Tackling Photovoltaic (PV) Estimation Challenges: An Innovative AOA Variant for Improved Accuracy and Robustness

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Abstract

Optimizing photovoltaic (PV) cell/module modeling is key to advancing solar power and achieving net zero carbon goals. Challenges in accurate PV parameter estimation arise from environmental variability, aging, and incomplete manufacturer data. Traditional Arithmetic Optimization Algorithm (AOA) often struggles with premature convergence due to imbalanced exploration and exploitation. This paper presents an enhanced AOA variant, incorporating chaotic maps and oppositional-based learning to better balance the optimization process. Our extensive simulations show that this improved AOA variant significantly enhances accuracy and robustness in PV cell/module parameter estimation compared to the conventional method.

Keywords: Photovoltaic module/cell, Parameter estimation, Arithmetic optimization algorithm

1. Introduction

The Intergovernmental Panel on Climate Change (IPCC) has underscored the urgent necessity to address global warming, advocating for significant efforts to attain net zero carbon emissions by 2050. This imperative demands a transition to renewable energy sources, with solar power emerging as a key player due to its sustainability and minimal environmental footprint [1]. Solar energy, captured through photovoltaic (PV) cells and modules, offers versatility, catering to a range of applications from residential heating to extensive solar farms [2]. Yet, the efficacy of solar systems is critically dependent on the performance of PV arrays, which are prone to degradation under harsh outdoor conditions.

Precision in PV system modeling is crucial for enhancing performance. This process encompasses various models, including single-diode, double-diode, and triple-diode, each demanding distinct parameter such as photocurrent and resistances [3]. Often, these parameters are not readily available from manufacturers, necessitating their estimation from experimental data. This task is further complicated by the aging of PV systems and fluctuating environmental factors [3]. The intricate and multimodal characteristics of PV parameter estimation, especially under diverse irradiance and temperature conditions, pose considerable challenges.

Existing photovoltaic (PV) cell/module parameter estimation approaches are broadly categorized into deterministic and metaheuristic methods. Deterministic methods, simpler and less computationally intensive, often fall short in accuracy under varied environmental conditions [3]. In contrast, metaheuristic methods, drawing inspiration from natural phenomena, exhibit superior global search capabilities, ease of implementation, and scalability. Consequently, they have become highly effective for diverse global optimization challenges [4], [5], [6], [7], [8], [9], [10], [11]. These metaheuristic methods also excel in addressing complex, multimodal PV cell/module parameter estimation problems [12], [13], [14], [15], [16]. Despite substantial progress using metaheuristic approaches, challenges persist due to the intricate, nonlinear interplay of PV module parameters and variable operating conditions. Therefore, developing robust metaheuristic methods for more precise PV parameter estimation is vital. Such advancements will enhance PV system optimization, maximizing solar energy utilization and contributing to a sustainable future.

Arithmetic Optimization Algorithm (AOA) [17] is a mathematics-inspired metaheuristic method that employs four basic arithmetic operations (division, multiplication, addition, and subtraction) with varying exploration and exploitation strengths for solving optimization problems.

In PV cell/module parameter estimation, the AOA population signifies diverse diode parameter combinations. Since its introduction, AOA and its variants have been effectively applied to various real-world optimization problems [18], [19], [20], [21], [22]. However, AOA, like many metaheuristic methods, relies on a conventional approach for generating its initial population, which often lacks intelligent, systematic initialization. This approach tends to produce initial solutions that are either trapped in local optimum or distant from the global optimum, thus impacting the solution's accuracy and the algorithm's convergence speed [23]. This limitation affects AOA's efficiency in complex, multimodal challenges such as PV cell/module parameter estimation.

In this paper, we introduce an enhanced variant of AOA, termed AOA with Modified Initialization Scheme (AOA-MIS), specifically designed to tackle complex and multimodal PV cell/module parameter estimation problems. The MIS module combines chaotic map strengths and dynamic oppositional learning (DOL) to generate a higher-quality initial population with improved fitness and diversity. Utilizing the non-repetitive and ergodic nature of chaotic maps, the MIS module enhances initial population diversity, thereby increasing the algorithm's robustness for complex issues. Concurrently, the DOL mechanism within MIS module effectively accelerates AOA's convergence by generating opposite solutions for those significantly distant from the global optimum. The efficacy of AOA-MIS, using various diode modeling techniques, is then benchmarked against the original AOA.

