

IEICE Proceeding Series

Insensitive Differential Evolution for Exploring Maximum Power Point

Naoto Ando, Masaya Muraoka, Toshimichi Saito

Vol. 2 pp. 197-200

Publication Date: 2014/03/18

Online ISSN: 2188-5079

Downloaded from www.proceeding.ieice.org

©The Institute of Electronics, Information and Communication Engineers

Insensitive Differential Evolution for Exploring Maximum Power Point

Naoto Ando[†], Masaya Muraoka[†] and Toshimichi Saito[†]

[†]EE Department, Hosei University, Tokyo 184-8584, Japan, Email: tsaito@hosei.ac.jp

Abstract—This paper studies an insensitive differential evolution and its application to exploring the maximum power point in photovoltaic systems. Depending on the insolation, the maximum power point varies and complicated multi-peak is generated. Our algorithm has a key parameter that controls particles insensitivity that can be effective to prevent trapping of particles. Performing basic numerical experiments, the algorithm efficiency is investigated.

1. Introduction

This paper studies the insensitive differential evolution (IDE) and its application to exploring the maximum power point in photovoltaic systems. Outline and background of DE:

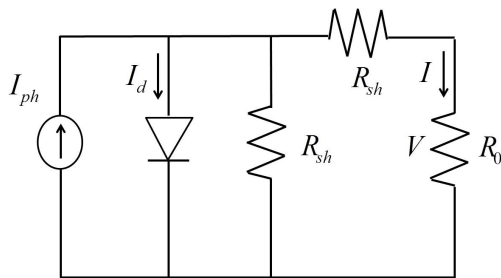


Figure 1: Equivalent circuit of a solar cell

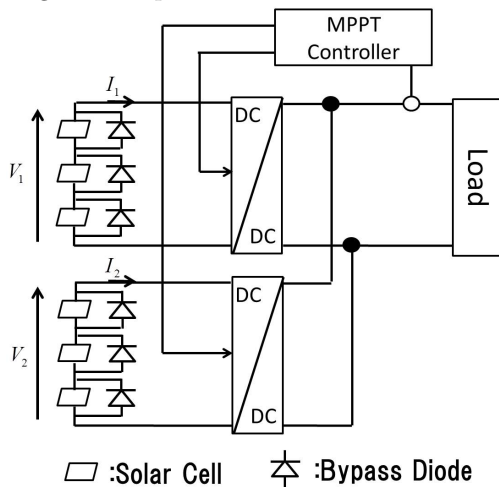


Figure 2: The paralleled PV system

The Difference Evolution (DE [1][2]) is an optimization technique. Each particle is a potential solution. Applying crossover and mutation, the particle location is updated and the particle try to find the optima. The DE is simple in concept, easy to implement and have been applied to various engineering systems: signal processing, power electronics, and communication systems[3][4].

This paper presents the IDE that can be insensitive depending on position of particles. In the IE, each particle has a territory. If the location of a particles is included in the territory, the particles movement is reinforced.

We apply the IDE to exploring problems of the maximum power point(MPP) in photovoltaic systems[5][6][7]. The MPP tracking is an important technique in renewable energy supply system. Depending on the isolation, the power characteristic varies and may become complicated multi-peak shapes.

If we apply standard DEs, it is hard to explore the MPP in the multi-peak problem because the particles often trapped into local peaks. The insensitivity of the IDE can be effective for escape from the trap. Performing basic numerical experiment for typical example, efficiency of the IDE is confirmed.

2. Objective Problem

Here we define the objective function. Figure 1 shows equivalent circuit of a solar cell. For simplicity, R_s and R_{sh} are ignored. The circuit is characterized by the parameters: I_{ph} =photo-generated current. I_{rs} =cell reverse saturation current. q =elementary charge. k =boltzman constant. A =diode ideality factor. The $V - I$ characteristics described by

$$I \equiv f(V) \equiv I_{ph} - I_{rs} \left(\exp \left(\frac{qV}{kATn_s} \right) - 1 \right) \quad (1)$$

We consider a multiple solararray system as shown in Fig.2. It includes two sets of three solar cells connected in series. They are controlled by single MPPT controller.

