_{i,j}\}_{j=1}^{n}$, and $P_i = \{P_{i,j}\}_{j=1}^{n}$ are applied to simplify the notation. The flow chart of the proposed S-Jaya algorithm for the MPPT is next elaborated by following steps.

<u>Step 1 Parameter setting</u>: The population size n is required by the Jaya algorithm. A good choice is to set n as the number of PV modules in series N_S as discussed in [26-28].

<u>Step 2 Jaya initialization</u>: Initial values of candidate solutions can be randomly generated or set into fixed values within [0, V_{OC}]. Under the standard test conditions (STC), $V_{OC\_STC} = N_S \cdot V_{MOC\_STC}$ and V_{MOC_STC} is specified by PV manufacturer. However, considering variations of V_{OC} with respect to the solar irradiance and the cell temperature [15, 29], the practical solution space, [$V_{\min}$, $V_{\max}$], is set to [$0.1 \cdot V_{MOC\_STC}$, $0.95 \cdot N_S \cdot V_{MOC\_STC}$]. Moreover, studies [28, 30] reported that peaks on P-V curve occurred around multiples of 80% of V_{MOC}. Hence, initial values are fixed by (13) when $n = N_S$.

$$V'_{1,j} = 0.8 \cdot j \cdot V_{\text{MOC\_STC}}, \ \text{for } j = 1, \ldots, N_S \quad (13)$$

<u>Step 3 Fitness evaluation</u>: The value of the fitness function, $P'_{i,j} = f(V'_{i,j})$, is observed through the PV system by applying the voltage setting, $V'_{i,j}$. The voltage settings are applied to the PV system at a fixed time interval, which is greater than the settling time of PV system.

<u>Step 4 Natural cubic spline based PV power prediction model</u>: A natural cubic spline [31] based prediction model, $P_S = S(V)$, is developed based on historical data points, ($\mathbf{V}$, $\mathbf{P}$). The natural cubic spline model is employed due to its simplicity and powerful capability in handling univariate nonlinear regression problems with limited samples. Let $\{(V_{(k)}, P_{(k)})\}_{k=1}^{m}$ denote the m elements of ($\mathbf{V}$, $\mathbf{P}$) in the order of $V_{(1)} < \ldots < V_{(m)}$. The essential idea of natural cubic spline is to fit a piecewise function of the form shown in (14)

$$S(V) = \begin{cases} S_1(V), & \text{if } V_{(1)} \le V \le V_{(2)} \\ \ldots & \\ S_{m-1}(V), & \text{if } V_{(m-1)} \le V \le V_{(m)} \end{cases} \quad (14)$$

where $S_k(V) = \sum_{p=0}^{3} a_{k,p}\left(V - V_{(k)}\right)^p$ for $k = 1, \ldots, m$-1, and $S(V)$ satisfies following conditions:

- $S_k(V_{(k)}) = P_{(k)}$ and $S_k(V_{(k+1)}) = P_{(k+1)}$ for $k = 1, \ldots, m$-1;
- $S_k(V_{(k+1)}) = S_{k+1}(V_{(k+1)})$ for $k = 1, \ldots, m$-2;
- $S'_k(V_{(k+1)}) = S'_{k+1}(V_{(k+1)})$ for $k = 1, \ldots, m$-2;
- $S''_k(V_{(k+1)}) = S''_{k+1}(V_{(k+1)})$ for $k = 1, \ldots, m$-2;
- $S''_1(V_{(1)}) = 0$ and $S''_{m-1}(V_{(m)}) = 0$.

The procedures to obtain $a_{k,p}$ based on the given conditions are described in **Algorithm 1**. As the complexity of the algorithm

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is $O(m)$, it is easy to be implemented on a digital signal processor.