2. PV Cell/Module Parameter Estimation Problem

The electrical properties of PV systems can be modeled using different approaches: single diode model (SDM), double diode model (DDM) and triple diode model (TDM) as shown in Fig. 1. Let $\boldsymbol{j} = \mathbf{1}, \ldots, \boldsymbol{J}$ be the diode index in the model, where $\boldsymbol{J} = \mathbf{1}$ is for SDM, $\boldsymbol{J} = \mathbf{2}$ for DDM and $\boldsymbol{J} = \mathbf{3}$ for TDM. For a given output voltage V, the output current I each diode model is determined as:

$$I = I_{ph} - \frac{V + IR_s}{R_{sh}} - \sum_{j=1 \to J} I_{ssdj} \left[e^{\left(\frac{q(V+IR_s)}{n_j kT}\right)} - 1 \right] \quad (1)$$

where I_{ph} and I_{sh} are the photogenerated line current and shunt resistor line current, respectively; I_{ssdj} is the saturation current of the j-th diode, R_s and R_{sh} are the series and shunt resistances, respectively; n_j is the ideality factor of the j-th diode, T is the absolute temperature, k is Boltzmann's constant, and q is the unit charge. Accurate modeling using SDM, DDM, and TDM necessitates the accurate estimation of parameters such as I_{ph}, R_s, R_{sh}, I_{ssdj} and n_j for $j = 1, \ldots, J$.

In PV cell/module parameter estimation using metaheuristic methods, appropriate objective functions are formulated based on the discrepancy between the experimental current and the model's predicted current. Considering X as a candidate solution with undetermined diode parameters, the error function for PV cells is expressed as:

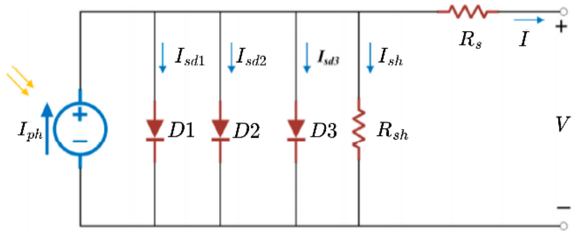

Fig.1 Equivalent circuit of PV using TDM with J = 3.

$$\begin{cases} f(X) = I_{ph} - \frac{V + IR_s}{R_{sh}} - \sum_{j=1 \to J} I_{ssdj} \left[e^{\left(\frac{q(V+IR_s)}{n_j kT}\right)} - 1 \right] - I \\ X = [I_{ph}, R_s, R_{sh}, I_{ssdj}, n_j], \qquad \text{for } j = 1, \ldots, J \end{cases} \quad (2)$$

Root mean square error (RMSE) is commonly employed as the objective function, defined as:

$$RMSE = \sqrt{\frac{1}{K} \sum_{k=1}^{K} f^2(X)} \quad (3)$$

where k and K represent the indices and total count of measured current data points, respectively. The aim is to find a solution that minimizes the RMSE in PV cell/module parameter estimation.

3. AOA-MIS

3.1. *Proposed MIS module*

The process of generating an initial population in the proposed MIS module is described as follows. Initially, a chaotic population of size N is generated using a modified sine chaotic map, a departure from the traditional initialization schemes. This map, based on deterministic equations, can display stochastic behavior at external levels. The ergodic and non-repetitive nature of chaotic map promotes a more comprehensive search in the solution space, preventing initial solutions from being trapped in local optima and thus enhancing the diversity and robustness of the initial population against premature convergence. Define $\boldsymbol{\vartheta_t}$ as the output of a chaotic variable at the t-th iteration, for $\boldsymbol{t} = \mathbf{1}, \ldots, \boldsymbol{T}$, updated as per the modified sine chaotic map with a bifurcation coefficient $\boldsymbol{\mu} = \boldsymbol{\pi}$:

$$\vartheta_{t+1} = \sin(\mu \vartheta_t) \quad (4)$$

The final iteration output $\boldsymbol{\vartheta_T}$ initializes the d-th dimension of each n-th chaotic solution, as in Eq. (5), where $\boldsymbol{X_d^L}$ and $\boldsymbol{X_d^U}$ are the lower and upper bounds of the d-th decision variable, respectively. This results in a chaotic population $\mathbf{P^C} = [\boldsymbol{X_1^C}, \ldots, \boldsymbol{X_n^C}, \ldots \boldsymbol{X_N^C}]$.

