



An ameliorated Social Group Optimization Technique for Parameter Estimation of Single and Double Diode Models of Photovoltaic Cells and Modules

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ABSTRACT

Accurate parameter estimation is essential for reliable electrical modelling of photovoltaic (PV) modules. This study proposes an ameliorated social group optimization algorithm (ASGO) to identify the five parameters of the single diode model and the seven parameters of the double diode model. The improving phase incorporates a Gaussian mutation, an adaptive current-to-best/2 mutation strategy, and a local search to enhance population diversity and reduce premature convergence, while retaining the original acquiring phase. Parameter identification minimizes the root mean square error between measured and calculated currents. Performance is evaluated against conventional social group optimization using the RTC France cell, the Photowatt PWP-201 module. Each algorithm is executed independently 50 times to assess accuracy, consistency, convergence, and computational time. Although both methods frequently achieve similar minimum errors, ASGO produces lower average errors and more consistent outcomes across repeated runs. Current-voltage curves reconstructed using parameters from the worst runs remain closer to experimental measurements with ASGO. Exploration and diversity analyses support its improved search behaviour. These results demonstrate that ASGO provides a reliable estimation approach for the tested photovoltaic models, with less controlling parameters tuning, faster convergence in iterations and a modest increase in execution time.

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1. Introduction

Accurate photovoltaic (PV) models are needed to reproduce the electrical response of solar cells and modules and to support performance prediction, system design, and control. Among the available equivalent-circuit representations, the single-diode model (SDM) and double-diode model (DDM) are widely used because they provide practical descriptions of the current–voltage (I–V) characteristic. The SDM contains five unknown parameters: photocurrent, diode saturation current, diode ideality factor, series resistance, and shunt resistance. The DDM introduces a second diode to represent additional recombination effects and consequently requires seven parameters. The usefulness of either model depends on how accurately these parameters are identified from measured electrical data [1,2].

PV parameter identification remains difficult because the model equations are nonlinear and implicit, while different parameter combinations may produce similar I–V curves. Analytical and numerical approaches can estimate the unknown parameters, but their results may depend on simplifying assumptions, the selected data points, or the initial values supplied to an iterative solver. Consequently, optimization methods are often used to minimize the discrepancy between measured currents and those calculated by a PV model. The root mean square error (RMSE) is a common objective function for this purpose [3,4]. A small RMSE is important, but it does not alone establish that an algorithm will return a similarly accurate solution when it is run again.

Recent research has explored several ways to improve the search for PV model parameters. Abdulrazzaq et al. [2] integrated genetic and particle swarm optimization for the SDM, whereas Parida et al. [3] introduced an enhanced differential evolution method with a stage-dependent mutation strategy. Qian et al. [4] investigated an adapted human evolutionary optimizer, and Sadeghi et al. [5] applied a PID-based metaheuristic search algorithm. These approaches illustrate the continued development of optimization strategies for matching calculated I–V characteristics to experimental measurements.

Other studies have focused more explicitly on search diversity and convergence. Li et al. [6] combined snake optimization with a sine–cosine strategy, while Wang et al. [7] used dynamic updating and multidirectional learning to reduce reliance on a single best solution. Dal et al. [8] applied frilled

lizard optimization to the SDM and DDM, and Madhiarasan et al. [9] examined the mountain gazelle optimizer across single-, double-, and triple-diode models. More recently, in Refs [10,11] combined starfish optimization with a secant-based modification of the objective function. Together, these studies show that improving exploration, local refinement, and convergence remains an active area of PV parameter estimation.

Despite these advances, the best result from one optimization run gives only a partial view of performance. Metaheuristic algorithms use stochastic search operations; therefore, their final solutions can vary between runs. An algorithm may achieve a low minimum RMSE yet still produce substantially higher errors in other runs. For PV modelling, this variation matters because the estimated parameters must reliably reconstruct the measured I–V and power–voltage (P–V) curves. It is therefore useful to assess not only the best solution, but also the mean and worst errors, their dispersion, the convergence behaviour, and the agreement of reconstructed curves with experimental data.

Social group optimization (SGO) is a population-based method in which candidate solutions improve through interactions with other members of a group and its best-performing individual. Its search process can, however, lose population diversity and converge prematurely when applied to a nonlinear, multimodal parameter-identification problem. To address this issue, the present study proposes an ameliorated social group optimization algorithm (ASGO). The proposed method incorporates Gaussian mutation, an adaptive current-to-best/2 mutation strategy, and local search to increase exploration while refining promising solutions. It retains a single control setting for the proposed modifications.

