A Two-Stage Particle Swarm Optimization Algorithm for MPPT of Partially Shaded PV Arrays

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Abstract: The power-voltage (P-V) characteristic curves of a PV array are nonlinear and have multiple peaks under partially shaded conditions (PSCs). This paper proposes a novel maximum power point tracking (MPPT) method for a PV system with reduced steady-state oscillation based on a two-stage particle swarm optimization (PSO) algorithm. The grouping method of the shuffled frog leaping algorithm (SFLA) is incorporated in the basic PSO algorithm (PSO-SFLA), ensuring fast and accurate searching of the global extremum. An adaptive speed factor is also introduced into the improved PSO to further enhance its convergence speed. Tests results show that the proposed method converges in less than half the time taken by the conventional PSO method, and the power is improved by 33% under the worst PSCs, which confirms the superiority of the proposed method over the standard PSO algorithm in terms of tracking speed and steady-state oscillations under different PSCs.

Keywords: Maximum Power Point Tracking (MPPT); Particle Swarm Optimization (PSO); Shuffled Frog Leaping Algorithm (SFLA); Adaptive Speed Factor; Photovoltaic (PV) System; Steady-state Oscillations; Under Partial Shading Conditions(PSCs)

1 Introduction

Solar energy has been actively explored as a sustainable and clean energy source, but still presents some urgent practical problems. One of these is designing a fast and accurate maximum power point tracking (MPPT) algorithm for PV systems working under partial shading conditions. Here unequal irradiation striking a PV panel causes mismatched characteristics of the PV cells and a reduction of the power output obtained from the panel. The PV output Power-Voltage (P-V) characteristic curves may also present multiple power peaks. This feature makes it difficult for traditional methods, such as the Perturb & Observe (P&O) method (Femia et al. 2005), incremental conductance (IC) method (Zhang et al. 2011) and Hill Climbing (Alajmi et al. 2011) to distinguish between local and global peaks.

Recent research in this area has seen the application of various artificial intelligence schemes, such as fuzzy logic controller (FLC) (Alajmi et al. 2011; Bendib et al. 2014) and neural network (NN) (Bendib et al. 2014; Zhang and Bai 2008; Boumaaraf et al. 2015; Arthishri et al. 2014; Ngan and Tan 2016). Though these methods have been shown to be effective in dealing with the nonlinear characteristics of the I–V curves, they incur considerable computational cost (Ishaque et al. 2012). For example, FLC has to deal with fuzzification, rule base storage, inference mechanism, and defuzzification operations. For NN, the large amount of data required for training and validating the NN models are a major constraint. Furthermore, as the operating conditions of the PV system vary continuously, MPPT has to respond to changes in insolation and temperature variations in real time (Ishaque et al. 2012).

Alternative approaches use evolutionary algorithms such as particle swarm optimization (PSO) algorithm (Eberhart and Kennedy 1995), artificial fish swarm algorithm (AFSA) (Li et al. 2002), artificial bee colony (ABC) algorithm (Karaboga 2005) or shuffled frog leaping algorithm (SFLA) (Eusuff and Lansey 2003). Among these, PSO has been applied to search the maximum power points (MPPs) by many researchers. Compared with the traditional MPPT methods such as P&O, IC, HC, FLC and NN etc., the conventional PSO converges faster and can locate the MPPs. However under continuous variation of PSCs, it can be slow to converge and the obtained power can be less than the global maximum. To address this issue, several researchers have proposed modifications to PSO to improve its performance in the maximum power point tracking (MPPT) under PSCs. The work in (Ishaque et al. 2012) employed PSO to locate the nearest section where the global MPP may lie, and then used Hill-Climbing to find the exact point. A hybrid PSO and Artificial Neural Network (PSO-ANN) algorithm was proposed in this article to detect the global peak power point in the presence of several local peaks (Ngan and Tan 2016). The authors in (Phimmasone et al. 2010) have updated the traditional PSO equations by adding various coefficients to improve the searching accuracy of the algorithm. Nevertheless, all the above did not address the restarting scheme which is necessary when weather conditions and the shading patterns change.

This paper presents a new scheme for global MPP tracking for a PV array operating under partial shading conditions. Taking into account multiple peaks in the output power-voltage curve of a PV array the proposed algorithm combines the basic PSO algorithm with the grouping idea of SFLA to divide the particle population into multiple group/swarms. This leads to a two-stage PSO algorithm, which benefits from the fast and accurate local search capability of PSO, and then uses the SFLA approach of exchanging results from parallel local sectors to converge to the global solution. The proposed algorithm uses variable parameters in PSO to speed up the searching process. The paper will describe the principles of this algorithm, analyse its convergence rate, and present simulation results under various operating conditions.