$$X_{n,d}^C = X_d^L + \vartheta_T \left(X_d^U - X_d^L\right) \quad (5)$$

Despite its advantages, chaotic map may still generate initial solutions far from the global optimum, potentially slowing algorithm convergence. To mitigate this, a DOL operator is applied to the chaotic population $\mathbf{P^C}$ to produce opposite solutions for each n-th chaotic solution. This DOL operator broadens the initial population's coverage of the solution space, enhancing the chance of finding fitter solutions. The opposite solution for each dimension, i.e., $\boldsymbol{X_{n,d}^{O}}$, is calculated using Eq. (6), corresponding to $\boldsymbol{X_{n,d}^{C}}$, where $\boldsymbol{r_1}, \boldsymbol{r_2} \in [\boldsymbol{0}, \boldsymbol{1}]$ are randomly generated numbers. This results in an opposition population, $\mathbf{P^O} = [\boldsymbol{X_1^O}, \dots, \boldsymbol{X_n^O}, \dots \boldsymbol{X_N^O}]$.

$$X_{n,d}^{O} = X_{n,d}^{C} + r_1 \left[r_2 (X_d^U + X_d^L - X_{n,d}^{C}) - X_{n,d}^{C} \right] \quad (6)$$

The two populations, $\mathbf{P^C}$ and $\mathbf{P^O}$, are combined into a single set $\mathbf{P^C} \cup \mathbf{P^O}$, resulting in a total population size of $2N$. Each solution within this merged population set is evaluated for fitness using Eq. (3), focusing on RMSE. The solutions are then rearranged based on their fitness values, from the best to the worst. The top N solutions from this sorted set $\mathbf{P^C} \cup \mathbf{P^O}$ are selected as the initial population for the AOA-MIS algorithm, denoted as $\mathbf{P} = [\boldsymbol{X_1}, \dots, \boldsymbol{X_n}, \dots, \boldsymbol{X_N}]$.

3.2. *Iterative Search Mechanisms of AOA-MIS*

After generating the initial population $\mathbf{P}$ with the proposed MIS module, each n-th solution of AOA-MIS is iteratively updated using search mechanisms akin to those in the original AOA.

At each iteration, the Math Optimizer Accelerated (MOA) function value is updated for the proposed AOA-MIS to toggle between exploration and exploitation:

$$MOA(C_{Iter}) = Min + C_{Iter} \left(\frac{Max - Min}{M_{Iter}} \right) \quad (7)$$

where C_{Iter} and M_{Iter} represent the current and maximum iteration numbers, respectively; Min and Max are the minimum and maximum values of MOA. Concurrently, the Math Optimizer Probability (MP) function, guiding the search range for each solution and influenced by the critical parameter θ for exploitation efficiency, is updated:

$$MP(C_{Iter}) = 1 - \left(\frac{C_{Iter}}{M_{Iter}} \right)^{1/\theta} \quad (8)$$

Based on MOA's value, a random number $\boldsymbol{rand1}$ decides the search strategy (exploration or exploitation) at each iteration for updating every d-th dimension of the n-th solution, $\boldsymbol{X_{n,d}}$. In the exploration phase ($\boldsymbol{rand1} > \boldsymbol{MOA}$), Multiplication or Division is randomly chosen:

$$X_{n,d}(C_{Iter}+1) = \begin{cases} best_d \div (MP + \varepsilon) \times [(X_d^U - X_d^L)\mu + X_d^L], & rand2 < 0.5 \\ best_d \times MP \times [(X_d^U - X_d^L)\mu + X_d^L], & \text{Otherwise} \end{cases} \quad (9)$$

where $rand2$ is a random number between 0 and 1; $best_d$ is the d-th dimension of the current best solution; ε is a small positive number preventing division by zero; μ is a control parameter.

In the exploitation phase ($rand1 \le MOA$), Addition or Subtraction operator updates $X_{n,d}$:

$$X_{n,d}(C_{Iter}+1) = \begin{cases} best_d - MP \times [(X_d^U - X_d^L)\mu + X_d^L], & rand2 < 0.5 \\ best_d + MP \times [(X_d^U - X_d^L)\mu + X_d^L], & \text{Otherwise} \end{cases} \quad (10)$$

The proposed AOA-MIS iterates through this search process, following Eqs. (7) to (10), until predefined termination criteria are met, as illustrated in Fig. 2. Upon completion, the optimal diode parameters in the best solution are decoded to address the PV cell/module parameter estimation problems.