Previous studies have addressed complementary aspects of photovoltaic (PV) systems. Ghanizadeh [12] proposed a local control scheme for voltage harmonic compensation and improved power sharing in PV inverters operating in islanded microgrids. Dadjé et al. [13] combined a modified social network search algorithm with Halley's method for parameter estimation in PV cells, modules, and arrays. Meanwhile, Madjoudj et al. [14] employed support vector machines to detect maximum power degradation in PV modules. These contributions provide a broader context for PV control, modelling, and performance assessment, within which the present study focuses on improving the accuracy and repeatability of parameter identification using ASGO.

The performance of ASGO is assessed against the original SGO for both the five-parameter SDM and the seven-parameter DDM. Three PV devices are considered: the RTC France cell, the Photowatt PWP-201 module. Repeated runs are used to compare estimation accuracy, stability, and convergence. Finally, I–V and P–V curves reconstructed from the estimated parameters are compared with the experimental data to determine whether the improvement in optimization results translates into accurate electrical modelling.

2. Related work

Recent studies have investigated hybrid optimization and data-processing strategies for photovoltaic parameter identification. A Bayesian neural network–artificial ecosystem optimization framework [15] used neural-network preprocessing to address noisy or incomplete measurements before extracting parameters for single-, double-, and three-diode models. This approach emphasizes the influence of data quality on estimation accuracy. Another study [16] combined improved artificial ecosystem optimization with the Newton–Raphson method. This integration connected population-based search with numerical current calculation, highlighting the importance of the solver embedded within the optimization process. The FVIM-DE approach [17] combined the Four Vector Intelligent Metaheuristic with differential evolution to extract photovoltaic model parameters. Its hybrid search strategy provides an alternative way of exploring the nonlinear parameter space. A comparative investigation published in 2026 [18] evaluated seven metaheuristic algorithms on solar-cell and commercial-module models. Its assessment included statistical analysis, convergence histories, boxplots, and model validation, providing a broader evaluation than comparison of minimum fitting errors alone. Finally, horse herd and elk herd optimizers [19] were investigated for single-, double-, and triple-diode models using measured characteristics of RTC France cells and Photowatt-PWP201 modules. Their evaluation also considered different irradiance and temperature conditions. These studies provide relevant comparisons for ASGO in terms of data preparation, numerical solution, search design, and repeated-run evaluation.

The results for competing algorithms in this subsection were taken from their original publications and were not independently reproduced under a common experimental protocol. Their population sizes, iteration budgets, parameter

bounds, stopping criteria, hardware, and implementations may differ from those used here. Moreover, equal iteration counts do not necessarily imply equal numbers of objective-function evaluations. The tabulated values therefore provide contextual comparisons rather than a fully controlled ranking. Small differences in reported fitting errors should be interpreted cautiously, and runtime values from different computational environments cannot establish relative computational efficiency. The controlled comparison in this study is between SGO and ASGO, evaluated using the same datasets, parameter bounds, computing environment, and model-specific population and iteration settings.

3. Optimization Formulation

The main objective of the parameter estimation process of SDM and DDM PV models is to find a set of parameters that reduces as much as possible the discrepancy between the measured and the simulated output currents. In such a way that the closer the two current values are to each other, the more precise the estimated parameters are. As a result, we get the best and closest approximation to describe the real behaviour of the PV cell/module/array whatever its external working conditions are.

One way to achieve this could be by considering the PV parameter estimation problem as an optimization problem. On this basis, PV models' unknown parameters represent the decision variables (z) or the solution vector that required to be solved, i.e: In the case of SDM, $z = [I_{pv}, I_0, a, R_s, R_{sh}]$ and in the case of DDM, $z = [I_{pv}, I_{01}, a_1, I_{02}, a_2, R_s, R_{sh}]$.

Indeed, several performance metrics [20–23] may be used as an objective function for minimizing the point-by-point disparity between the calculated I–V curve and the measured dataset, for example but not limited to: The absolute error (AE), the mean squared error (MAE), the sum squared error (SSE), the root mean square error (RMSE) and The weighted RMSE (ξ).