2 Modelling and output characteristics of PV Panel under PSCs

2.1 PV cell model under PSCs

PV panel partial shading is one of the main causes of electrical mismatching of series connected PV cells, and can lead to the eventual avalanche breakdown of shaded cells (Su et al. 2001). The junction temperature increases considerably due to high avalanche current, causing thermal breakdown of the shaded cell.

The model for the shaded PV cell proposed by J.W. Bishop (Bishop 1998) is shown in Fig. 1 (a). It has the same configuration as the well-known PV equivalent circuit model except that the shunt resistance branch includes a multiplication factor $M(V_j)$. This describes avalanche breakdown effect on the shunt leakage current I_{sh}, and is expressed as follows:

$$M(V_j) = 1 + a(1 - \frac{V_j}{V_{br}})^{-m} \tag{1}$$

where V_j is the P-N junction voltage, V_{br} is the junction breakdown voltage which is negative, while a is the fraction of ohmic current, and m is the avalanche breakdown exponent. These elements represent the reverse characteristics which may occur under PSCs. Thus the panel shunt leakage current is

$$I_{sh} = \frac{V_j}{R_{sh}} M(V_j) \tag{2}$$

For un-shaded case, V_j holds a small value below p-n junction threshold value, so $M(V_j)$ is about 1. Under shading, V_j approaches the break down voltage V_{br}, and hence $M(V_j)$ becomes large, resulting in high shunt current.

The output current of a single cell is expressed as

$$I_{out} = I_{ph} - I_s(\exp\left[\frac{q\left(V_{out} + R_s I_{out}\right)}{AKT_c}\right] - 1) - I_{sh} \tag{3}$$

where I_{ph} is the photocurrent, I_s is the reverse saturation current of diode D, A is diode ideality factor, q is the electron charge (1.609×10^{-19}C), T_c is the cell absolute temperature in K, K is Boltzmann's constant. The cell output voltage is given by

$$V_{out} = V_j - R_s I_{out} \tag{4}$$

The single cell equation can be extended to represent a PV array with N_P cells in parallel and N_S cells in series, expressed as

$$I_{out} = N_P I_{ph} - N_P I_s \left[\exp\left(\frac{q\left(V_{out} / N_S + I_{out} R_{ST}\right)}{AKT_c} \right) - 1 \right] - \frac{V_{jtotal}}{R_{PT}} M(V_{jtotal}) \tag{5}$$

where $V_{jtotal} = V_{out} N_P / N_S + I_{out} R_{ST}$, $R_{ST} = \frac{N_S}{N_P} R_S$ and $R_{PT} = \frac{N_P}{N_S} R_P$. It can be seen from Eq. (5) that the maximum power extraction from a PV array is a challenging task because of its non-linear characteristics, which change under different environmental conditions. In particular since each of the PV arrays is composed of multiple PV modules connected in a chain, e each module may be exposed under different light levels (e.g., due to moving clouds, shading from surrounding buildings, trees or poles, and building integrated PV applications, etc.), then the output characteristics of the PV array exhibits multiple local maxima, resulting in the energy loss (Wang and Hsu 2010; Patel and Agarwal 2008). The power dissipated across the cell will be in the form of heat. This is commonly known as a hot spot. Hot spot heating will not only reduce the array power output, but it will damage cell materials, putting entire arrays out of action (Bishop 1998). It is therefore vital to find a way to solve this problem.

The I-V characteristic curve of a simulated PV cell under shading condition is shown in Fig. 1(b). As can be seen, under normal irradiation condition the PV cell junction voltage rises to its open circuit value, $V_{OC,}$ which is about 0.6V, and the short circuit current I_{SC} at V_j =0 is according to light intensity. The reverse mode of the PV cell is up to the rated p-n junction breakdown voltage which can be -12 to -20V for poly-si PV cells or -30V for mono-Si PV cell (Alkaisi and Aldawody 1990; Herrmann 1997; Wohlgemuth and Herrmann 2005; Deline 2009; Shimizu 2003; Abdalla 2013).

For a PV module formed by connecting many PV cells in series and in parallel, the model can be represented as shown in Figure 1(c). Clearly this model treats the condition of shading on a single cell or a group of cells as the shading of the entire module. Bypass diodes are typically used to reduce reverse breakdown and hot-spots.

