# Parameter Estimation of Photovoltaic Model, Using Balancing Composite Motion Optimization

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*Abstract: This paper investigates the dynamic parametric estimation of a solar cell system, by using balancing composite motions optimization (BCMO). The BCMO technique was first online published in 2019, the main idea is to balance composite motion properties of individuals in solution space, to equalize global and local searchability. To evaluate the performance of BCMO, experimental tests are carried out in photovoltaic cell parameters estimation of R.T.C.France which is collected under 1000 W/m$^2$ at 33$^o$C, by changing the population size of BCMO. And then, the performance of BCMO is compared with well-established parameters estimation methods in terms of convergence speed, computation time, and RMSE value. The results demonstrate that the proposed approach can be accurately estimated for photovoltaic model parameters.*

*Keywords: Balancing Composite Motions Optimization (BCMO); Photovoltaic Model; Parametric Estimation*

# 1 Introduction

In order to cope with air pollution and climate change, renewable energy sources such as solar, wind, hydro and biomass energy are increasingly widely used and become mainstream worldwide. Among them, solar energy is one of the highest attention for generating electricity based on photovoltaic (PV) technology in recent years. To study the maximum power extracted from PV cells, characteristics including open-circuit voltage (V), short circuit current (I), and maximum power point (MPP) must be identified [1-3]. Many approaches have been proposed to model characteristics of PV cells used of the equivalent circuit models such as the single diode model (SDM) and double diode model (DDM) [4], and three diodes model (TDM) [5].

To solve the PV cell parameters extraction, deterministic and metaheuristics optimization techniques have been widely developed. With a deterministic method-based approach, Paper [6] identified the five parameters of SDM of PV cells using a least-squares method. Paper [7] proposed a comparison of the Newton-Raphson method and the Levenberg–Marquardt algorithm in the PV cell parameters extraction. Paper [8] presented a Lambert W-function to extract seven parameters of DDM of the PV cell. However, these methods are easily trapped in local optima and sensitive to the initial condition.

On the contrary, the metaheuristics techniques are good at exploration and diversification to globally optimal solutions that do not need initial condition sensitivity and gradient information. These techniques have been applied to solve real-world problems recently such as analysis of geometry parameters variations for FinFET device based whale optimization algorithm (WOA) [9], optimizing of type-2 fuzzy controllers based slime mold algorithm [10], optimizing type-1 and type-2 fuzzy controllers based, grey wolf optimizer (GWO) [11], optimal production strategy using NSGA-II algorithm [12], cancer biomarkers identification using artificial bee colony based on dominance (ABCD) algorithm [13], deep reinforcement learning models with evolutionary algorithms [14], load forecasting based grasshopper optimization and neural network [15] and so on. To obtain the accuracy of PV cell parameters extraction, metaheuristics algorithms and variants were continuously proposed such as adaptive differential evolution (L-SHADE) algorithm [16], memetic differential evolution with Nelder-Mead simplex [17], JAYA and IJAYA [18], hybrid differential evolution with whale optimization algorithm (DE-WOA) [19], performance-guided Jaya algorithm (PGJAYA) [20], teaching-learning-based artificial bee colony (TLABC) [21], an advanced onlooker-ranking-based adaptive differential evolution (ORcr-IJADE) [22], adaptive Harris hawks optimization (AHHO) [23], comprehensive learning Rao-1 (CLRao-1) [24], random reselection particle swarm optimization (PSOCS) [25], radial movement optimization (RMO) [26], manta ray foraging optimization (MRFO) [27], improved gaining sharing knowledge (IGSK) algorithm [28], hybrid Jaya and DE algorithm (MJAYA) [29], salp swarm algorithm (SSA) [30], combining multi-task optimization and DE algorithm (SGDE) [31].

Recently, many new algorithms have been introduced such as Honey Badger Algorithm (HBA) [32], Artificial Gorilla Troops Optimizer (GTO) [33], Henry gas solubility optimization (HGSO) [34], Lévy flight distribution [35], Rao-1 [36] and logistic chaotic Rao-1 optimization algorithm (LCROA) [37]. Among them, Balancing Composite Motions Optimization (BCMO), which was first published online in 2019 [38], is via a probabilistic selection model that creates a movement mechanism of each individual to equal a global and local search in solution space. The purpose of this paper is to apply the BCMO algorithm for estimating the parameters of PV cells. To survey the effectiveness of BCMO, experimental tests are carried out in extracting parameters of SDM and DDM by changing the population size of BCMO. And then, BCMO is compared with other well-established parameters extraction methods such as JAYA [18], DE [19], MJAYA [29], SGDE [31], Rao-1, and LCROA [37].

The main contributions of this paper are given as follows:

- Investigate the influence of the population size - NP on the performance of the BCMO algorithm when estimating the PV cell parameters.
- The effectiveness of the BCMO algorithm is conducted by parameter extraction of R.T.C.France solar cell described in [31], which was collected under 1000 W/m$^2$ at 33$^o$C.
- Perform PV parameter estimation using the classical GA, DE, JAYA, and BCMO algorithms to analyze the convergence speed and computation time between these algorithms.
- Experiments are conducted to verify the superiority of the BCMO algorithm in comparison to other well-established parameters extraction methods such as JAYA [18], DE [19], MJAYA [29], SGDE [31], Rao-1, and LCROA [37]. The results prove that BCMO can be accurately identified and are highly competitive with other PV parameters extraction methods.