Where M signifies the length of experimental or measured current-voltage pairs (V_j, I_j) with $j \in M$ and $I_{est}(V_j, z)$ is the estimated output current value that depends on the unknown parameters z .

In this work, the RMSE is selected to be the objective function $O.F$ as expressed by Eq. (4), where theoretically it should equal to zero if the exact values of PV models parameters are all known. However, it is not the case in practice since the datasheets provided by PV modules manufacturers contain no information regarding these values.

Therefore, the smaller the obtained $RMSE$ value is, the more accurate the candidate solution vector is and the more competitive the used optimization algorithm is [24,25].

$$AE = \sum_{j=1}^M |I_j - I_{est}(V_j, z)| \quad (1)$$

$$MAE = \frac{1}{M} \sum_{j=1}^M |I_j - I_{est}(V_j, z)| \quad (2)$$

$$SSE = \sum_{j=1}^M (I_j - I_{est}(V_j, z))^2 \quad (3)$$

$$RMSE = \sqrt{\frac{1}{M} \sum_{j=1}^M (I_j - I_{est}(V_j, z))^2} \quad (4)$$

$$\xi = \frac{RMSE}{I_{sc}} = \frac{1}{I_{sc}} \sqrt{\frac{1}{M} \sum_{j=1}^M (I_j - I_{est}(V_j, z))^2} \quad (5)$$

$$O.F = \min(RMSE) = \min \left(\sqrt{\frac{1}{M} \sum_{j=1}^M (I_j - I_{est}(V_j, z))^2} \right) \quad (6)$$

Subject to the following constraints [21]:

For SDM:

$$\begin{cases} I_{pv_{min}} \leq I_{pv} \leq I_{pv_{max}} \\ I_{0_{min}} \leq I_{pv} \leq I_{0_{max}} \\ a_{min} \leq a \leq a_{max} \\ R_{s_{min}} \leq R_s \leq R_{s_{max}} \\ R_{sh_{min}} \leq R_{sh} \leq R_{sh_{max}} \end{cases} \quad (7)$$

For DDM:

$$\begin{cases} I_{pv_{min}} \leq I_{pv} \leq I_{pv_{max}} \\ I_{01_{min}} \leq I_{01} \leq I_{01_{max}} \\ a_{1_{min}} \leq a_1 \leq a_{1_{max}} \\ I_{02_{min}} \leq I_{02} \leq I_{02_{max}} \\ a_{2_{min}} \leq a \leq a_{2_{max}} \\ R_{s_{min}} \leq R_s \leq R_{s_{max}} \\ R_{sh_{min}} \leq R_{sh} \leq R_{sh_{max}} \end{cases} \quad (8)$$

Where subscript min and max stand for low and upper bounds for each parameter.

Additionally, it should be noted that Eqs. (4) and (8) are implicit in nature, which means that it is not

possible to express the estimated output current $I_{est}(V_j, z)$ for SDM and DDM as a function of voltage. Thus, the passage by a numerical technique such as Newton Raphson method (NRM) is mandatory to get these values through solving equation $f(I_{est}(V_j, z)) = 0$. NRM steps are as follows:

At first, by subtracting the right and left sides from Eqs. (4) and (8), one can get and calculate the following equations $f(I_{est}(V_j, z))$, as expressed by Eqs. (9) and (10) [24].

$$f(I_{est}(V_j, z)) = I_{pv} - I_{01} \cdot \left[e^{q \cdot \frac{V_j + I_{est}(V_j, z) \cdot R_s}{n \cdot k \cdot T}} - 1 \right] - \frac{V_j + I_{est}(V_j, z) \cdot R_s}{R_{sh}} - I_{est}(V_j, z) \quad (9)$$

$$f(I_{est}(V_j, z)) = I_{pv} - I_{01} \cdot \left[e^{q \cdot \frac{(V_j + I_{est}(V_j, z) \cdot R_s)}{a_1 \cdot k \cdot T}} - 1 \right] - I_{02} \cdot \left[e^{q \cdot \frac{(V_j + I_{est}(V_j, z) \cdot R_s)}{a_2 \cdot k \cdot T}} - 1 \right] - \frac{V_j + I_{est}(V_j, z) \cdot R_s}{R_{sh}} \quad (10)$$

