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Application of Artificial Bee Colony Algorithm to Maximum Power Point Tracking in Photovoltaic Systems

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Abstract—This paper studies application of the artificial bee colony algorithm to maximum power point tracking in Photovoltaic systems. Depending on insolation and temperature, the voltage-power characteristic becomes a complex multi-model shape and the maximum power point becomes time-variant. In order to track the maximum power point, this paper presents an improved algorithm including flexible re-assignment of individuals. Performing basic numerical experiments, the algorithm efficiency is investigated. The results are compared with several existing algorithms.

1. Introduction

The artificial bee colony algorithm (ABC) is known as an effective search algorithm in the swarm intelligence [1] [2]. The ABC is inspired by gulping behavior of honeybees and consists of two sub-routine: many points search and probabilistic search. The ABC is simple in concept, is easy to implement, and has been applied to various engineering systems including power electronics, analog-to-digital converters, and digital filters.

This paper studies application of the ABC to the maximum power point tracking (MPPT) of voltage-power characteristics in photovoltaic systems. The photovoltaic systems have studied as important renewable energy supply systems. The MPPT is an important problem in efficient renewable energy supply and has been studied extensively [3] [4]. However, depending on insolation and temperature, the voltage versus power characteristics become complicated dynamic multi-peak shape. It is not easy to realize the MPPT in such complicated characteristics.

In order to approach the MPPT, this paper presents an improved version of the ABC. In the ABC, the best individual is preserved and the other ones are re-assigned depending on stagnation of the search. The re-assignment is able to track the dynamic MPP flexibly.

Performing basic numerical experiments, the algorithm efficiency is investigated. The results are compared with several existing methods including individual swarm optimizers (PSOs [5]).

2. Photovoltaic system and cost function

Figure 1 shows the photovoltaic system. We apply the ABC to the MPPT in this system. The voltage-current characteristic is described by

$$
\begin{aligned}
i_j &= f(v_j, S_j) = I_{ph} - I_{rs}(\exp(\frac{qv_j}{kATn_s}) - 1) \\
I_{ph} &= (I_{scr} + k_i(T_s - T_r))\tfrac{S_j}{100},\ j = 1 \sim 3
\end{aligned}
\tag{1}
$$

where I_{ph} is the photo-generated current and n_s is the number of cells. q is the elementary charge and k is the Boltzman constant. I_{scr} is the cell short-circuit current. I_{rs} is the reverse saturation current. A is the diode ideality factor, and T_s is the temperature of solar cell. For simplicity, T_s does not vary as time goes. S_j is insolation of solar cells. Figure 2 shows insolation signals defined by

$$
\begin{aligned}
S_1 &= 15\cos(\frac{5t}{16} + \frac{7\pi}{6}) + 85) \\
S_2 &= 20\cos(\tfrac{5t}{32} + \tfrac{5\pi}{3}) + 50) \\
S_3 &= 10\cos(\tfrac{5t}{32} + \tfrac{3\pi}{2}) + 30)
\end{aligned}
\tag{2}
$$

Since the voltage-current characteristic is one-to-one for its, we describe the characteristic of each cell as a function of current and time:

$$
\begin{aligned}
v_1 &= g_1(i_1) = f^{-1}(v_1, S_1) \\
v_2 &= g_2(i_2) = f^{-1}(v_2, S_2) \\
v_3 &= g_3(i_3) = f^{-1}(v_3, S_3)
\end{aligned}
\tag{3}
$$

The whole characteristic is given by

$$
v = G(i) = \begin{cases} g_1(i_1) & (i_2 \le i < i_1) \\ g_1(i_2) & (i_3 \le i < i_2) \\ g_1(i_3) & (0 \le i < i_3) \end{cases}
\tag{4}
$$

Figure 3 is shows each voltage-current characteristic and whole voltage-current characteristic. Using this function, we obtain the objective time-variant cost function of the voltage-power characteristic:

$$
F(v) = vi = vG^{-1}(v)
\tag{5}
$$

Figure 4 is shows snapshots of the cost function . Our purpose is to track time-variant MPPs in this cost function.