Algorithm 1: Natural cubic spline

Input: $\{(V_{(k)}, P_{(k)})\}_{k=1}^{m}$ where $V_{(1)} < ... < V_{(m)}$;
Output: $a_{k,p}$ for $k = 1, ..., m-1$ and $p = 0, ..., 3$;
for $k := 1$ *to* $m-1$ **do**
  $h_k = V_{(k+1)} - V_{(k)}$;
end
for $k := 2$ *to* $m-1$ **do**
  $\alpha_k = 3(P_{(k+1)} - P_{(k)})/h_k - 3(P_{(k)} - P_{(k-1)})/h_{k-1}$;
end
Set $l_1 = 1$;$\mu_1 = 0$;$z_1 = 0$;
for $k := 2$ *to* $m-1$ **do**
  $l_k = 2(V_{(k+1)} - V_{(k-1)}) - h_{k-1}\mu_{k-1}$;
  $\mu_k = h_k/l_k$;
  $z_k = (\alpha_k - h_{k-1}z_{k-1})/l_k$;
end
Set $a_{m,2} = 0$;
for $k := m-1$ *to* 1 **do**
  $a_{k,2} = z_k - \mu_k a_{k+1,2}$;
  $a_{k,0} = P_{(k)}$;
  $a_{k,1} = (P_{(k+1)} - P_{(k)})/h_k - h_k(a_{k+1,2} + 2a_{k,2})/3$;
  $a_{k,3} = (a_{k+1,2} - a_{k,2})/(3h_k)$;
end

Step 5 Prediction model guided solution update: The natural cubic spline model predicts the fitness $S(V'_{i,j})$ of a $V'_{i,j}$. The update of the candidate solution is checked by assessing:

$$S\left(V'_{i,j}\right) > P_{i,j} \tag{15}$$

If (15) is met, $V'_{i,j}$ will be applied to the PV system; otherwise, a new $V'_{i,j}$ is generated until (15) is satisfied or a maximal number of update iterations, d, is reached. The process of the natural cubic spline guided candidate solution updates is described in **Algorithm 2**.

Algorithm 2: SJaya_update(V_i, P_i, S)

Set $n \leftarrow$ the number of particles;
Set $d \leftarrow$ the maximum number of repetition;
Get $V_{i,best}$ and $V_{i,worst}$ from V_i based on P_i;
for $j := 1$ *to* n **do**
  Set $k = 1$;
  repeat
    Set $r_{i,1}$ = a random number from $[0, 1]$;
    Set $r_{i,2}$ = a random number from $[0, 1]$;
    Set $V'_{i,j} = V_{i,j} + r_{i,1}(V_{i,best} - |V_{i,j}|)$
      $-r_{i,2}(V_{i,worst} - |V_{i,j}|)$;
    Set $k = k + 1$;
  until $k > d$ *or* $S(V'_{i,j}) > P_{i,j}$;
end
return $V'_i = \{V'_{i,j}\}_{j=1}^{n}$;

Step 6 Convergence criterion: The S-Jaya algorithm will stop and output the best voltage setting if the voltage deviation between the best candidate solution and the worst candidate solution is smaller than a threshold ε, or a maximal number of algorithm iterations I is reached. A larger value of ε results in a faster convergence but a lower accuracy.

Step 7 Re-initialization: The S-Jaya algorithm will be re-initialized when the change of shading patterns is detected by checking:

$$\frac{\left|P_{\text{PV, New}} - P_{\text{PV, Last}}\right|}{P_{\text{PV, Last}}} > \Delta P \tag{16}$$

The $\Delta P = 0.1$ is applied according to [26].

IV. Simulation Studies and Analyses

A. Simulation setup

The block diagram of a voltage-based PV control system is depicted in Fig. 5. The simulation study is implemented under MATLAB/Simulink. A controlled voltage source is utilized to replace conventional DC-DC converter to concentrate on the MPPT method. Thereby, the voltage reference from the MPPT is utilized to drive the voltage of the controlled voltage source and the PI controller is not required.

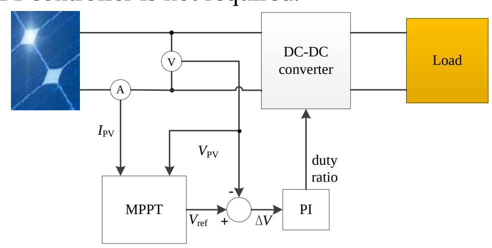

Fig. 5. Block diagram of PV control system.