Then, the derivative equations are computed for SDM via Eq. (11) and DDM via Eq. (12) as follows [24]:

$$\frac{\partial(I_{est}(V_j, z))}{\partial I_{est}(V_j, z)} = -\frac{I_{01} \cdot R_s \cdot q}{a \cdot k \cdot T} \cdot \left[e^{q \cdot \frac{(V_j + I_{est}(V_j, z) \cdot R_s)}{a \cdot k \cdot T}} - 1 \right] - \frac{R_s}{R_{sh}} - 1 \quad (11)$$

$$\frac{\partial f(I_{est}(V_j, z))}{\partial I_{est}(V_j, z)} = -\frac{I_{01} \cdot R_s \cdot q}{a_1 \cdot k \cdot T} \cdot \left[e^{q \cdot \frac{(V_j + I_{est}(V_j, z) \cdot R_s)}{a_1 \cdot k \cdot T}} - 1 \right] - \frac{I_{02} \cdot R_s \cdot q}{a_2 \cdot k \cdot T} \cdot \left[e^{q \cdot \frac{(V_j + I_{est}(V_j, z) \cdot R_s)}{a_2 \cdot k \cdot T}} - 1 \right] - \frac{R_s}{R_{sh}} - 1 \quad (12)$$

After that, the root $I_{est}(V_j, z)$ is found by Eq. (13) [24,26]:

$$I_{est}(V_j, z) = I_{est}(V_j, z) - \frac{f(I_{est}(V_j, z))}{\frac{\partial f(I_{est}(V_j, z))}{\partial I_{est}(V_j, z)}} \quad (13)$$

The evaluation of the function value of $f(I_{est}(V_j, z))$ is repeated until meeting the stopping condition $|f(I_{est}(V_j, z))| \leq 10^{-5}$.

4. The Methodology

The following subsections give a complete overview of the working principle of SGO and the proposed ASGO as well as the different phases and steps included in each method to solve the considered problem.

4.1. Social group optimization (SGO)

Every human being is inherently endowed with many behavioural traits, such as: integrity, sympathy, kindness, bravery, anxiety, justice, fairness, or patience to name a few, as well as a certain level of intelligence and skills, which enables him/her to perform complicated tasks in life. However, there are situations when an individual is unable to solve a problem because he/she lacks a required set of skills or he/she does not have enough intelligence or even enough behavioral traits to counteract it.

Complicated challenges are frequently handled through the impact of traits/characteristics from one individual to another or from one group to another in society [27]. Humans have been known to be excellent mimics when it comes to solving any assignment. In leveraging and examining diverse characteristics of each member in the group to solve a particular challenge, group-solving capability has evolved to be more successful than individual capability [27,28]. This knowledge exchange in the pursuit of a solution to an individual's problem is formulated and arranged in the social group optimization (SGO) algorithm.

SGO is a population-based algorithm consisting of two main sections. The first section is the improving phase, while the second part is the acquiring phase. The knowledge level of each member in the group is increased during the improving phase, owing to the impact of the best person in the group. The one with the greatest amount of knowledge and ability to tackle the problem is the best member. During the acquiring phase, each individual improves his/her knowledge by mutual engagement with another member of the group and the best member of the group at the time. The following is a rudimentary mathematical understanding of these notions.

4.1.1. Notation

Coding the estimation problem is the first step to define. In this context, the population in the social group includes N individuals/members, which i^{th} person/member is regarded as a candidate solution and it can be expressed as a row vector given by $Y_i^t = [Y_{i,1}^t, Y_{i,2}^t, Y_{i,3}^t, \dots, Y_{i,d}^t]$ at iteration t , where d is the number of person characteristics, which is equivalent to the problem dimension, i.e., the number of the PV model unknown parameters considered. The associated fitness function value referred to $f(Y_i^t)$ is his/her capability to solve problems.

4.1.2. Initialisation phase

Resembling other MH techniques, the SGO relies on a uniform distribution to randomly create the initial population along the search space, which is restricted by the upper and lower limits defined as U and L . The first population is specified by Eq. (14) [29].

$$Y_{i,h}^{\text{initial}} = L_h + R \times (U_h - L_h) \Big|_{\substack{i=1,2,3,\dots,N \\ h=1,2,3,\dots,d}} \quad (14)$$

$$L = [L_1, L_2, L_3, \dots, L_d] \Big|_{h=1,2,3,\dots,d} \quad (15)$$

$$U = [U_1, U_2, U_3, \dots, U_d] \Big|_{h=1,2,3,\dots,d} \quad (16)$$

Where, $Y_{i,h}^{\text{initial}}$ means the initial ' i^{th} ' person possessing ' h ' number of traits and R is a randomly selected number from 0 to 1.