The rest of the paper is organized as follows. The mathematics of the solar cell and the optimization problem in modeling PV models is presented in Section 2. Section 3 introduces the BCMO technique and how to parameter extraction of the solar cell model. Section 4 shows the experimental results and analysis. Finally, the conclusions are presented in Section 5.

# 2 Problem Formulation

In general, there are two most commonly used in practice to describe the nonlinear features of the solar cell model, the single diode model (SDM) and the double diode model (DDM).

## 2.1 Single Diode Model

The equivalent circuit of a solar cell with a single diode includes a diode, a current source, a shunt resistor, and series resistance is illustrated in Fig. 1. In which, $I_{PH}$ is a photogenerated current, $I_{SD}$ is a reverse saturation current, n is a diode quality factor, $R_S$ is a series resistance, and $R_{SH}$ is shunt resistance.

According to Kirchhoff's current law, the output current $I_L$ can be calculated as:

$$I_L = I_{PH} - (I_D + I_{SH}) \tag{1}$$

Where $I_{PH}$ is the photogenerated current in a cell; $I_D$ represents acquired by Shockley formula Eq. (2); $I_{SH}$ is the shunt resistor current acquired by Eq. (3).

$$I_D = I_{SD}\left[\exp\left(\frac{q(V_L + R_S I_L)}{nkT}\right) - 1\right] \tag{2}$$

$$I_{SH} = \frac{V_L + R_S I_L}{R_{SH}} \tag{3}$$

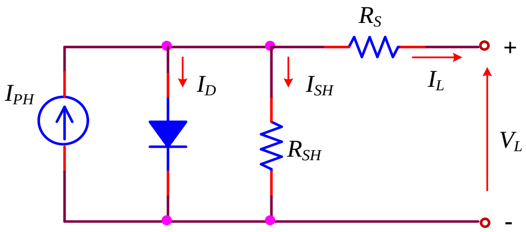


Figure 1
Equivalent circuit of SDM

In which, $V_L$ mean for the output voltage. *n*, *k*, *q*, and *T* represent the diode ideality factor, the Boltzmann constant ($1.3806503\times10^{-23}$ J/K), the elementary charge ($1.60217646\times10^{-19}$ C), and the cell temperature in Kelvin. Hence, Eq. (1) can be rewritten as,

$$I_L = I_{PH} - \left\{ I_{SD}\left[\exp\left(\frac{q(V_L + R_S I_L)}{nkT}\right) - 1\right] + \frac{V_L + R_S I_L}{R_{SH}} \right\} \tag{4}$$

It can be seen from Eq. (4) that there are five unknown parameters (i.e. $I_{PH}, I_{SD}, R_{SH}, R_S$ and $n$) that need to be extracted.

## 2.2 Double Diode Model

As shown in Fig. 2, the idea equivalent circuit model of a solar cell using a double diode model (DDM) consists of two diodes paralleled with both the shunt resistance and current source to shunt the photo-produced current source.

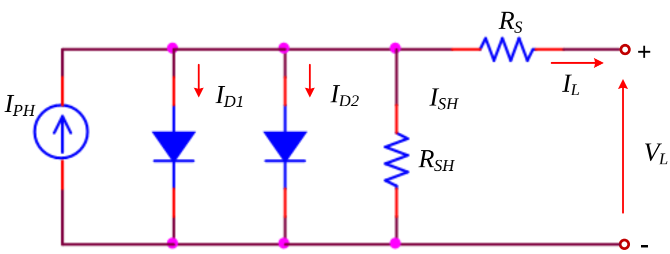


Figure 2
Equivalent circuit of DDM

According to Kirchhoff's current law, the output current is calculated as:

$$I_L = I_{PH} - (I_{D1} + I_{D2} + I_{SH}) \tag{5}$$

Moreover, currents $I_{D1}$, $I_{D2}$ calculated by Shockley formula, therefore:

$$I_L = I_{PH} - \left\{ I_{SD1}\left[\exp\left(\frac{q(V_L + R_S I_L)}{n_1 kT}\right) - 1\right] + I_{SD2}\left[\exp\left(\frac{q(V_L + R_S I_L)}{n_2 kT}\right) - 1\right] + \frac{V_L + R_S I_L}{R_{SH}} \right\} \tag{6}$$

Where $I_{D1}$ and $n_1$ are diffusion and diffusion ideality factors, respectively. $I_{D2}$ and $n_2$ are saturation current and recombination diode ideality factors, respectively.

Obviously, there are seven unknown parameters (i.e. $\left[I_{PH}, I_{SD1}, I_{SD2}, R_S, R_{SH}, n_1, n_2\right]$) that need to be extracted.

## 2.3 Objective Function

The problem of PV cell parameters extraction can be solved by minimizing the root mean square error (RMSE) between the experimental data and simulated data which is defined as follows:

$$RMSE(\mathbf{x}) = \sqrt{\frac{1}{N}\sum_{i=1}^{N} f_i(V_L, I_L, \mathbf{x})^2} \tag{7}$$

Where I-V data $(V_L, I_L)$ obtained from the experimental PV cell. $N$ is the number of samples of the experimental data. **x** is the set of the extracted parameters.