TABLE I
Specifications of CS6P-260P Module

Maximum Power (P_{MPP})	260 W
Open Circuit Voltage (V_{MOC_STC})	37.5 V
Short Circuit Current (I_{MSC_STC})	9.12 A
Voltage at P_{MPP} (V_{MPP})	30.4 V
Current at P_{MPP} (I_{MPP})	8.56 A
Temperature Coefficient of V_{OC}	-0.31%/°C
Temperature Coefficient of I_{SC}	0.053%/°C
Cells Per Module	60

In the simulation study, two PV array configurations, 5S and 4S2P based on CS6P-260P PV modules are considered. The specifications of the module are given in Table I. In order to present the effectiveness and efficiency of the proposed S-Jaya based MPPT method under various environmental conditions, the following scenarios are considered:

Scenario 1: The partial shading patterns depicted in Fig. 6 are considered. As the Jaya search process is stochastic, the tracking process will be repeated 1000 times to obtain a more meaningful performance assessment.

Fig. 6. *P-V* curve under considered shading patterns

Scenario 2: The proposed MPPT method is tested on 1000 randomly and sequentially generated partial shading patterns which imply great variations of the magnitude and location of the GMPP on *P-V* curves. In this scenario, the solar irradiance

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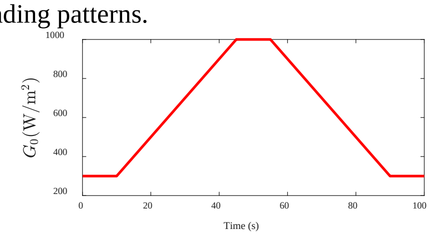
on each module is randomly sampled from [100W/m^2, 1000W/m^2]. The cell temperature T is described by the ambient temperature T_{amb}, irradiance G, wind speed WS, and PV mounting technique [32]:

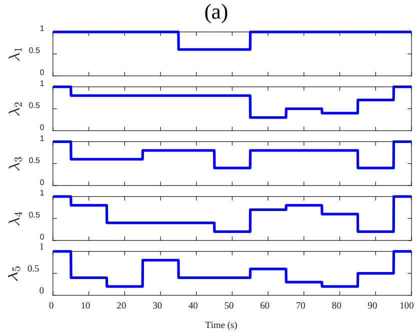
$$T = G \cdot \mathrm{e}^{(a+bWS)} + T_{\text{amb}} + \frac{G}{G_{\text{STC}}} \cdot \Delta T \qquad (17)$$

In (17), a and b are empirically determined coefficients. A typical value, 2°C to 3°C, of ΔT is considered for flat-plate modules in an open-rack mount. Random sampling is also applied to T_{amb} from [5°C, 30°C] and WS from [0m/s, 20m/s].

Scenario 3: Tests considering dynamical solar irradiance are conducted based on the PV array configuration, 5S. The irradiance profile G_0 in EN50530 standard is depicted in Fig. 7a. Fig. 7b presents different profiles for simulating partial shading described by ratios λ_i between the effective irradiance G_i of the i^{th} module and G_0 where $\lambda_i = G_i/G_0$. In this scenario, after the S-Jaya algorithm terminates, the P&O algorithm is applied to capture the evolution of the solar irradiance until the S-Jaya algorithm is re-activated due to the change of partial shading patterns.



(a)



(b)

Fig. 7. Dynamic test profiles, (a): ambient irradiance; (b): effective irradiance level of each module

The performance of the proposed S-Jaya algorithm is compared with generic Jaya algorithm and well-tuned PSO. The general parameters are set as follows: the population size $n = N_S$ (4 for 4S2P configuration and 5 for 5S configuration), the sampling interval $Ts = 0.05$s, and the convergence criterion $\varepsilon = 0.5$V. The maximum number of algorithm iteration I is set to 40 in Scenarios 1 and 2 in order to ensure all the applied algorithms converge thereby to make a more reasonable comparison in convergence speed of different MPPT methods. In Scenario 3, the maximal iterations of executing the algorithm, I, is set to 10 to capture the evolution of the solar irradiance over time. In PSO, algorithm-specific parameters including inertial weight ω, cognitive coefficient c_1, and social coefficient c_2 are iteratively updated to improve PSO performance as in [27], and the initial velocities of particles are set to zero.