Accordingly, the initial objective function associated to each individual can be evaluated as given by Eq. (17).

$$f^{\text{initial}} = [f(Y_1^{\text{initial}}), f(Y_2^{\text{initial}}), f(Y_3^{\text{initial}}), \dots, f(Y_N^{\text{initial}})]^T \quad (17)$$

4.1.3. Improving phase

The best individual in any social group seeks to spread information among all members, which in turn encourages other individuals in the group to advance their knowledge. During the improving phase, every individual receives knowledge from the group's best person/ the leader/ the influencer, denoted by G^{best} , whom behavioral characteristics

influence to change the other individuals' behavioral characteristics.

For solving a minimization problem, which is the case of PV parameter identification issue, the optimal solution attained so far is defined by [27]:

$$[f_{G^{best}}, index_1] = \min \left\{ f(Y_i^t) \right\}_{i=1,2,3,\dots,N} \quad (18)$$

$$G^{best} = Y_{index_1}^t \quad | \quad i = \forall h, h=1,2,3,\dots,d \quad (19)$$

Where, $f_{G^{best}}$ and $index_1$ are the objective function value and the location corresponding to the best member in the social group at the improving phase, respectively.

Each person's updating is calculated as the following [27]:

$$Y_{i,h}^{t+1} = c_{SGO} \times Y_{i,h}^t + R_1 \times (G_h^{best} - Y_{i,h}^t) \quad (20)$$

Where, $Y_{i,h}^{t+1}$ indicates the newly generated solution at the subsequent iteration, c_{SGO} denotes the self-introspection coefficient and R_1 is a randomly selected number from 0 to 1.

4.1.4. Acquiring phase

During the acquiring phase, every member of the society makes an interaction with the group's best person, who has the highest level of knowledge among all the members denoted by P^{best} , and also communicates randomly with other individuals in that group. By this process, he/she will learn something new and acquire knowledge from another person in the group if the latter is more knowledgeable than him/her. Besides, given that the leader of the social society communicates with every member in the population. He/she has the most influence on others' learning. The acquiring phase is represented as follows: The best solution attained so far is defined by [27]:

$$[f_{P^{best}}, index_2] = \min \left\{ f(Y_i^t) \right\}_{i=1,2,3,\dots,N} \quad (21)$$

$$P^{best} = Y_{index_2}^t \quad | \quad i = \forall h, h=1,2,3,\dots,d \quad (22)$$

Where, $f_{P^{best}}$ and $index_2$ are the objective function value and the position of the corresponding to the best member in the social group at the acquiring phase, respectively.

Each person's updating is calculated as the following [27]:

$$Y_{i,h}^{t+1} = Y_{i,h}^t + R_2 \times (Y_{i,h}^t - Y_{p,h}) \quad (23)$$

$$+ R_3 \times (P_h^{best} - Y_{i,h}^t) \quad f(Y_i^t) < f(Y_p)$$

$$Y_{i,h}^{t+1} = Y_{i,h}^t - R_2 \times (Y_{i,h}^t - Y_{p,h}) \quad (24)$$

$$+ R_3 \times (P_h^{best} - Y_{i,h}^t) \quad f(Y_i^t) > f(Y_p)$$

Where, R_2, R_3 are random numbers generated from the uniform distribution in the range of 0 and 1, Y_p is the partner, which is another member chosen randomly in the social group, such that $p \neq i$.

4.1.5. Bounding procedure

After each individual update performed at the improving phase or the acquiring phase, the newly generated candidate solution may violate the lower or the upper bound of the search space. Therefore, bounding is carried out to each new solution to bring it back to its lower or upper limit as illustrated in Figure 1.

4.1.6. Greedy selection procedure

Each new candidate solution, resulting from the improving phase or the acquiring phase, is chosen by employing a greedy selection procedure between recently generated individual and the old individual. Through this strategy, it is determined whether to approve or reject the new solution by assessing the objective function values of both the current and the subsequent individual as illustrated in Figure 2.