The PV characteristics is shown in Fig.3. Note that the cells have different isolation. The power characteristics is given by

$$F(V_1, V_2) \equiv V_1 f(V_1) + V_2 f(V_2) \quad (2)$$

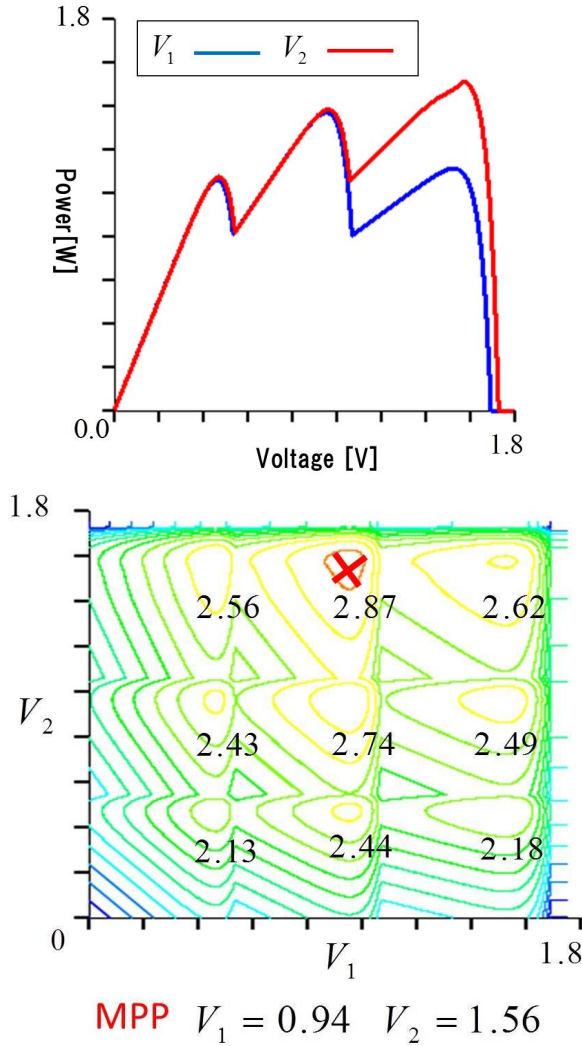


Figure 3: Objective function

Figure 4 show the contour map. The function F is the fitness of the IDE in this paper.

3. Insensitive Differential Evolution

The IDE operation is based on the location of particles and the fitness function. Let x_i^n be the i -th particle position at step n . We use plural particles in this paper. However, note that MPPT controller has single operating point corresponding single particle. It is hard to use plural operating point in practical system. Applying virtual particle technique is [8], the single particle can be translated in plural particles.

Step 1 (Initialization): Let step $n = 0$. The particles location X are initialized. The particles location are set randomly in the search space S_0

Step 2 (Mutation): The Gbest x_B^n is selected. Two vectors x_{x1}^n and x_{x2}^n selected randomly. offspring

is genelated by the following:

$$x_i^{new} = x_B^n + S(x_{p1}^n - x_{p2}^n) \quad (3)$$

where S is scaling parameter.

Step 3 (Crossover): Applying crossover to the offspring and the parent x_i^n , we obtain the next offspring x_i^{new} . where $i = 1 \sim N$. The offspring is inherited with probability CR . The CR is referred to as the crossover rate.

Step 4 (Survival):

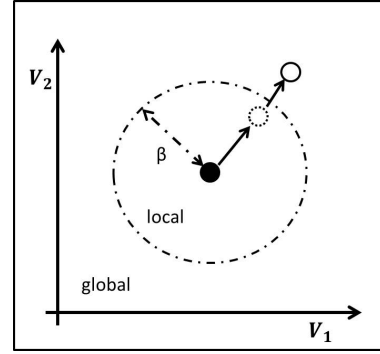


Figure 4: Neighbour-dependent insensivity

The distane of particle movement is measured and is reinforced as illustrated in fig.3. The offspring location is updated as the following:

$$x_i^{new} = x_i^{new} + \alpha(x_i^{new} - x_i^{n-1}) \quad \text{if } (x_{ix}^{new} - x_{ix}^{n-1})^2 + (x_{iy}^{new} - x_{iy}^{n-1})^2 \leq \beta^2 \quad (4)$$

where α is the scattering rate. β is the territory radius. The location is measured by the Euclidean distance.

The parent x_i^n is updated as the following:

$$f(x_i^n) < f(x_i^{new}) \text{ then } x_i^n = x_i^{new} \quad \text{otherwise : } x_i^n = x_i^{n-1} \quad (5)$$

Step 5 (Termination Condition): Let $n=n+1$, go to Step2 and repeat until the time limit n_{max} .