B. Results and analysis

Three metrics, the convergence speed, overall tracking efficiency, and accuracy, are utilized to evaluate the MPPT performance. The overall tracking efficiency η is computed by

$$\eta = \frac{\int P(t)\,dt}{\int P_{MPP}(t)\,dt} \times 100\,(\%) \qquad (18)$$

where $P(t)$ and $P_{\text{MPP}}(t)$ are the measured power and the maximum power on the P-V curve at time t. The steady state MPPT efficiency defined in (19) provides the accuracy in tracking the GMPP of MPPT methods.

$$\eta_0 = \frac{P_0}{P_{\text{MPP}}} \times 100\,(\%) \qquad (19)$$

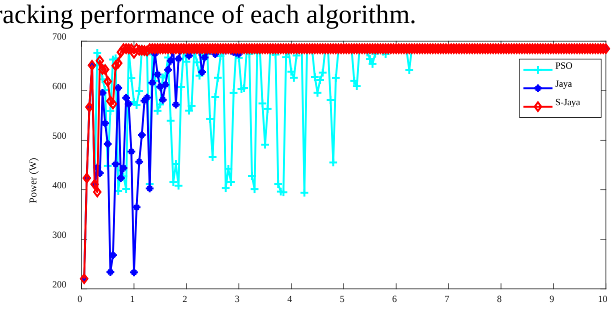
where P_0 is the PV power output corresponding to the computed optimal voltage setting.

The simulation results of Scenarios 1 and 2 are summarized in Table II. It is observable that the S-Jaya algorithm beats the benchmarking algorithms in terms of the convergence speed and overall tracking efficiency, while all three algorithms can track the GMPP at a high accuracy. The lower standard deviation of the convergence speed and tracking efficiency of the S-Jaya algorithm demonstrates its better capability in maintaining its performance.

TABLE II
SIMULATION RESULTS, MEAN AND STANDARD DEVIATION (SD) OF DIFFERENT METRICS, FOR SCENARIOS 1 AND 2.

Sce.	PV	Algo.	Convergence time (s)		η (%)		η_0 (%)	
			mean	SD	mean	SD	mean	SD
1	4S2P	PSO	5.49	1.05	90.92	1.63	99.99	<0.01
		Jaya	3.10	0.99	92.88	3.84	99.99	<0.01
		S-Jaya	1.18	0.20	98.94	0.1	99.98	<0.01
	5S	PSO	6.88	1.67	92.68	1.39	99.98	0.2
		Jaya	3.82	0.81	95.32	1.7	99.99	<0.01
		S-Jaya	1.62	0.36	98.86	0.18	99.98	<0.01
2	4S2P	PSO	5.24	1.39	93.73	2.15	99.95	0.35
		Jaya	3.40	1.53	94.18	4.89	99.95	0.34
		S-Jaya	1.26	0.29	98.59	0.88	99.80	0.7
	5S	PSO	6.88	1.75	92.66	2.5	99.95	0.4
		Jaya	4.49	1.86	93.15	5.64	99.95	0.39
		S-Jaya	1.67	0.45	98.48	0.78	99.83	0.64

Figs. 8 and 9 depict the typical tracking waveforms of different MPPT methods under the considered partial shading patterns in Scenario 1. In both figures, the convergence time of a specific algorithm equals to its mean convergence time given in Table II; hence, these plots present the general tracking performance of each algorithm.



(a)