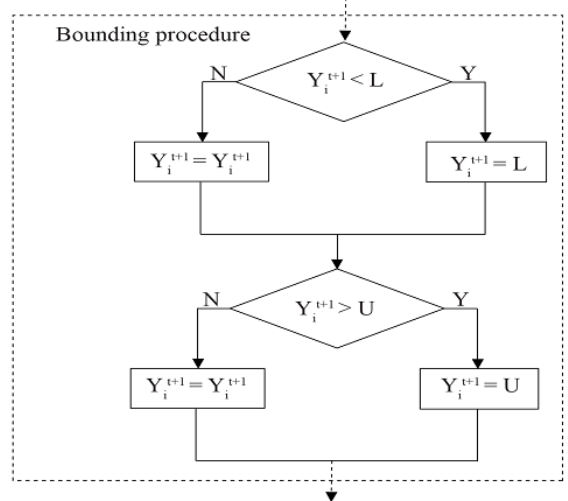


Figure 1. Flowchart of the bounding procedure

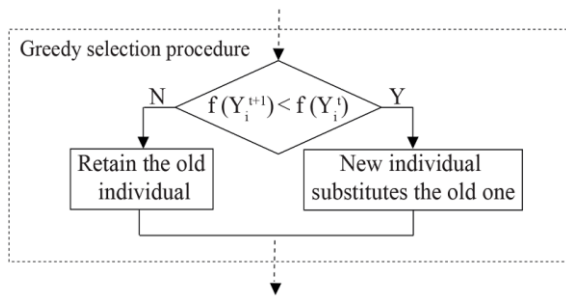


Figure 2. Flowchart of the greedy selection procedure

4.1.7. Termination criterion

Several stopping conditions can be used to bring the optimization process to a halt. Some of the most common criteria are based on: limiting the maximum optimization time, attaining the maximum number of iterations, reaching a predefined accuracy for the objective function's minimum value or once there is no improvement in the estimation of global best value for a certain time. In this work, we choose the maximum number of iterations (t_{max}) as a stopping criterion for SGO and ASGO techniques as it is the most used.

4.2. Ameliorated social group optimization (ASGO)

Although SGO is an effective algorithm to solve complex engineering issues, it shows some drawbacks that call in question when dealing with new optimization issues, especially those related to multimodal ones, such as the problem regarded in this paper. The most important of these drawbacks are highlighted below:

- SGO suffers from lower population diversity [30], which will prevent it from discovering new regions. That means that its exploratory ability is weak. In return, the process for producing new locations as stated in Eq. (20) permits the members to more effectively exploit around the best individual. However, if the best individual is not close to the global optimum, a risk exists that the solutions produced through such mechanism could fall in local optima trap, which can induce premature convergence.
- Each Individual progress depends not only on the influence of the best member, but also on the degree of self-introspection (refer to Eq. (20)), which the coefficient c_{SGO} represents. If the latter did not exist, the position of the best individual in the group remains unchangeable

across iterations i.e. equals to its initial value, since the difference in Eq. (20) will be equal to zero and subsequently stagnation of the other candidate solution. On the other hand, c_{SGO} is fixed and equals to 0.2 in [27], while keeping a low value for c_{SGO} is only meaningful at initial iterations and as the individual knowledge increases, the self-learning rate needs also to rise gradually [31], which is not taken into consideration in the basic SGO technique.

Considering the above drawbacks, we propose an enhanced version of SGO, named as ameliorated social group optimization (ASGO), which enables obtaining high-quality solutions by working on increasing the exploration capability and thus enhancing the population diversity and avoiding falling into the trap of the local minima.

ASGO maintains the same stages as the conventional SGO algorithm, enhancements are applied to the improving phase, which already focuses on both the explorative and the exploitative capabilities, while the acquiring phase remains the same as that in SGO, which in turn works to enhance the exploitative ability of the original algorithm.

The contribution of ASGO lies in the coordinated integration of established search operators into the improving phase of SGO, rather than in introducing a new mutation operator. Gaussian mutation updates the best individual, while the remaining individuals are updated through an iteration-dependent combination of current-to-best/2 differential evolution mutation and local search. Four distinct random partners provide two difference vectors to promote population diversity, whereas the adaptive weighting progressively shifts the search towards local refinement. The acquiring phase, bounding procedure, and greedy selection of the original SGO are retained. Unlike conventional SGO, this formulation explicitly perturbs the best solution and adapts the balance between exploration and refinement throughout the optimization process. Its intended benefit is to reduce premature convergence and improve estimation consistency. Table 1.A (in Appendix) provides a general comparison among different methods, including SGO and ASGO.

