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Evolutionary Computation based Dynamic Maximum Power Point Tracking

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Abstract

This paper presents a sensitive particle swarm optimizer (SPSO) for maximum power point tracking in photovoltaic power generation under partial shading condition. The cost function corresponds to the voltage-versus-power characteristic of the photovoltaic power generation. Depending on external environment, the cost function and its MPP vary in a complicated way. In order to track the dynamic MPP, the PSO has two strategies: the particles consisting of sampled voltages for real-time operation, we do not use the past history for adaptation to dynamic environment. Performing numerical experiments for basic artificial problems, the efficiency of the SPSO is confirmed.

1. Introduction

This paper studies an application of the particle swarm optimizer (PSO) to the maximum power point tracking (MPPT) of a photovoltaic power generation system under partial shading condition. The cost function corresponds to a voltage-versus-power characteristic of a photovoltaic power generation system and the maximum value of the cost function is the maximum power point (MPP). In real environment, depending on insolation, the cost function becomes a complex multi-model shape and the MPP becomes time-variant. The MPPT is an important problem in renewable energy supply technology and has been studied extensively [1]-[4]. In the studies, the most popular hill climbing method aims mainly at search of unimodal power characteristics in a time-invariant environment. It is not easy to track the dynamic MPP of multi-model cost function.

On the other hand, the PSO is well known as a population-based search algorithm. It is simple in concept, is easy to implement, and has been applied to optimization problems in various systems, e.g., nonlinear dynamical systems [6], signal processors [5], and renewable energy systems [7]-[9].

However, when PSO is applied to the Dynamic MPPT (DMPPT), it is difficult to track Dynamic MPP because past information adversely affects the update formula.

In order to realize a PSO-based DMPPT, this paper presents the sensitive particle swarm optimizer (SPSO). Furthermore, we propose an algorithm that does not use past history in order to escape from the local optima. Using the simple examples, the algorithm performance is evaluated.

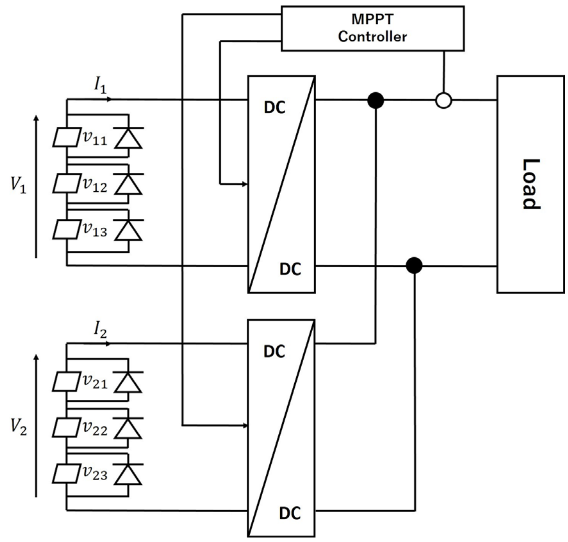

Figure 1: The paralleled PV system

2. Dynamic cost function

We define dynamic cost function. This paper uses paradelle photovoltaic (PV) system. Fig. 1 shows the parallel PV system. Fig. 2 shows dynamic cost function and MPP position. N cells connected in series with the bypass diode. M solar cell modules connected in parallel are controlled.

The cost function is based on the following voltage-current characteristics derived from a circuit model of solar cell [1] [2]

$$i_{jm} = f\left(v_{jm}, S_{jm}(t)\right) = I_{phm}(t) - I_{rr}\left(\exp\left(\frac{qv_j}{kAT}\right) - 1\right)$$
$$I_{phm}(t) = I_{scr}\frac{S_{jm}(t)}{100}, \quad j = 1 \sim N_C, \quad m = 1 \sim M \tag{1}$$

where v_{jM} [V] and i_{jM} [A] are the terminal voltage, current of the j-th cell and M is the number of dimensions, respectively. The parameters and symbols are defined/fixed as the following.