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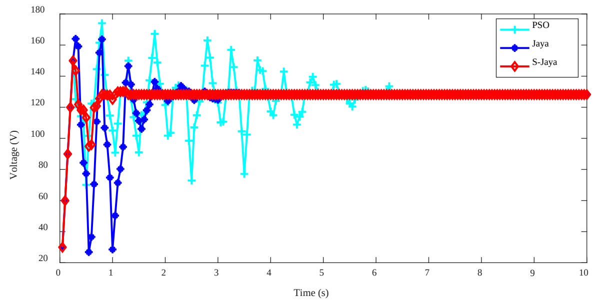
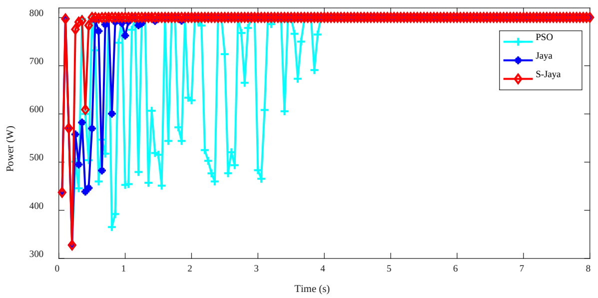
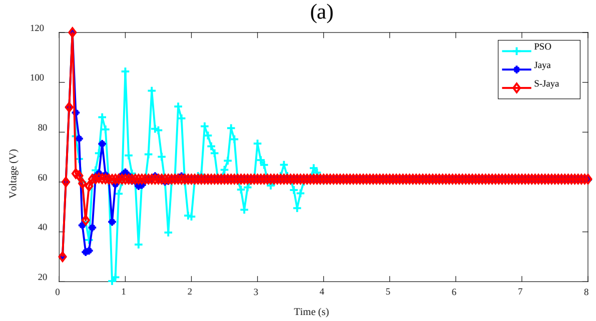


(b)

Fig. 8. Tracking waveforms under shading pattern I. (a): power; (b): voltage.



(a)



(b)

Fig. 9. Tracking waveforms under shading pattern II. (a): power; (b): voltage.

Based on Figs. 8 and 9, it is observable that the S-Jaya algorithm converged to the GMPP much faster and with lower oscillations than other algorithms.

The MPPT performance of considered methods under the dynamic solar irradiance and shading patterns in Scenario 3 is illustrated in Fig. 10. The overall tracking efficiencies of S-Jaya, Jaya, and PSO are 98.25%, 95.59%, and 95.50% respectively. Results demonstrate that the proposed S-Jaya performed well in tracking the GMPP under the dynamic solar irradiance and shading patterns due to its high convergence speed.

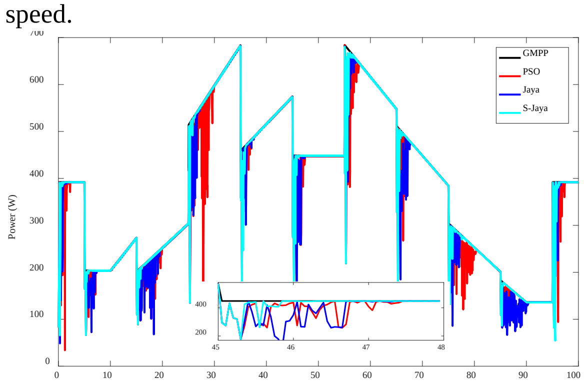


Fig. 10. Tracking waveforms under dynamic irradiance and shading patterns.

C. Discussion

Simulation results illustrate that the S-Jaya converges to the GMPP with a higher speed and a lower oscillation. As shown in Table II, the average improvements of S-Jaya against PSO and Jaya in terms of the convergence speed for various Scenarios are 4.7s and 2.3s respectively. This is achieved by discarding negative updates of solutions based on the natural cubic spline model. The effectiveness of this mechanism relies on the prediction accuracy. The predicted *P-V* curve by the natural cubic spline model trained on 16 data points collected from the measured *P-V* curve under partial shading pattern II is illustrated in Fig. 11. It is observable that the natural cubic spline model well depicts the trend of the curve in each sub-interval. The mean absolute percentage error (MAPE) and normalized root mean square error (nRMSE) of the prediction model are 3.4% and 5.3% respectively. The high accuracy and stable prediction performance of the natural cubic spline model ensures the effectiveness of the S-Jaya algorithm based MPPT method. To maintain the prediction accuracy under dynamic environmental conditions, the prediction model can be updated by latest observations.