4. Numerical Experiments

In order to confirm the algorithm efficiency, we have performed basic numerical experiment. The scattering rate α is selected as a control parameter. For simplicity, the other parameters are fixed: scaling parameter $S = 0.6$, crossover rate $CR = 0.7$, the number of particles $N = 10$, time limit $n_{max} = 30$ scattering rate $\alpha = 0.35$ and territory radius $\beta = 0.7$. In order to evolute the performance, we introduce two measures:

SR: The rate of successful runs where the Gbest exceed $2.86[w]$ (The $MPP = 2.86$).

#ITE: The average number of iterations in successful runs.

Figures 4 (a) and (b) show typical examples of snapshot in the search process of IDE and DE, respectively. Figures 5 (a) and (b) show search process of IDE and DE, respectively. In the IDE, the particles are distributed and can find the MPP. In the DE, the particles tend to be trapped into the local peaks, and hard to approach the MPP. Figures 7 (a) and (b) show the SR and #ITE for α . As α increases the particles tend not to be trapped into local peak and the search speed becomes slow. $\beta = 0.7$ gives the highest SR. There exists a trade-off between the SR and #ITE as expected.

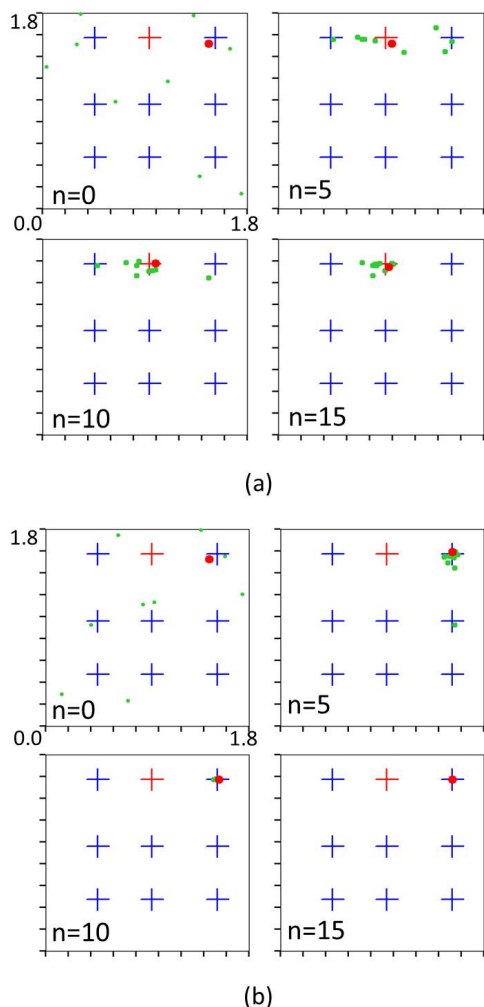


Figure 5: Typical examples of exploring the MPP. (a) A successful run of IDE (b) A failed run of DE The red circle is the gbest

5. Conclusions

Territory-dependent IDE and application to MPP search are studied in this paper. Exploring basic problem, we have confirmed that the diversity of particles

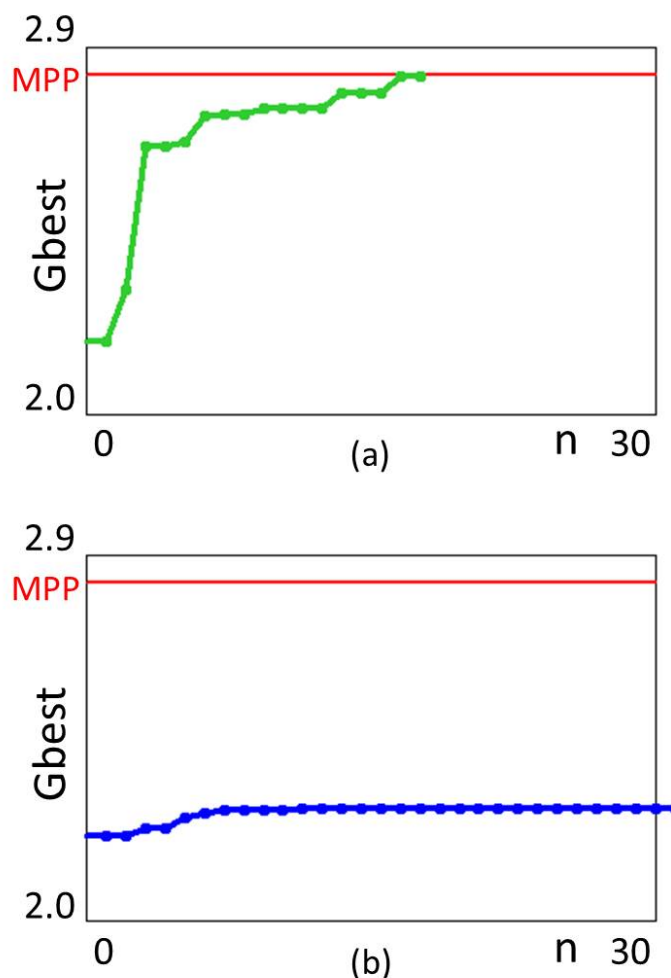


Figure 6: Exploring process (a) A successful run of IDE (b) A failed run of DE

can be controlled and the MPP can be found successfully. Future problems include analysis of relation between effect and various parameters.