$S_j(t)$[mW/cm^2] insolation signal of the j-th cell.
N_C the number of cells.

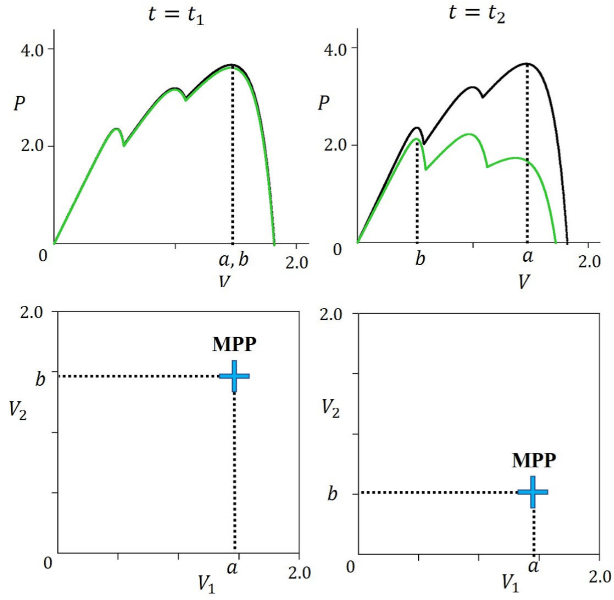

Figure 2: Dynamic cost function. $t1 < t2$.

$I_{scr} = 2.52$ [A]: cell short-circuit current.
I_{ph} [A] the photo-generated current.
$I_{rr} \doteq 20$ [μA]: the cell reverse saturation current.
$q \doteq 1.6 \times 10^{-19}$ [C] electronic charge.
$k \doteq 1.38$ [J/°K] the Boltzman's constant.
$T = 301$[°K]: cell temperature of the cell.
$A = 1.92$: the ideality factor.

The dynamic (time-variant) voltage-power characteristics of the PV array is given by

$$\begin{aligned} &P = (V_1, V_2) = V_1 I_1 + V_2 I_2 = F(V, t) \\ &V_1 = v_{11} + v_{12} + v_{13} \\ &v_2 = v_{21} + v_{22} + v_{23} \\ &v_{11} = r_{11}(i_{11}, t) = g^{-1}(v_{11}, S_{11}(t)) \\ &\vdots \\ &v_{mNc} = r_{mNc}(i_{mNc}, t) = g^{-1}(v_{mNc}, S_{mNc}(t)) \end{aligned} \tag{2}$$

where $v_{mNc} = g^{-1}(v_{mNc}, t)$ is the inverse function of $v = r(i_{mNc}, t)$ for i. $F(v_{mNc}, t)$ is the cost function and its MPP is the target of the search. The shape of the cost function depends on the insolation signal $S_{mNc}(t)$.

3. MPP search algorithm

Normal PSO controls multiple particles simultaneously. However, in an actual system, at a certain time. Since the operating point can take only one value, a plurality of operations. It is difficult to generate a plurality of particles corresponding to a voltage.

In order to approximate this, K sample values of (V_1, V_2) in the past history are defined as K imaginary particles, thereby a virtual particle group is constituted. In order to associate the number of particle positions with the sampling time.

$$\begin{array}{ll} 1 \le n \le N & 2 \le n \le N+1 \\ \boldsymbol{X_1}=\boldsymbol{x(1)} & \boldsymbol{X_1}=\boldsymbol{x(2)} \\ \boldsymbol{X_2}=\boldsymbol{x(2)} & \boldsymbol{X_2}=\boldsymbol{x(3)} \\ \vdots & \vdots \\ \boldsymbol{X_N}=\boldsymbol{x(N)} & \boldsymbol{X_N}=\boldsymbol{x(N+1)} \end{array}$$

There are various combinations of particles. In this paper, we use ring topology. In consideration of this, the parameters are set as follows.

n_{max} = 500: the operating step.
N: number of particles.
$\boldsymbol{X(n)}$: position of particles.
$\boldsymbol{Y(n)}$: velocity of particles.
Lb_i: position of Local best (Lbest).
F_{Lbi}: the evaluation value of Lbest.
$F(x(n))$: the fitness.