2.2 Output characteristics of PV array under PSCs

As a result of the partial shading, the generated current of a PV array having multiple modules connected in series is limited by that of the shaded PV ones. The terminal voltages corresponding to the peak power points of a PV array is a key piece of information for the MPPT algorithm under PSCs. This work considers a PV array consisting of three PV modules of identical type, and all having 20 chained cells in series and one string in parallel. The irradiation levels on the modules may be different, and are taken to range from 100 to 1000 W/m^2 as illustrated in Figure 2.

The parameters of a single cell in this PV array, obtained from the component datasheet, are listed in Table 1. The P-V and I-V characteristics of the array under different irradiation levels are simulated at the fixed temperature of 25°C. Figure 3 shows the 3-D plots of the obtained power-voltage (P-V) and current-voltage (I-V) curves as functions of irradiation. Thereinto, Figure 3(a) shows P-V curves of the PV array under 5 different light intensity conditions, including: (1000W/m^2, 1000W/m^{2,} 1000W/m^2), (1000W/m^2, 900W/m^{2,} 750W/m^2), (1000W/m^2, 700W/m^{2,} 500W/m^2), (1000W/m^2, 500W/m^{2,} 300W/m^2) and (1000W/m^2, 350W/m^{2,} 100W/m^2). I-V curves of the PV array under 5 different light intensity conditions are shown in Figure 3(b). These correlate well with the characteristics provided by the array manufacturer. Therefore this model is used for testing the MPPT algorithms.

3 Proposed MPPT Algorithm

The proposed new MPPT method which combines the improved PSO algorithm with the SFLA is presented below in this section.

3.1 Principles of PSO Algorithm

PSO is an evolutionary computation technique proposed by Kennedy and Eberhart in 1995 [10]. Originated from observing the behavior of bird flocks searching food in an area, PSO adopted the scenario and applied it to solve the optimization issues. In PSO, a set of randomly placed particles is initialized; each particle represents a potential solution and has a corresponding fitness value based on a fitness function to be optimized. The objective is to search the optima by updating generations of particles. Assuming in a space containing S particles, the velocity and position of the i_{tch} particle are respectively denoted as v_i and x_i. In the iterative process, the position of this particle at the kth time step is influenced by the information of its own best P_i and the global best solution P_g. The particle position update formulas are written as follows:

$$v_i^{k+1} = \omega v_i^k + c_1 r_1 \left(P_i^k - x_i^k\right) + c_2 r_2 \left(P_g^k - x_i^k\right) \tag{6}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{7}$$

where ω is the inertia weight factor, c_1 and c_2 are the acceleration factors, r_1, r_2 are random values $\in(0, 1)$, and k is the iterative order. To prevent the particles searching blindly, their velocities and positions are limited in the ranges defined respectively by $[v_{min}, v_{max}]$ and $[x_{min}, x_{max}]$.

Applying the PSO algorithm to search the MPPs of a PV array with multiple modules in a chain and operating under PSC, the set of particles is the voltage values. The fitness function is based on the model of the PV array given by eq. (3). The fitness value for each particle (voltage) is evaluated as the product of updated voltage and the result of the model which is the corresponding current. The size of the population can be large since it needs to cover the array's entire operating voltage range from short to open circuit.

The traditional PSO algorithm has been shown to give good performance in many applications. However it has some defects which need to be resolved. For example for accuracy the algorithm must have a large population size to cover a wide area which is certain to contain all the optima. In addition the searching velocity cannot be too high in case it misses the optimal particle. Hence the algorithm is slow to converge. On the other hand a larger searching velocity may result in low precision and a relapse into local optimization.

3.2 Two-Stage PSO Algorithm with the SFLA

The proposed PSO algorithm takes into account the specific feature of a PV generation system operating under PSCs, namely that the P-V characteristic exhibits multiple peaks. The number of these peaks depends on the number of chained modules and their respective illumination levels, and only one of them corresponds to the global maximum power point (MPP), as shown in Figure 3(a). Since the PSO algorithm can only deal with local search effectively, it is natural, in this application, to combine it with a scheme which can partition the searching space into multiple sectors corresponding to the number of modules in a PV array so that local parallel searching leading to the global solution can be performed. SFLA (shuffled frog leaping algorithm) is considered ideal for performing this with PSO due to its special features. This is a meta-heuristic algorithm, and its working principle is summarized as follows. The algorithm works on a population of particles (frogs), each of which has a fitness value which measures its quality in terms of the required solution. By partitioning these particles into multiple subsets also called meplexes, according to their ranking orders, the algorithm performs local searches for optimal solutions within each memeplex. The results obtained are then shuffled so that the information can be passed. This local search and shuffling process continues until a defined convergence criterion is met (Eusuff and Lansey 2003). Applying this to MPPT for a PV array under PSCs, we firstly use the SFLA concept to assess a population of particles; these are the voltage values covering the whole P-V curve of an array according to a fitness function which is defined as the output power of the PV array using the product of V_{out} and I_{out} by Eq. (5). These can then be partitioned into several groups and in this case the division can be made according to the number of modules in the array. As shown in Figure 4, in this paper G_1, G_2 and G_3 represent three different groups or swarms and for simplicity each group is made up of three particles. In the second step PSO is applied to perform searching for the peak power point in each group. Each of these groups has its own voltage searching range, based on its short and open circuit voltage values. As seen in the diagram P_g, P_{m1} and P_{m2} are the best positions of particles within their respective groups, i.e. the local MPPs. These are then shuffled with each other as well as all other particles for finding the global best.