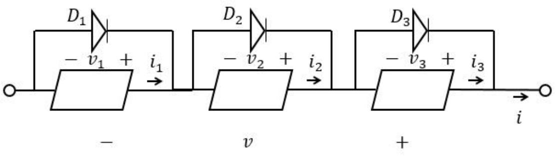

Figure 1: Photovoltaic System

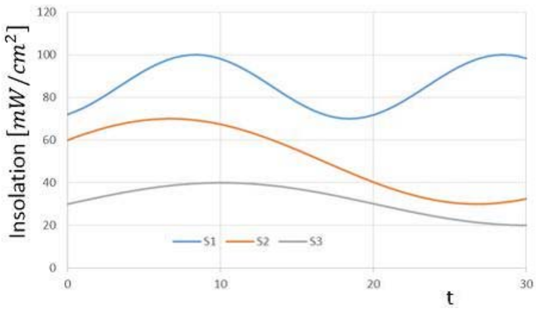

Figure 2: isolation signal

3. Artificial Bee Colony algorithm

In order to define the ABC, we give several basic definitions. The problem is tracking MPPs of the cost function in Equation (5).

ABC has 3 steps in search. The first step is global search. This step updates all particles depending on themselves and reference particles The second step is local search. This step updates only one individual depending on relative value probability. Last step is re-assign. This step is re-assigned by some particles when stop updating.

In the conrational ABC, all particles update at the same time. But, operating point is only one point at MPPT in real systems. So, it is difficult that all individuals update at the same time. This paper defines only one particles update at every sampling time $t = n\Delta t$, where $\Delta t = 1/M$ is the sampling interval, M is the number of particles. Here we defined the algorithm.

Step 1 Initialization
Using the voltage $v(t)$, the individual positions are initialized.

$$x_n = v(\Delta t) \tag{6}$$

Each individual has a counter T_n. T_n is initialized $T_n = 0$. If individuals do not update. T_n is updated; $T_n \leftarrow T_n + 1$.

Step 2 Global search
According to Equation (7), a candidate individual x_c is generated.

$$x_c = x_n + \phi(x_n - x_r) \tag{7}$$

where x_r is the reference individual. Reference individual is chosen randomly. ϕ is a random number in $[-1, 1]$. According to Equation (8), an individual is updated.

$$x_n \leftarrow \begin{cases} x_c & (F(x_c) > F(x_n)) \\ x_n & (F(x_c) \leq F(x_n)) \end{cases} \tag{8}$$

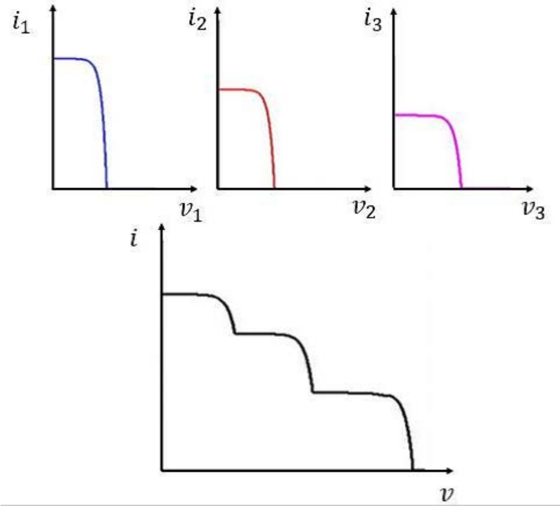

Figure 3: Voltage-current characteristics

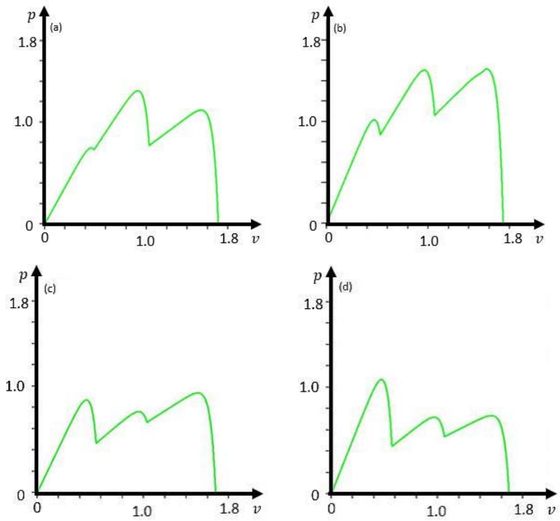

Figure 4: Time-variant voltage-power characteristic. (a) $t = 0$[s]. (b) $t = 12$. (c) $t = 24$. (d) $t = 30$.

Step 3 Local search
According to Equation (9), all individuals make relative value with probability P_n

$$P_n = \frac{F(x_n)}{\sum_{m=1}^{M} F(x_m)} \tag{9}$$

Using relative value probability P_n, one individual is chosen.

Step 4 The individual chosen by Step 3 repeats Step 2 for Mtimes.

Step 5 Replace
If T_n exceeds a threshold limit T_{lim}, x_n is re-assigned into search area.