In Eq. (7), for SDM model:

$$f_{SDM}(V_L, I_L, \mathbf{x}) = I_L - I_{PH} + I_{SD}\left[\exp\left(\frac{q(V_L + R_S I_L)}{nkT}\right) - 1\right] + \frac{V_L + R_S I_L}{R_{SH}} \tag{8}$$

$$\mathbf{x} = \left[I_{PH}, I_{SD}, R_{SH}, R_S, n\right] \tag{9}$$

for DDM model:

$$\begin{aligned} f_{DDM}(V_L, I_L, \mathbf{x}) = I_L - I_{PH} &+ I_{SD1}\left[\exp\left(\frac{q(V_L + R_S I_L)}{n_1 kT}\right) - 1\right] \\ &+ I_{SD2}\left[\exp\left(\frac{q(V_L + R_S I_L)}{n_2 kT}\right) - 1\right] + \frac{V_L + R_S I_L}{R_{SH}} \end{aligned} \tag{10}$$

with $\mathbf{x} = \left[I_{PH}, I_{SD1}, I_{SD2}, R_S, R_{SH}, n_1, n_2\right]$ (11)

# 3 Balancing Composite Motions Optimization (BCMO) for Photovoltaic (PV) Parameter Estimation

## 3.1 BCMO Algorithm

The balancing composite motions optimization (BCMO) was first introduced in 2019 [38]. The BCMO algorithm includes the main phase as follows,

**Initialization**. Assume that it needs to minimize a *d* real-parameter function optimally. The population size (*NP*) of *d* real-parameter is defined. In the first generation, the population distribution is uniformly generated within the search space as follows:

$$\mathbf{x}_i = \mathbf{x}_i^{\min} + \mathbf{rand}(1, d)(\mathbf{x}_i^{\max} - \mathbf{x}_i^{\min}) \tag{12}$$

where $\mathbf{x}_i^{\min}, \mathbf{x}_i^{\max}$ are the min and max boundaries of the $i^{th}$ individual, respectively. rand (1,d) is a uniformly distributed random number from [0,1]. Then, all individuals in population are ranked, based on the following sorting:

$$\mathbf{x} = \arg sort\{f(\mathbf{x})\} \tag{13}$$

In which, $f(\mathbf{x})$ is the objective function values.

**Determination of the instant global point and the best individual.** We define an instant global optimum point $\mathbf{O_{in}}$ in the search space. The way to determine $\mathbf{O_{in}}$ in the $t^{th}$ generation is as follows:

$$\mathbf{x}_{o_{in}}^t = \begin{cases} \mathbf{u}_1^t & if \quad f(\mathbf{u}_1^t) < f(\mathbf{x}_1^{t-1}) \\ \mathbf{x}_1^{t-1} & otherwise \end{cases} \tag{14}$$

Where, $\mathbf{x}_1^{t-1}$ is the best individual in the previous generation. A trial individual $\mathbf{u}_1^t$ is indicated by using the population of the previous generation as:

$$\mathbf{u}_1^t = \mathbf{u}_c + \mathbf{v}_{k_1/k_2}^t + \mathbf{v}_{k_2/1}^t \tag{15}$$

Where $\mathbf{u_c}$ is a center point of the search space [min*B*, max*B*] and can be expressed:

$$\mathbf{u}_c = \frac{\min B + \max B}{2} \tag{16}$$

$\mathbf{v}_{k_1/k_2}^t$ and $\mathbf{v}_{k_2/1}^t$ are the relative movement of the $k_1^{th}$ individual concerning the $k_2^{th}$ and the $k_2^{th}$ individual to the previous best one. $k_1$ is randomly in a range [2, NP] and $k_2 < k_1$.

**Composite motion of individuals in solution space.** To balance the exploiting and exploring ability, the movement of the global search $\mathbf{v}_j$ is calculated as:

$$\mathbf{v}_j = \alpha_j \left( \mathbf{x}_{o_{in}} - \mathbf{x}_j \right) \tag{17}$$

Where $\alpha_j$ is the first-order derivative of the movement distance $\left( \mathbf{x}_{o_{in}} - \mathbf{x}_j \right)$ and is expressed as follows:

$$\alpha_j = L_{GS} \times \mathbf{dv}_j \tag{18}$$

Where $L_{GS}$ is the global step size scaling the movement of the j[th] individual and $dv_j$ is a direction vector. $L_{GS}$ and $dv_j$ are calculated based on a trial number $TV_j$ which is generated uniformly from [0,1] as follows:

$$L_{GS} = \begin{cases} e^{-\frac{1}{d}\frac{j}{NP} r_j^2} & if \quad TV_j > 0.5 \\ e^{-\frac{1}{d}\left(1-\frac{j}{NP}\right) r_j^2} & otherwise \end{cases} \tag{19}$$

$$\mathbf{dv}_j = \begin{cases} rand\left(1,d\right) & if \quad TV_j > 0.5 \\ -rand\left(1,d\right) & otherwise \end{cases} \tag{20}$$