The above two-stage procedure and the equations used are detailed as follow.

Stage (1): All particles are divided into several groups according to the grouping idea of the SFLA, and in each group/swarm, with the local best already obtained, the speed and position of each particle within the group are updated by using the equations:

$$v_{mn}^{k+1} = \omega v_{mn}^{k} + c_1 r_1 \left(P_m^k - x_{mn}^k \right) \tag{8}$$

$$x_{mn}^{k+1} = x_{mn}^{k} + v_{mn}^{k+1} \tag{9}$$

where m =1, 2, …, M being the number of groups, and n = 1, 2, …, N, where N is the number of particles within a group. P_m is the best position of particles in the m_{th} group. Having obtained n particle positions at the (k+1)th step, we evaluate their fitness values which are the power values and then acquire the best particle. Subsequently, a new local best position for the m_{th} group, P_m, is derived.

Stage (2): Using m local best particles to find the one giving the maximum power amongst them, this is chosen as the optimal for the entire population at the kth iteration step, i.e the global best. The speed and position of the local best particles are updated by the formulas:

$$v_m^{k+1} = c_2 r_2 \left(P_g^k - P_m^k \right) \tag{10}$$

$$P_m^{k+1} = P_m^k + v_m^{k+1} \tag{11}$$

where P^k_g is the best position of particles in the entire swarm at the kth iteration.

It is worth highlighting that this updating process is fast since the population size is determined by the number of groups and this is small. In the current application m=3. In the iterative procedure, when the best value within a group is equal to the global best value, the (P_g-P_m) in eq. (10) is zero. The iterative process converges. The algorithm also stops when a fixed iteration count J is reached.

3.3 PSO with adaptive inertia weight factor

In the above two-stage PSO algorithm, the first iterative process for updating n particles uses the inertia weight factor ω. According to Shi and Eberhart's analysis in (Shi and Eberhart 1998), the inertia weight is critical in balancing the global and local search. A larger inertia weight facilitates global exploration while a smaller one helps the local refinement (Shi and Eberhart 1998). It is beneficial in this application to apply a damping mechanism to ω so as to obtain a stable global exploration in the initial stages, and fast local exploitation when the swarm is closer to the source (Zou et al. 2015). Thus linearly decreasing ω with the iterative generation index is adopted and is expressed by the following equation as:

$$\omega = \omega_{max} - \left(\omega_{max} - \omega_{min} \right) \frac{K}{J} \tag{12}$$

where K is the generation index representing the current number of evolutionary generations, and J is a predefined maximum number of generations. The maximal and minimal weights ω_{max} and ω_{min} have been set to 0.9 and 0.4.

3.4 Algorithm Restart Condition

The MPP of a PV array is greatly influenced by the insolation and temperature, so it is necessary to restart the algorithm to track the MPP again when the weather condition changes. At the present, most PV systems using MPPT schemes restart the searching algorithms after a fixed elapsed time. Such a method lacks flexibility, and frequent auto restart results in power losses. The restarting scheme proposed here checks the actual power output of the PV array under the real measured light levels, after and compares it with the rated value to determine whether the PV array is partially shaded. The expected power defined as

$$P_{real} < P_{pv}(\frac{G}{G_{STC}})[1+\alpha_p(T-T_{STC})] = P_e \tag{13}$$

is used to trigger the restarting process. In Eq.(13) P_{pv} is the rated power of the array, G is the actual solar insolation, G_{STC} is the insolation (1000W/m^2) under the standard test condition, α_p is the temperature coefficient of power of PV module (-0.35%/°C), T is the actual temperature of the PV module, and T_{STC} the temperature (25°C) under the standard test condition.