In DMPPT, particles may be captured by local optima. On the other hand, we propose a method that does not hold past information. Each step is defined below.

Step 1 (initialization): Take N sample values. Let $t = 0$ be the number of steps. The sample value is taken as the initial value. Update the position and velocity of N particles.

Step 2 (Lbest update):

$$\begin{array}{ll} Lb_i \leftarrow \boldsymbol{X_j(n)} & \text{if } \boldsymbol{X_j(n)} > Lb_i, \;\; j \in \{i-1, i, i+1\} \\ Lb_i \leftarrow Lb_i & \text{otherwise} \end{array} \tag{3}$$

Step 3 (Update of velocity and position):

$$\begin{aligned} \boldsymbol{Y(n)} &\leftarrow W\boldsymbol{Y(n)} + C(Lb_i - \boldsymbol{X(n)}) \\ \boldsymbol{X(n)} &\leftarrow \boldsymbol{X(n)} + \boldsymbol{Y(n)} \end{aligned} \tag{4}$$

where W and C are deterministic parameters. After trial-and-errors, we have fixed the parameter values: C=1.4, W=0.7

Step 4 (local best reset):

$$\begin{aligned} Lb_i &\leftarrow 0 \\ F_{Lbi} &\leftarrow 0 \end{aligned} \tag{5}$$

Step 5: Let $n \leftarrow n + 1$, let $i \leftarrow n$ mod 10, go to Step 2, and repeat until the maximum search step limit $n = 500$.

4. Numerical Experiments

We apply the SPSO to two examples of artificial DMPPT problems. The example is based on the decreasing insolation signal.

Fig. 3 shows snapshots of tracking process. The blue mark is MPP. Fig. 4 shows tracking process of SPSO. Fig.5 shows instantaneous tracking efficiency of SPSO. Fig. 6 and Fig. 7 shows result local PSO (LPSO).

LPSO cannot track MPP. Because particles were influenced by past history. Therefore, the particles search stopped.

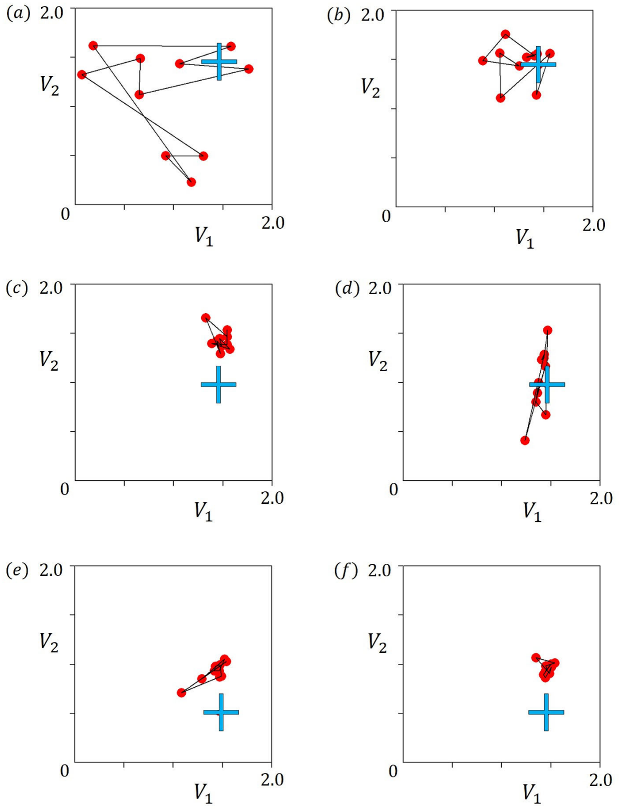

Figure 3: Decreasing insolation signal and snapshots of the dynamic cost function with SPSO. (a) $1 \leq n \leq 10$. (b) $91 \leq n \leq 100$. (c) $191 \leq n \leq 200$. (d) $291 \leq n \leq 300$. (e) $391 \leq n \leq 400$. (f) $491 \leq n \leq 500$.