Where $r_j$ is a distance from the j[th] individual to $O_{in}$ and is determined as:

$$r_j = \left\| \mathbf{x}_{o_{in}} - \mathbf{x}_j \right\| \tag{21}$$

Similarly, $\mathbf{v}_j$, the relative movement $\mathbf{v}_{i/j}$ of the i[th] individual concerning the j[th] one can be calculated by $\mathbf{x}_i$ and $\mathbf{x}_j$ as:

$$\mathbf{v}_{i/j} = \alpha_{ij} \left( \mathbf{x}_j - \mathbf{x}_i \right) \tag{22}$$

Where $\alpha_{ij}$ is expressed as follows,

$$\alpha_{ij} = L_{LS} \times \mathbf{dv}_{ij} \tag{23}$$

$L_{LS}$ can be fixed at 1 for balancing the local exploration and exploitation abilities of the i[th] individual. $\mathbf{dv}_{ij}$ is calculated as in Eq. (20).

The updated i[th] individual in the next generation is determined as follows:

$$\mathbf{x}_i^{t+1} = \mathbf{x}_i^t + \mathbf{v}_{i/j} + \mathbf{v}_j \tag{24}$$

## 3.2 Applied BCMO for Estimating the PV Parameters

BCMO is used to estimate the parameters of the PV model (five for the SDM and seven for the DDM) by minimizing the RMSE as shown in Fig. 3. The Pseudocode of the BCMO for PV parameters estimation is illustrated in Algorithm 1.

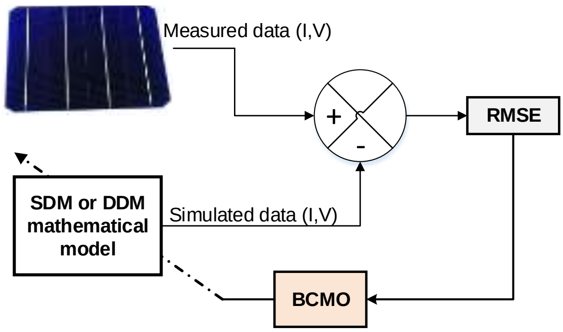


Figure 3

Block diagram of PV cell parameters estimation using BCMO algorithm

In which, *MinRMSE* is allowed error, *MaxIter* is the maximum number of generations. BCMO is a parameter-free optimization algorithm and the performance of BCMO only depends on the population size NP selected for each specific optimization problem.

**Algorithm 1:** The pseudo-code of BCMO used in parameter extraction

1: Generate the initial population
$x = [I_{PH}, I_{SD}, R_S, R_{SH}, n]$ or $x = [I_{PH}, I_{SD1}, I_{SD2}, R_S, R_{SH}, n_1, n_2]$
2: Evaluate the fitness of each individual in the population
3: Rank the population and find the best individual
4: **while**(*MinRMSE is attained or t < MaxIter*) **do**
5: Generate a trial individual $\mathbf{u}_1^t$ by Eq. (15) and Eq. (16).
6: Calculate $RMSE(\mathbf{u}_1^t)$
7: Determine $\mathbf{x}_{o_{in}}^t$ by Eq. (14)
8: $\mathbf{x}_1^t = \mathbf{x}_{o_{in}}^t$
9: **for** i = 2 **to** *NP* **do**
10: Calculate $r_j$ by Eq. (21); $L_{LS} = 1$
11: *% Determine the global search of the i^th individual*
12: $TV_j = rand[0, 1]$
13: **if** $TV_j > 0.5$
14: $L_{GS} = e^{-\frac{1}{d}\frac{j}{NP} r_j^2}$

$\mathbf{dv}_j = rand(1,d)$; $\mathbf{dv}_{ij} = rand(1,d)$
**else**
$L_{GS} = e^{-\frac{1}{d}\left(1-\frac{j}{NP}\right)r_j^2}$
$\mathbf{dv}_j = -rand(1,d)$; $\mathbf{dv}_{ij} = -rand(1,d)$
**end**
$\alpha_j = L_{GS} \times \mathbf{dv}_j$
$\mathbf{v}_j = \alpha_j\left(\mathbf{x}_{o_{in}} - \mathbf{x}_j\right)$
*% Determine the local search of the i$^{th}$ individual*
$\alpha_{ij} = L_{LS} \times \mathbf{dv}_{ij}$
$\mathbf{v}_{i/j} = \alpha_{ij}\left(\mathbf{x}_j - \mathbf{x}_i\right)$
$\mathbf{x}_i^{t+1} = \mathbf{x}_i^t + \mathbf{v}_{i/j} + \mathbf{v}_j$
**end for**
Rank the individuals
t = t + 1
**end while**

# 4 Results and Analysis

In order to prove the effectiveness of BCMO, it is used to extract parameters of two different PV cell models, i.e. single diode model (SDM) and double diode model (DDM) in comparison to other related studies. The benchmark I–V (current-voltage) data of PV cells was described in [39], which is collected on a 57 mm diameter commercial (R.T.C.France) PV cell under 1000 W/m$^2$ at 33 $^oC$. The lower and upper bounds of the PV cell parameters are shown in Table 1.