Under PSCs, when actual power P_{real} is significantly below P_e, the MPPT control will be restarted. In this paper, the restart condition is set as

$$\frac{|P_{real} - P_e|}{P_e} > \Delta P \tag{14}$$

where ΔP is the required fractional deficit in output power. The value ΔP = 5% was found to be appropriate, based on the simulation results.

3.5 Implementation Procedure of the Proposed Algorithm

This is shown in the flowchart in Figure 5. Initially a set of particles is randomly chosen, these being voltage values within the output voltage range of the PV array, or duty ratios when a DC-DC converter is used. These are divided into groups according to the module number, and the maximum P_m in each group is determined by evaluating their respective fitness function values. Then the proposed two-stage PSO is applied to update the individual particle positions in each group using eqs. (8) and (9), and the local maximum P_m using eqs.(10) and (11). These result in m newly updated local peaks, and the one giving the highest power is set as the global peak at the kth iteration. The process is repeated until the iteration process converges.

4 Empirical Evaluations

To evaluate the proposed method, a PV array with a Boost converter is utilized, and the schematic diagram of this system is shown in Figure 6(a). This converter is designed with the following parameters: inductor L=0.15mH, input capacitance C_1=47μF, output capacitance C_2=82μF, resistance R_{load}=50Ω, and the converter switching frequency is 20 kHz. Experiments were performed by using the MATLAB R2016a on a computer with Intel(R) Core(TM) i5 CPU 3.10GHz 8G RAM, and Windows 64 bit operation system. The PV array has three modules connected in series. The parameters of the single module under the standard test condition are as shown in Table 1.

To check the effectiveness of the proposed method under partial shading, it has been compared with the traditional PSO algorithm for the above PV system in simulation. Table 2 shows the basic parameters used in the traditional PSO method and the proposed method, including the inertia weightω, acceleration factors c_1 and c_2, number of particles S, number of groups M, and maximum iterative number J.

To study the algorithms three different light conditions are set for this PV system: Case 1, G_1=1000W/m^2, G_2=1000W/m^2, G_3=1000W/m^2; Case 2, G_1=1000W/m^2, G_2=300W/m^2, G_3=500W/m^2; Case 3, G_1=1000W/m^2, G_2=700W/m^2, G_3=800W/m^2. Figure 6(b) shows the P-V curves corresponding to these cases, and MPPs (P_{mpp}) for each case, incuding: Case 1, P_{mpp}= 249.85W, Case 2, P_{mpp}= 148.81W, and Case 3, P_{mpp}= 62.13W, can be clearly seen. Starting from case 1 initially, the switch to case 2 occurs at t = 0.2 sec. and case 2 to case 3 at t = 0.4 sec. as shown in Figure 7(a).

Figure 7(b) shows the variations of PV array output voltage (V_{pv}), output power (P_{out}) and duty cycle (D), using the traditional PSO algorithm, and Figure 7(c) presents the same parameters obtained from using the proposed algorithm. Clearly, as can be observed, compared to the traditional PSO algorithm, the three results for the latter have less oscillation during the MPP searching processes. In particular the output power converges to the peak points with little ripple. Also the proposed two-stage PSO converges much faster, taking only about 0.0137 sec. on average, but PSO's average time is about 0.0362 sec. In one case the poor convergence of PSO leads to high error of 26.332%. The quantitative results for the MPPT in the three cases are shown in Table 3. Furthermore, Table 4 shows the computational cost time of two MPPT methods in the five separate operations and average cost time of computational cost times of the five separate operations. It can be seen from Table 4 that the computational cost time of the proposed method is also less than the traditional PSO method's. Therefore, from Figure 7, Table 3 and Table 4, it is very obvious that the proposed algorithm is superior in the convergence speed, output accuracy and stability under different PSCs. This method can locate the precise MPP, reduce the oscillation and increase the output power effectively.

5 Conclusions

In this paper, we proposed an improved two-stage PSO algorithm using a grouping concept for the MPPT control in a PV system under PSCs. The grouping approach derived from the SFLA is introduced into the basic PSO algorithm, ensuring high speed of convergence and good accuracy. In addition an adaptive inertia factor is introduced into the improved PSO to further improve its convergence rate. Finally, numerical simulation experiments were performed to compare the proposed method with the traditional PSO under the same parameter settings and light conditions. The experimental results show: (i) the proposed method with appropriate parameters outperforms the original PSO algorithm in most cases; (ii) the proposed method has the benefits of fast and accurate searching for MPPs and can adapt quickly to the changes of light and temperature levels, demonstrating its superior performance for locating the global MPPs under PSCs.

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