Step 6 Update
The best individual Chose in all indivisuals.

Step 7 Repeat
Let $\leftarrow n+1$, go to step 2,and repeat until $n\Delta t = t_{max}$, where t_{max} is maximum time.

Replacing Step 5 with the following Step 5′, we obtain the RABC.

Step 5' Replace
If T_n exceeds a threshold limit T_{lim} and x_n is not best individual then x_n is re-assigned into search area.

4. Experiments

We apply the Rule-changed ABC (RABC) to the cost function Equation (5). After trial-and-error, the parameters are selected: $\Delta t = 0.2$, $t_{max} = 30$,$M = 5$, $T_{lim} = M$.

Figure 5 shows snapshots in trace process. For $t > 0$ can search the MPPs. The individuals have not accumulated and have kept diversity. Figure 6 shows MPPT process of ABC and RABC. RABC and ABC can almost trace MPP. But the individuals is apart from the MPP for $10 < t < 20$. RABC returns the MPP for $t < 16$. It is efficiency that the condition of re-assigned changes. After 100 times trials, in order to quantify the trace performance of the MPP, we have used Equation (10).

$$
\begin{aligned}
P_{ef} &= \sum_{k=1}^{100} P^k_{error}[\%] \\
P^k_{er} &= \frac{\sum_{n=1}^{Mt_{max}}(P_n - MPP_n)}{Mt_{max}} \\
MPP_n &= \text{MPP at time } t \\
P_n &= \text{power of time } t
\end{aligned}
\qquad (10)
$$

Table 1 shows performance of the MPPT of RABC. ABC and SDLPSO. The P_{ef} of RABC is compared with that of ABC and SDLPSO.

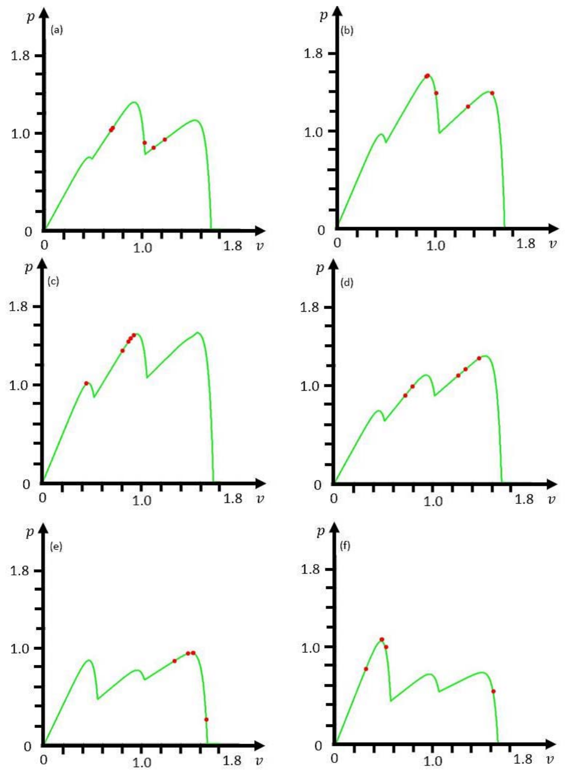

Figure 5: Snapshots of trace process of RABC. (a) $t = 0$[s]. (b) $t = 30$. (c) $t = 60$. (d) $t = 90$. (e) $t = 120$. (f) $t = 150$.

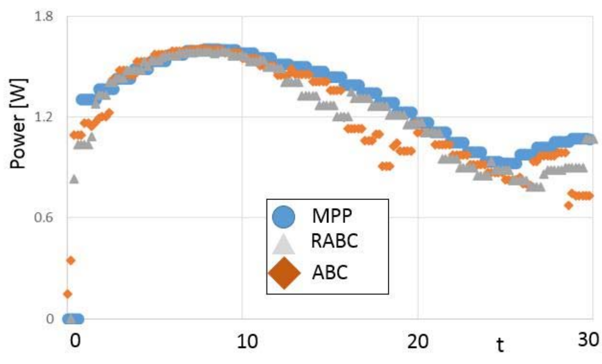

Figure 6: MPPT process.

Table 1:MPPT perfomance in three algorithms

	RABC	RBC	SDLPSO
P_{ave}	6.29	6.12	6.36

5. Conclusion

The RABC is presented and is applied to the MPPT in this paper. The algorithm include flexible re-assignment of individuals and can be effective to track dynamics MPPTs. The algorithm performance is investigated in basic numerical experiments and has been compared with several existing algorithms.

Future problems include analysis of search process and optimization of algorithm parameters.

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