Table 1
Parameters range for SDM and DDM model

| Parameter | Lower | Upper |
|---|---|---|
| $I_{PH}\,(A)$ | 0 | 1 |
| $I_{SD}\,(\mu A)$ | 0 | 1 |
| $R_S\,(\Omega)$ | 0 | 0.5 |
| $R_{SH}\,(\Omega)$ | 0 | 100 |
| n | 1 | 2 |

Verification of the effectiveness of BCMO includes 2 steps, first, we evaluate the performance of the BCMO algorithm by changing the population size NP to estimate the PV cell parameters. And then, BCMO is compared with other well-established methods such as JAYA [18], DE [19], MJAYA [29], SGDE [31], Rao-1 algorithm, and logistic chaotic Rao-1 optimization algorithm (LCROA) [37]. The parameters of these methods are listed in Table 2. All methods are run from 30 to 50 independent times.

Table 2
Parameters setting of other related methods

| **Method** | **Parameter setting** |
|---|---|
| JAYA [18] | NP = 20; *MaxIter = 50000; 30 runs* |
| DE [19] | The mutation scaling factor F and crossover rate Cr are uniformly distributed in (0.1,1) and (0,1); *MaxIter = 10000; 50 runs* |
| MJAYA [29] | Hybrid DE and JAYA; DE's parameters Cr = rand[0.7, 1.0]; F = rand[0.4, 1.0]; NP = 10*d (d = 5 with SDM and d = 7 with DDM). |
| SGDE [31] | NP = 150, LP = 20, \|h\|=60; MaxIter = 50000; 30 runs. |
| Rao-1, LCROA [37] | 1000 iterations and 10 population; 30 runs. |

## 4.1 Results on SDM Parameters Estimation

The results in terms of the best, worst, mean, STD (standard deviation) and the cost time computation for SDM are described in Table 3. The comparison convergence rates in changing NP of the BCMO algorithm are shown in Fig. 4. From Table 3 and Fig. 4, it can be seen that BCMO provides the least RMSE value (9.8602e-4) and BCMO will converge quickly about 3000 generations in the case of NP = 50*d. Where d is the number of parameters to be estimated for the SDM model (d = 5). When increasing the population size NP, the cost computation will be increased, on the contrary, the quality and convergence speed of PV parameters estimation achieve higher accuracy. Additionally, the I-V curve between the estimated data achieved by BCMO and experimental data for the SDM model in the case of NP =50*d is described in Fig. 5. Results prove that the parameters estimated by BCMO are of a high accuracy.

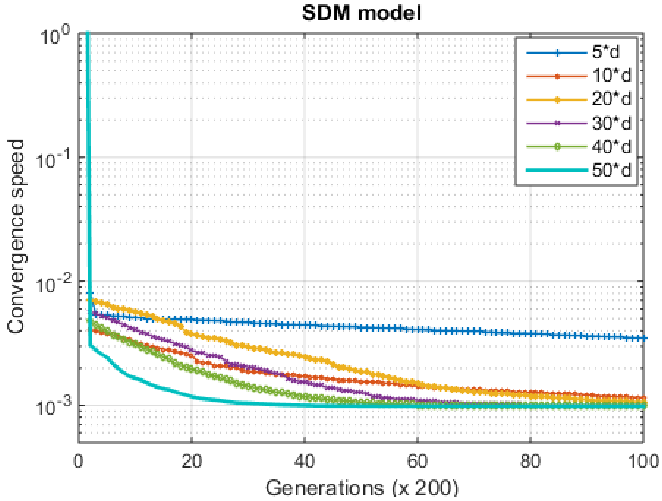


Figure 4
The convergence curve when changing NP for SDM

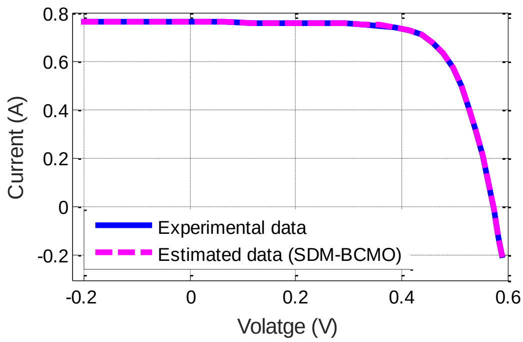


Figure 5
Comparison of the real data and the estimated data for SDM

Table 3
Comparisons of various NP extraction methods for SDM

| **NP** | **RMSE** | | | | |
|---|---|---|---|---|---|
| | **Best** | **Worst** | **Mean** | **Std.** | **Run(seconds)** |
| 5*d (25) | 0.0010 | 0.0089 | 0.0043 | 0.0028 | 333.8 |
| 10*d (50) | 0.0011 | 0.0024 | 0.0015 | 5.33e-4 | 555.8 |
| 20*d (100) | 9.87e-4 | 0.0011 | 0.0010 | 5.37e-5 | 864.6 |
| 30*d (150) | 9.8613e-4 | 9.9509e-4 | 9.8722e-4 | 2.78e-6 | 1189.1 |
| 35*d (175) | 9.8605e-4 | 9.9064e-4 | 9.8666e-4 | 1.43e-6 | 1341.0 |
| 50*d (250) | 9.8602e-4 | 9.8603e-4 | **9.8603e-4** | **3.08e-9** | **1835.1** |

## 4.2 Results on DDM Parameters Estimation

Table 4 shows the performance of BCMO when changing NP for DDM parameter extraction in terms of the best, worst, mean, std. Fig. 6 describes the comparison of convergence rates in changing NP of the BCMO algorithm. From Table 4 and Fig. 6, it can be seen that BCMO provides the least RMSE value (9.8635e-4) and BCMO will converge quickly at about 1.500 generations in the case of NP = 50*d. Where d is the number of parameters to be estimated for the DDM model (d = 7). When changing NP from 20*d to 50*d, the performance of BCMO gives a nearly equal quality. Fig. 7 shows the I-V curve between the estimated data achieved by BCMO and experimental data for the DDM model in the case of NP =50*d.