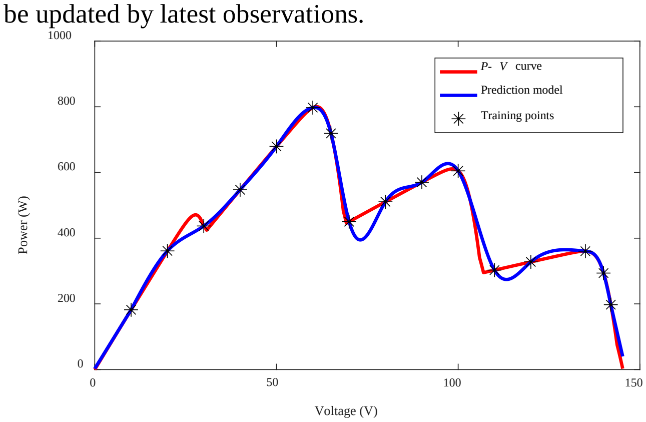


Fig. 11. Demonstration of predicted *P-V* curve by the prediction model.

V. Experiment Validation

A. Experiment platform

An experiment platform composed of a 3 kW grid-connected inverter (model no.: ProVista SGB30) and a PV simulator (model no.: Magna Power TSD100020) shown in Fig. 12 is employed to validate the feasibility of the proposed MPPT method. The model of the microcontroller utilized in the experiment is TMS320F2808 with 100MHz clock, 128 kB flash, 36 kB SRAM, and 12-bit ADC. The proposed MPPT method is implemented in the grid-connected inverter. As shown in Fig. 5, the PV voltage, V_{PV}, and the current, I_{PV}, sampled by the ADC unit are transmitted to the proposed MPPT method which produces a voltage reference command, V_{ref}, for a PI controller. The PI controller removes the error between V_{PV} and V_{ref} by controlling the DC-DC converter with a suitable duty ratio. The detailed structure of the inverter is described in [33]. The specification of system parameters is provided in Table III. In the experiment, the PV voltage has to be restricted within a pre-specified range as shown in Table III to protect the inverter.

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TABLE III
SYSTEM PARAMETERS IN THE EXPERIMENT.

Symbol	Definition	Values
f_{sampling}	ADC Sampling frequency	20 kHz
f_{MPPT}	Execution frequency of MPPT	3.33 Hz
$V_{\text{PV, max}}$	Maximum designed PV voltage	350 V
$V_{\text{PV, min}}$	Minimum designed PV voltage	190 V

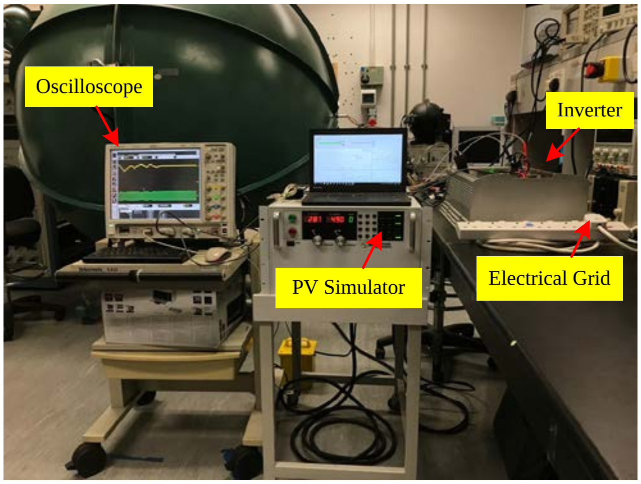


Fig. 12. Experiment platform.

Two PV profiles with multiple peaks shown in Fig. 13 are programmed into the PV simulator. Profiles are generated by the MATLAB/Simulink considering a PV string of 10 CS6P-260P PV modules in series and the non-uniform solar irradiance for simulating the partial shading conditoins. In the profile I, the maximum power, 1411W, is reached at 287V while the GMPP in the profile II, 1113W, is reached at 250V. In the MPPT method, four particles within the pre-specified PV voltage range are applied.