AOA-MIS for PV Cell/Module Parameter Estimation

Inputs: *D*, *N*, M_{Iter}, *T*, Max, Min, θ
Initialize $\mathbf{P^C} \leftarrow \emptyset$, $\mathbf{P^O} \leftarrow \emptyset$ and $C_{Iter} \leftarrow 0$;
for each n-th solution **do**
  for each d-th dimension **do**
    Randomly generate $\vartheta_t \in [0,1]$, where $t = 0$;
    while $t \le T$ **do**
      Update ϑ_t using Eq. (4);
      Update $t \leftarrow t + 1$;
    end while
    Calculate $X_{n,d}^{C}$ with Eq. (5);
    Calculate $X_{n,d}^{O}$ with Eq. (6);
  end for
  Update $\mathbf{P^C} \leftarrow \mathbf{P^C} \cup X_{n,d}^{C}$ and $\mathbf{P^O} \leftarrow \mathbf{P^O} \cup X_{n,d}^{O}$;
end for
Merge two populations as $\mathbf{P^C} \cup \mathbf{P^O}$;
Fitness evaluation of all solutions stored within the merged population set of $\mathbf{P^C} \cup \mathbf{P^O}$ using Eq. (3);
Sort the solutions within $\mathbf{P^C} \cup \mathbf{P^O}$ from best to worst based on their fitness values;
Select the top *N* solutions from the sorted $\mathbf{P^C} \cup \mathbf{P^O}$ as the initial population, i.e., $\mathbf{P} = [X_1, \dots, X_n, \dots, X_N]$.
Assign the first solution of **P** and its fitness as *best* and $f(best)$, respectively;
while $C_{Iter} \le M_{Iter}$ **do**
  Update *MOA* and *MP* with Eqs. (7) and (8);
  for each n-th solution **do**
    if $rand1 > MOA$ **then** /**Exploration**/
      Update $X_{n,d}(C_{Iter}+1)$ with Eq. (9);
    else /**Exploitation**/
      Update $X_{n,d}(C_{Iter}+1)$ with Eq. (10);
    end if
    Fitness evaluation of $X_n(C_{Iter}+1)$ with Eq. (3);
    Update the X_n, $f(X_n)$, $best$ and $f(best)$, with greedy selection method;
  end for
  $C_{Iter} \leftarrow C_{Iter} + 1$;
end while
Output: $best$ and the corresponding PV model;

Fig.2 Workflow of proposed AOA-MIS in solving the PV cell/module parameter estimation problems.

4. Results and Discussions

4.1. *Simulation settings*

In this section, the proposed AOA-MIS is applied to solve the PV cell parameter estimation problem involves the test case of R.T.C. France solar cell using SDM, DDM and TDM approaches. The proposed AOA-MIS and original AOA are implemented in MATLAB 2021a on a personal computer consisting of an Intel® Core™

i7-HQ CPU, 2.50 GHz, and 16 GB RAM laptop. For all compared techniques, the population size and maximum iteration numbers are set as 30 and 1000, respectively.

4.2. *Performance analysis*

The current and voltage experimental values for the R.T.C. France solar cell were recorded under standard conditions: 1000 W/m² at 33°C. This subsection applies the proposed AOA-MIS to estimate five and seven unknown parameters of the SDM and DDM, respectively, representing the R.T.C. solar cell at these conditions. The AOA-MIS results are compared with those from the original AOA. RMSE serves as the performance index to evaluate AOA-MIS's effectiveness.

Table 1 and Table 2 showcase the optimized parameters derived from AOA-MIS and the original AOA for the R.T.C. France solar cell, using the SDM and DDM, respectively, along with their corresponding RMSE values. Parameters yielding better results, as indicated by lower RMSE values, are highlighted in bold. Table 1 reveals that AOA-MIS's estimation of the five parameters (i.e., I_{ph}, R_s, R_{sh}, I_{ssd} and n) for the SDM leads to higher modeling accuracy for the R.T.C. France solar cell, as evidenced by lower RMSE values, compared to the original AOA. Similarly, Table 2 shows that AOA-MIS's estimation of the seven parameters (i.e., I_{ph}, R_s, R_{sh}, $I_{ssd,1}$, $I_{ssd,2}$, n_1 and n_2) for the DDM yields more competitive RMSE values.

Table 1. Optimized parameters obtained for R.T.C France solar cell using SDM.

Parameters	AOA	AOA-MIS
I_{ph}	0.75483	0.75822
R_s	0.052023	0.039672
R_{sh}	97.805	69.689
I_{ssd}	1.5746×10^{-8}	1.5411×10^{-7}
n	1.2485	1.4316
RSME	5.3572×10^{-3}	**3.2507×10^{-3}**

Table 2. Optimized parameters obtained for R.T.C France solar cell using DDM.