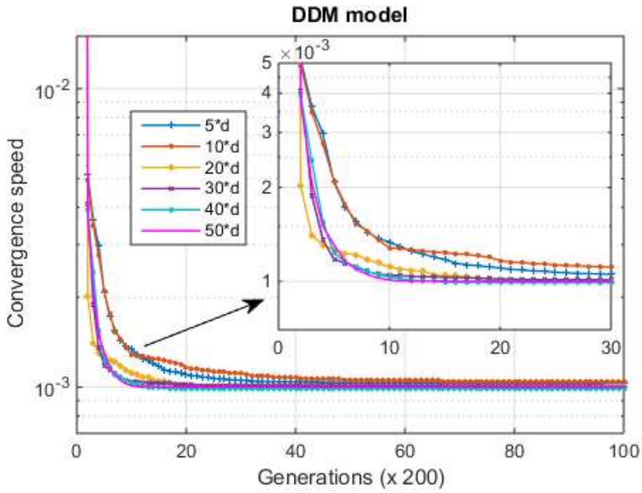


Figure 6

The convergence curve when changing NP for DDM

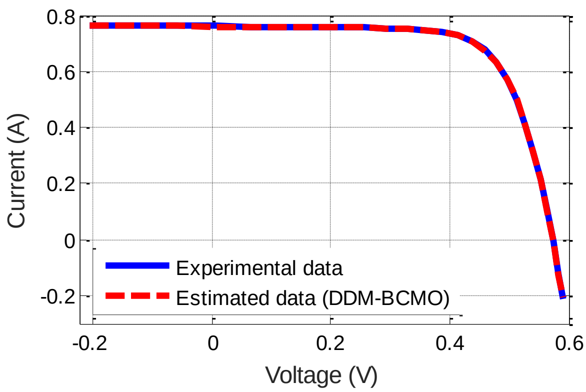


Figure 7

Comparison of the real data and the estimated data for DDM

Table 4
Comparisons of various NP extraction methods for DDM

| NP | RMSE | | | | |
|---|---|---|---|---|---|
| | Best | Worst | Mean | Std. | Run(seconds) |
| 5*d (35) | 9.8533e-4 | 0.0015 | 0.0011 | 1.69e-4 | 462.7 |
| 10*d (70) | 9.8600e-4 | 0.0014 | 0.0011 | 1.47e-4 | 702.9 |
| 20*d (140) | 9.8619e-4 | 0.0010 | 9.9563e-4 | 1.65e-5 | 1156.5 |
| 30*d (210) | 9.8579e-4 | 0.0011 | 9.9776e-4 | 2.27e-5 | 1613.0 |
| 35*d (245) | 9.8538e-4 | 0.0011 | 9.9755e-4 | 2.54e-5 | 1811.9 |
| 50*d (350) | 9.8371e-4 | 9.8727e-4 | **9.8635e-4** | **8.03e-7** | **2597.3** |

## 4.3 Comparison with Other Techniques

**For SDM**, the RMSE value in terms of the best, mean, worst, and standard deviation (Std.) are shown in Table 5. The estimated parameters of the SDM model are described in Table 6.

Based on the results in Table 5 and Table 6, it can be proved that BCMO has better performance than those of classical JAYA, DE, and Rao-1. Details as, in term of average and standard deviation, JAYA, DE, Rao-1 and BCMO obtain (1.1617e-3, 1.88e-4), (1.0212e-3, 1.4469e-4), (9.912816e-4, 1.861748e-4) and (9.8603e-4, 3.08e-9), respectively. When compared with a modified classical algorithm, BCMO gives the same performance as MJAYA and SGDE and is better than LCROA. Moreover, the standard deviation of BCMO obtained 3.08e-9 proves that BCMO has robustness capabilities in PV cell parameters estimation.

Table 5
Comparisons of other well-established parameters extraction methods for SDM

| **Method** | **RMSE** | | | |
|---|---|---|---|---|
| | **Best** | **Worst** | **Mean** | **Std.** |
| JAYA [18] 2017 | 9.8946e-4 | 1.4783E−3 | 1.1617E−3 | 1.88E−4 |
| DE [19] 2018 | 9.860219e-4 | 1.810590e-3 | 1.0212e-3 | 1.4469e-4 |
| MJAYA [29] 2020 | 9.860218e-4 | 9.860218e-4 | 9.860218e-4 | 1.99e-17 |
| SGDE [31] 2020 | 9.860219e-4 | 9.860354e-4 | 9.86022e-4 | 2.47465e-9 |
| Rao-1 [37] 2021 | 7.749435e-4 | 1.348222e-3 | 9.912816e-4 | 1.861748e-4 |
| LCROA [37] 2021 | 7.730063e-4 | 1.348222e-3 | 1.272813e-2 | 4.054798e-2 |
| BCMO (NP = 50*d) | 9.8602e-4 | 9.8603e-4 | 9.8603e-4 | 3.08e-9 |