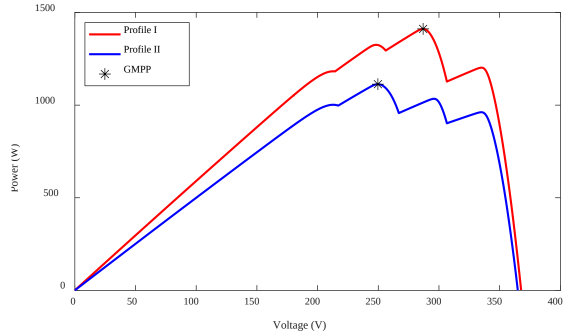
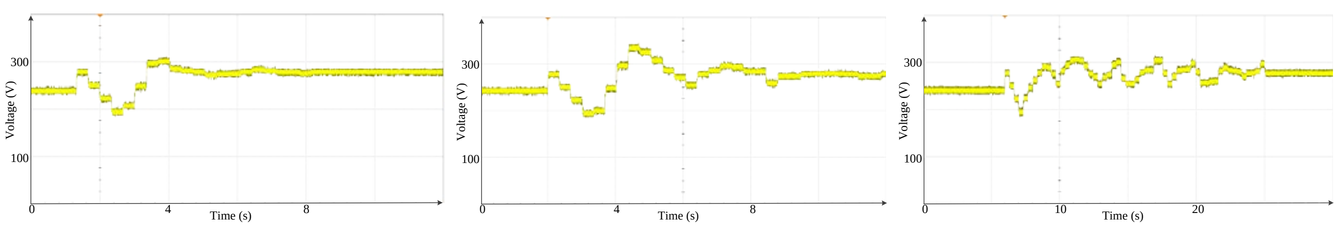


Fig. 13. PV profiles utilized in the experiment.

B. Experimental Results

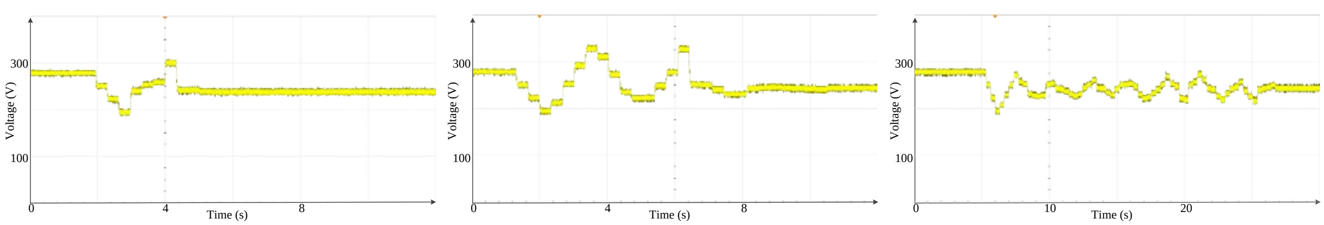
In the experiment, two profiles are switched every 60s in the PV simulator. The experimental tracking waveforms of S-Jaya, Jaya, and PSO algorithms are presented in Figs 14-15. It is observable that the tracking speed of the S-Jaya algorithm is the highest as it takes 4s and 2.67s to track the GMPP in profile I and profile II respectively according to Figs. 14-15. The generic Jaya algorithm takes 8s and 6.67s and the PSO algorithm takes 18.48s and 21.33s. This confirms the faster tracking speed of the S-Jaya algorithm by comparing with the benchmarking methods.

The comparison of the power generation sampled by the PV simulator (sampling interval = 1s) is depicted in Fig. 16. It further illustrates that the S-Jaya algorithm converges to the GMPP with a higher speed and lower oscillations. The overall tracking efficiencies of different algorithms for each cycle in Fig. 17 are provided in Table IV. From Table IV, the proposed S-Jaya provides a higher overall tracking efficiency.



(a) (b) (c)

Fig. 14. Tracking waveforms of profile I: (a) S-Jaya; (b) Jaya; (c) PSO.



(a) (b) (c)

Fig. 15. Tracking waveforms of profile II: (a) S-Jaya; (b) Jaya; (c) PSO.