References

- [1] A. P. Engelbrecht, Fundamentals of computational swarm intelligence, Wiley, 2005.
- [2] R. Storn and K. Price, "Differential evolution - a simple and efficient heuristic for global optimization over continuous spaces", Journal of Global Optimization, Vol. 11, pp. 341-359, 1997.
- [3] H. Lampinen, and O. Vainio, "An optimization approach to designing OTAs for low-voltage sigmadelta modulators", Proc. of the 2001 WCCI, pp. 1665- 1671, 2001.
- [4] B. Luitel and G. K. Venayagamoorthy, "Differential evolution particle swarm optimization for digital filter design", Proc. of the 2008 IEEE, pp. 3954-396, 2008.
- [5] M. Miyatake, M. Veerachary, F. Toriumi, N. Fujii and H. Ko, "Maximum Power Point Tracking of Multiple Photovoltaic Arrays: A Particle Swarm Optimization Approach" IEEE Transactions on Aerospace and Electronic Systems, Vol. 47, No. 1, pp. 367-380, 2011.

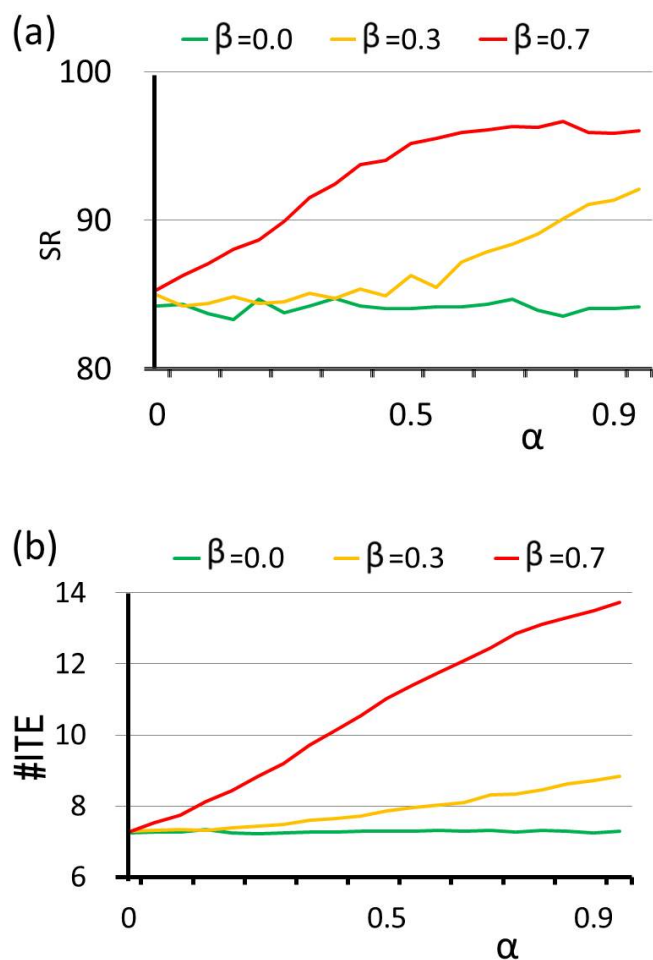


Figure 7: Performance for control parameter α . (a) The average successful rate (b) The average number of iterations

- [6] T. L. Nguyen and K.-S. Low, "A Global Maximum Power Point Tracking Scheme Employing DIRECT Search Algorithm for Photovoltaic Systems", IEEE Trans. Industrial, Vol. 57, No.10, pp. 3456-3467, 2010.
- [7] G. Vachtsevanos and K. Kalaitzakis, "A Hybrid Photovoltaic Simulator for Utility Interactive Studies", IEEE Transactions on Energy Conversion, Vol. EC- 2, No. 2, pp. 227-231, 1987.
- [8] M. Muraoka, N. Mikami and T. Saito, Exploring Maximum Power Point by Population-Based Optimization Algorithms, Proc. NOLTA, pp. 618-621, 2012