Table 6

Details estimated results of SDM

| **Parameters** | $I_{PH}(A)$ | $I_{SD}(\mu A)$ | $R_S(\Omega)$ | $R_{SH}(\Omega)$ | $n$ | **RMSE** |
|---|---|---|---|---|---|---|
| JAYA [18] 2017 | 0.7608 | 0.3281 | 0.0364 | 54.9298 | 1.4828 | 9.8946E−4 |
| DE [19] 2018 | 0.76078 | 0.32302 | 0.03638 | 53.71852 | 1.48118 | 9.860219e-4 |
| MJAYA [29] 2020 | 0.7608 | 0.3230 | 0.0364 | 53.7185 | 1.4812 | 9.860219e-4 |
| SGDE [31] 2020 | 0.76078 | 0.32302 | 0.03638 | 53.71853 | 1.48118 | 9.860219e-4 |
| LCROA [37] 2021 | 0.76079 | 0.31068 | 1.51690 | 0.03655 | 52.88979 | 7.730063 |
| BCMO (NP = 50*d) | 0.76078 | 0.3230 | 0.0364 | 53.7185 | 1.4812 | 9.8602e-4 |

**For DDM,** Table 7 gives the comparison of BCMO with other well-established parameters extraction methods in terms of the best, mean, worst, and Std. The estimated optimal parameters of the DDM model are described in Table 8.

Table 7

Comparisons of other well-established methods for DDM

| **Method** | **RMSE** | | | |
|---|---|---|---|---|
| | Best | Worst | Mean | Std. |
| JAYA [18] 2017 | 9.8934e-4 | 1.1767e-3 | 1.4793e-3 | 1.93e-4 |
| DE [19] 2018 | 9.829363e-4 | 2.009408e-3 | 1.068617e-3 | 2.233253e-4 |
| MJAYA [29] 2020 | 9.824848e-4 | 9.860218e-4 | 9.8260e-4 | 6.46e-7 |
| SGDE [31] 2020 | 9.84413e-4 | 9.86022e-4 | 9.85774e-4 | 4.01504e-7 |
| Rao-1 [37] 2021 | 7.60703e-4 | 1.66267e-3 | 1.05394e-3 | 2.65619e-4 |
| LCROA [37] 2021 | 7.49007e-4 | 6.61635e-2 | 1.41491e-2 | 2.18517e-2 |
| BCMO (NP = 50*d) | 9.8371e-4 | 9.8727e-4 | 9.8635e-4 | 8.03e-7 |

Table 8

Details estimated results of DDM

| Parameters | $I_{PH}(A)$ | $I_{SD1}(\mu A)$ | $R_S(\Omega)$ | $R_{SH}(\Omega)$ | $n_1$ | $I_{SD2}(\mu A)$ | $n_2$ | RMSE |
|---|---|---|---|---|---|---|---|---|
| JAYA [18] | 0.7607 | 0.00608 | 0.0364 | 52.6575 | 1.8436 | 0.3151 | 1.4788 | 9.893e-4 |
| DE [19] | 0.76078 | 0.49922 | 0.0366 | 54.8509 | 1.9979 | 0.2559 | 1.4615 | 9.829e-4 |
| MJAYA [29] | 0.7608 | 0.22597 | 0.0367 | 55.4854 | 1.4510 | 0.7494 | 2.000 | 9.825e-4 |
| SGDE [31] | 0.76079 | 0.2807 | 0.0365 | 54.3667 | 1.4697 | 0.2499 | 1.9323 | 9.844e-4 |
| LCROA [37] | 0.7608 | 0.14582 | 0.0372 | 54.8589 | 1.4554 | 0.7351 | 1.8937 | 1.415e-2 |
| BCMO (NP = 50*d) | 0.7608 | 0.20588 | 0.0364 | 53.9364 | 1.4786 | 0.7494 | 2.000 | 9.837e-4 |

Based on results in Table 7 and Table 8, it can be seen that BCMO gets the smallest RMSE value in terms of the average and standard deviation has a better performance compared to those of JAYA, DE, Rao-1, and LCROA. When compared with a modified classical algorithm, BCMO gives slightly worse than MJAYA and SGDE but not significantly.

## 4.4 Discussions of Convergence and Computation Time

In this part, we perform PV parameter estimation using the original GA, DE, JAYA, and BCMO algorithms to analyze the convergence speed and computation time between these algorithms. In which, the mutation scaling factor F and crossover rate Cr for DE are uniformly distributed in (0.1,1) and (0,1) [19]. BCMO and JAYA are parameter-free optimization algorithms. The crossover and mutation factors of GA are selected by trial and error method and are equal to 0.9 and 0.01, respectively. The simulations were performed by Matlab version 2014b on an Intel Core i3 computer with a clock rate of 2.53 GHz and 2.00 GB of RAM. All methods are run 30 independent times and MaxIter = 20000 generations.