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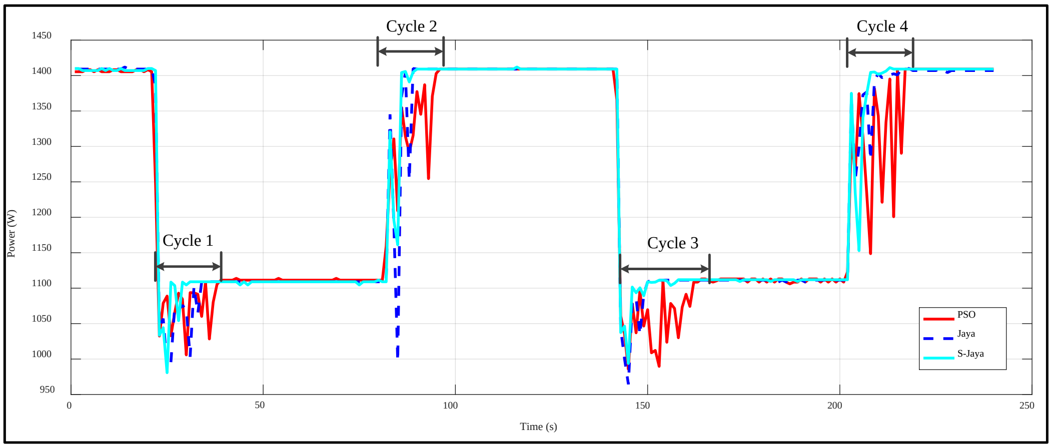

Fig. 16. Comparison of power generations based on different MPPT methods

TABLE IV
COMPARISON OF OVERALL TRACKING EFFICIENCY η.

Algorithm	Cycle 1	Cycle 2	Cycle 3	Cycle 4	Average
PSO	96.16%	93.71%	96.10%	92.28%	94.56%
Jaya	98.13%	94.43%	98.33%	97.46%	97.09%
S-Jaya	99.83%	97.35%	98.91%	97.47%	98.39%

Results of conducted experiments strongly support that the proposed S-Jaya algorithm can efficiently solve the MPPT problem of PV systems exposed to partial shading conditions, which indicates more power could be generated by PV systems under complicated partial shading conditions.

VI. CONCLUSIONS

A novel MPPT method based on our proposed S-Jaya algorithm for PV systems under partial shading conditions was presented in this study. The MPPT problem of PV system exposed to partial shading conditions was described. The model of PV power generations was multimodal and its form varied nonlinearly with the non-controllable parameters. Hence, model-free solution algorithms were employed to address the MPPT problem for PV systems under partial shading conditions.

The Jaya algorithm, a variant of the swarm intelligence, did not require algorithm-specific parameters and this advantage made it an attractive solution algorithm for the MPPT of PV systems compared with other heuristic search algorithms. However, random numbers in the generic Jaya algorithm could produce possible negative solution updates and thereby degraded the MPPT performance. In this study, the generic Jaya algorithm was extended to an S-Jaya algorithm by integrating a natural cubic spline model which offers accurate predictions to guide the iterative updates of candidate solutions. In the S-Jaya algorithm, the natural cubic spline model predicted the effectiveness of the updated solutions and negative updates were discarded. To validate the feasibility and effectiveness of the proposed MPPT method, comprehensive simulation studies and experiments were conducted. The performance of the MPPT based on the S-Jaya algorithm was compared with the MPPT based on the generic Jaya algorithm and well-tuned PSO algorithm.

Results of the simulation studies and experiments demonstrated that the S-Jaya algorithm outperformed benchmarking algorithms in terms of the convergence speed, the oscillations in the convergence, and the overall tracking efficiency. This finding supported that the proposed S-Jaya algorithm could track the GMPP more effectively and efficiently.

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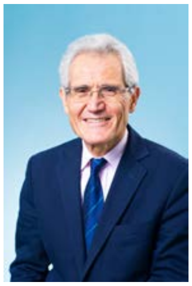
include time- and frequency-domain analysis of power electronic circuits, switched-capacitor-based converters, random-switching techniques, control methods, digital audio amplifiers, soft-switching converters, and electronic ballast design. He has edited one book, and authored eight research book chapters, and over 390 technical papers including 180 refereed journal papers in his research areas, and holds 40 patents. Dr. Chung is currently Editor-in-chief of the IEEE Power Electronics Letters, and Associate Editor of the IEEE Transactions on Power Electronics, and IEEE Journal of Emerging and Selected Topics in Power Electronics.



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