Parameters	AOA	AOA-MIS
I_{ph}	0.73552	0.80916
R_s	0.0044392	0
R_{sh}	2.668	1.7305
$I_{ssd,1}$	0	0
$I_{ssd,2}$	0	0
n_1	1.1428	1.0141
n_2	1.9816	1.235
RSME	1.7449×10^{-1}	**1.705×10^{-1}**

To further assess the effectiveness of the proposed AOA-MIS in addressing the PV cell/module parameter estimation problems, Table 3 provides a statistical analysis of the RMSE values for the R.T.C. France solar cell using both SDM and DDM models, comparing AOA-MIS and the original AOA. This analysis includes performance metrics such as the minimum (Min), maximum (Max), mean (Mean), and standard deviation (SD) of the RMSE values from multiple simulation runs for both algorithms. The data in Table 3 reveal that AOA-MIS consistently outperforms the original AOA in terms of Max, Min, and Mean RMSE values. Additionally, AOA-MIS shows superior consistency in achieving lower RMSE values, as evidenced by lower SD values in both SDM and DDM test cases.

Table 3. Statistical results of the RMSE values of R.T.C France solar cell represented by different diode modelling methods

Model	RSME	AOA	AOA-MIS
SDM	Min	5.3572×10^{-3}	**3.2507×10^{-3}**
	Mean	3.0009×10^{-2}	**2.4830×10^{-2}**
	Max	1.4549×10^{-1}	**6.7476×10^{-2}**
	SD	4.2432×10^{-2}	**2.0059×10^{-2}**
DDM	Min	1.7449×10^{-1}	**1.7050 ×10^{-1}**
	Mean	1.9299 ×10^{-1}	**1.7875 ×10^{-1}**
	Max	2.1688×10^{-1}	**1.8938 ×10^{-1}**
	SD	1.2098 ×10^{-2}	**5.8922 ×10^{-3}**

The superior performance of the proposed AIA-MIS over the original AOA can be attributed to several factors. PV cell/module parameter estimation is a complex, multimodal real-world optimization problem, largely due to the nonlinear relationship between model parameters and varying operating conditions such as temperature and irradiance levels. The complexity of this problem escalates with the number of diodes used in modelling (e.g., five parameters in SDM, seven parameters in DDM and so on), further complicating the optimization task. Table 1, Table 2, and Table 3 suggest that the quality of the initial population is crucial in enabling AOA to accurately model PV cell/module parameters. The original AOA, using a conventional initialization scheme, tends to generate the initial solutions in local or non-optimal regions, leading to premature convergence due to the absence of intelligent methods and knowledge of the surrounding search environment. Moreover, there is a significant risk of initializing solutions far from the global optimum, slowing down the algorithm's convergence speed. In contrast, the MIS module in AOA-MIS generates an initial population of higher quality in terms of fitness and diversity. The chaotic map's non-repetitive and ergodic nature in the MIS module promotes a more comprehensive search of the solution space, minimizing the risk of local optima entrapment and premature convergence. DOL, another key mechanism in MIS, accelerates convergence by enhancing the exploration of search range through generating opposite solutions from those initialized by the chaotic map. This synergistic effect of the chaotic map and DOL in the MIS module bolsters AOA-MIS's robustness in navigating complex, multimodal search spaces, thereby enhancing its accuracy in solving PV cell/module parameter estimation problems.

5. Conclusion

In this paper, we introduce an enhanced version of the Arithmetic Optimization Algorithm, termed AOA-MIS, to address the complex and multimodal challenges of PV cell/module parameter estimation. The innovation of AOA-MIS lies in integrating chaotic maps and DOL mechanisms into the Modified Initialization Scheme (MIS) module, thereby generating an initial population with improved fitness and diversity. Simulation results reveal that AOA-MIS, with its superior initial population quality, outperforms the original AOA in estimating parameters for the SDM and DDM in representing the R.T.C. France solar cell, tested under standard conditions of 1000 W/m² at 33°C. As one of the future works, AOA-MIS could be further enhanced by incorporating an adaptive search mechanism, potentially increasing its robustness and efficacy in addressing various complexities in PV cell/module parameter estimation.

Acknowledgements

This work was supported by UCSI University's Research Excellence & Innovation Grant (REIG) with project code of REIG-FETBE-2022/038 and Billion Prima Sdn. Bhd.'s Industry Research Grant with project code of IND-FETBE-2023/006.

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