The convergence rate of the original GA, JAYA, DE, and BCMO algorithms is shown in Fig. 8. For SDM model estimation, it can be seen that BCMO has a slightly worse convergence rate than JAYA and DE algorithms. For DDM model estimation, BCMO has a competitive convergence rate with the DE algorithm and a faster convergence rate than JAYA and GA algorithms. This proves that BCMO has good exploration ability and is highly competitive with other methods.

From the results described in Table 9 and Table 10, it can be seen that BCMO needs a longer computation time when compared with those of GA, DE, and JAYA algorithms. Specifically, for SDM model estimation, the average computation time of BCMO is 555.8 seconds, about 5 times compared to the JAYA in the case of NP = 50. When BCMO achieves the best accuracy results with NP = 250, the average time of BCMO is 1835.1 seconds, about 15 times compared to the JAYA.

Table 9

Comparisons of various NP extraction methods for SDM

| NP | Methods | RMSE | | | | |
|---|---|---|---|---|---|---|
| | | **Best** | **Worst** | **Mean** | **Std.** | **Run (seconds)** |
| 50 | GA | 0.0483 | 0.1901 | 0.1417 | 0.0541 | 104.2 |
| | JAYA | 9.8602 e-4 | 9.8602 e-4 | 9.8602 e-4 | 1.3525e-12 | 120.8 |
| | **DE** | **9.8602e-4** | **9.8602e-4** | **9.8602e-4** | **1.0114e-12** | **152.4** |
| | BCMO-50 | 0.0011 | 0.0024 | 0.0015 | 5.33e-4 | 555.8 |
| 250 | BCMO-250 | 9.8602e-4 | 9.8603e-4 | 9.8603e-4 | 3.08e-9 | 1835.1 |

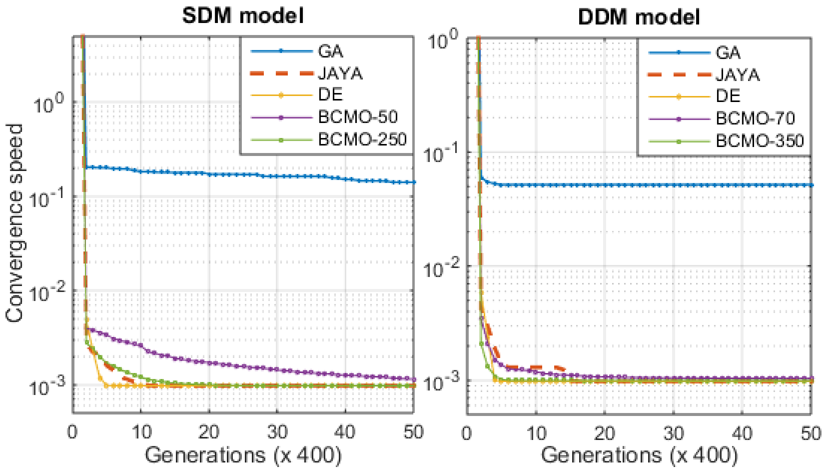


Figure 8
The convergence curve of the original GA, JAYA, DE, BCMO algorithms

Table 10
Comparisons of various NP extraction methods for DDM

| NP | Methods | RMSE | | | | |
|---|---|---|---|---|---|---|
| | | Best | Worst | Mean | Std. | Run (seconds) |
| 70 | GA | 0.05192 | 0.13003 | 0.07718 | 0.0328 | 149.3 |
| | JAYA | 9.8248e-4 | 0.0012 | 0.0010 | 8.0306e-5 | 141.8 |
| | **DE** | **9.8248e-4** | **9.8602e-4** | **9.8366e-4** | **1.7258e-6** | **186.9** |
| | BCMO | 9.8600e-4 | 0.0014 | 0.0011 | 1.47e-4 | 702.9 |
| 350 | BCMO | 9.8371e-4 | 9.8727e-4 | 9.8635e-4 | 8.03e-7 | 2597.3 |

In summary, the above discussions indicate that BCMO can be accurately identified and are highly competitive convergence rate with other PV parameters extraction methods. But the computational cost of BCMO has longer than other algorithms such as GA, DE, and JAYA algorithms.

## Conclusions

In this paper, BCMO has been applied to estimate PV cell parameters. The experimental results on benchmark test PV cell models, i.e., a single diode model and a double diode model in terms of the convergence speed, computation time, and the RMSE value are analyzed. First, we survey the impact of a population size NP on the quality of the BCMO algorithm. And then, the estimated performance of the BCMO algorithm is compared with other algorithms including classical algorithms and variants. The experimental results strongly proved that BCMO performs significantly better convergence speed and RMSE value than the classical JAYA [18], DE [19], Rao-1 [37] and is highly competitive with some modified algorithms published in 2020-2021 such as MJAYA [29], SGDE [31], and LCROA [37]. For computation time criteria, BCMO has longer than the classical GA, DE, and JAYA algorithms. In summary, BCMO can be used as a promising method for the parameter estimation problem in energy systems. In future work, we will perform further enhance the BCMO algorithm and apply it for real-time model-based fault diagnosis of the PV system.

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## Data link

https://drive.google.com/drive/folders/1KgYhhKGiSLPe9zIJXArJFjmewXD_MRf7?usp=sharing

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