However, SPSO was able to search longer than LPSO by resetting past information. So, the particles were able to escape from the local optima. We define the instantaneous tracking efficiency (ITE) and average tracking efficiency (ATE).

$$\text{ITE}(n) = \frac{f(X(n), n)}{\text{MPP}} \times 100 \ \ [\%] \qquad (6)$$

$$\text{ATE} = \frac{1}{n_{max}} \sum_{n=0}^{n_{max}} \text{ITE}(n) \ \ [\%] \qquad (7)$$

tab. 1 shows average for 100 different initial values.

ATE was confirmed that SPSO is more efficient than LPSO. : ATE = 89.8 for SPSO, ATE = 86.7 for LPSO.

5. Conclusions

The SPSO is presented and is applied to the DMPPT in this paper. In order to track MPP of the dynamic cost function, the SPSO uses imaginary particles, the flexible Lbest reset and don't use Pbest. Performing numerical experiments for basic artificial the problems. the efficiency of the SPSO is confirmed.

Future problems include optimal setting of parameter values for each problems, analysis of the tracking process, and fabrication of a test hardware for laboratory experiments.

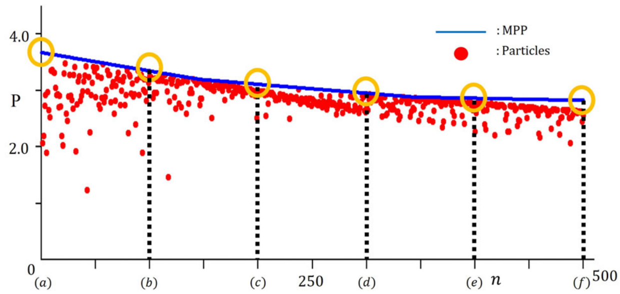

Figure 4: Tracking process of SPSO.

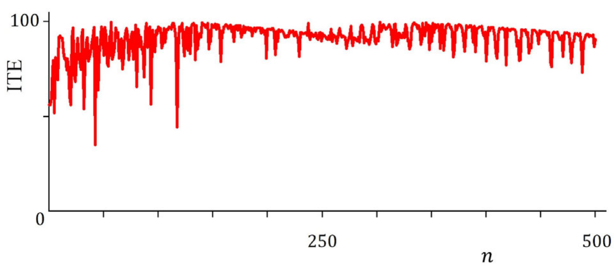

Figure 5: Instantaneous tracking efficiency of SPSO. ATE=91.4

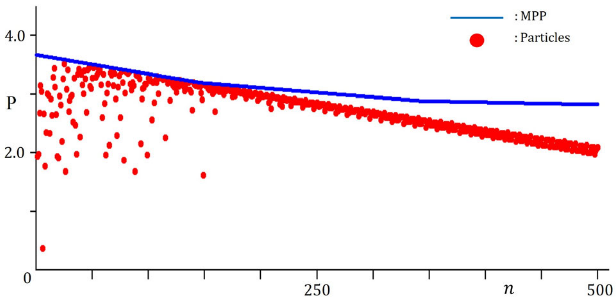

Figure 6: Tracking process of LPSO.

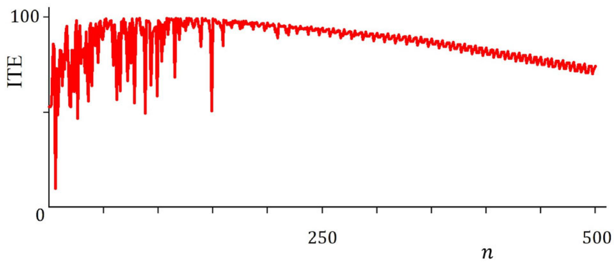

Figure 7: Instantaneous tracking efficiency of LPSO. ATE=86.9.

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