ASGO is built according to the best individual in the group, since he/she is the largest contributor to producing a new member from the old member of the group in both improving and acquiring phases. We summarize below the main steps taken to do so:

When the individual is the best member of the group, his/her position is updated, at each iteration, via a Gaussian mutation strategy as follows [32]:

$$G^{best} = G^{best} + (U - L) \cdot \text{Gaussian}(0, b) \quad (25)$$

Where b is the standard deviation of the Gaussian probability distribution.

In this way, we avoid resorting to the use of the parameter c_{SGO} .

As for the rest of the individuals, the DE mutation strategy appears suitable for updating each new solution. In fact, there are various DE-based mutation schemes used to boost the exploration capability of any MHAs. They are often represented by the following format x/n , where x indicates the vector to be muted and n stands for the number of different solutions (random vectors) required for mutation. In this paper, we suggest using the current-to best/2 mutation strategy because it is the mutation scheme that combines the best individual and the current solution together. Thus, it will maintain the same concept used in the original technique. This is with regard to x , while what concerns n , it is chosen to be equal to 2 based on what was found in the investigation carried by Zhang et al. in [33], which demonstrated that the statistical distribution of two difference vectors, displays a bell-shaped, can deliver better perturbation for detecting new regions.

$$Y_{i,h}^{1|t+1} = Y_{i,h}^t + F_{ASGO} \cdot (G_h^{best} - Y_{i,h}^t) + F_{ASGO} \cdot (Y_{p_1,h} - Y_{p_2,h}) + F_{ASGO} \cdot (Y_{p_3,h} - Y_{p_4,h}) \quad (26)$$

Where F_{ASGO} is the scaling factor, Y_{p_1} , Y_{p_2} , Y_{p_3} and Y_{p_4} are four random partners wherein p_1, p_2, p_3 and $p_4 \in \{1, 2, \dots, N\}$ and $p_1 \neq p_2 \neq p_3 \neq p_4 \neq i$.

With the help of four random individuals, to update each new person in the group, it becomes clear that if the differences between $(Y_{p_1,h} - Y_{p_2,h})$ and $(Y_{p_3,h} - Y_{p_4,h})$ are large, the newly generated members will be dispersed over the entire search space, taking advantage of the various experiences acquired by each member, which will enhance the exploration capabilities of the algorithm and subsequently increases the chances of reaching the

most promising areas. In contrast, if these differences are small, the new generated individuals will be clustered in a confined area. i.e., so the closer and closer the solutions values are to each other, the less and less capable and fast the algorithm is exploring the nearest neighbourhood since the values of the differences mentioned above tend to zero. Hence, the use of the mutation alone is not effective.

As members are expected to quickly approach the promising regions of the search space in its early stages of the optimization process and to boost their local search capability over the later stages, it is appropriate to combine Eq. (26) with a local search strategy, as shown in Eq. (27) to form Eq. (28):

$$Y_{i,h}^{2|t+1} = Y_{i,h}^t + R_4 \cdot (G_h^{best} - Y_{i,h}^t) \quad (27)$$

$$Y_{i,h}^{3|t+1} = \left(1 - \frac{t}{t_{max}}\right) \cdot Y_{i,h}^{1|t+1} + \frac{t}{t_{max}} \cdot Y_{i,h}^{2|t+1} \quad (28)$$

By following the adaptive formula mentioned in Eq. (28), we find that in the early stages of the proposed method, t is small and in turn the coefficient multiplied by $Y_{i,h}^{1|t+1}$ is large, the current-to best/2 mutation strategy prevails the optimization process. Thus, random collaborative learning among the individuals guarantees population diversity. The more the iterations increase in value, the effect of the mutation strategy decreases gradually and at the same time the effect of local search increases, due to the increase in the coefficient multiplied by $Y_{i,h}^{2|t+1}$, which helps to discover the neighborhood region and subsequently accelerate the convergence of the algorithm.

Figure 3 depicts the flowcharts for the application of the SGO and ASGO techniques, respectively to the PV cell/module parameter identification problem.

Table 1. A (in Appendix) provides a general comparison among five MHAs, including SGO and ASGO.

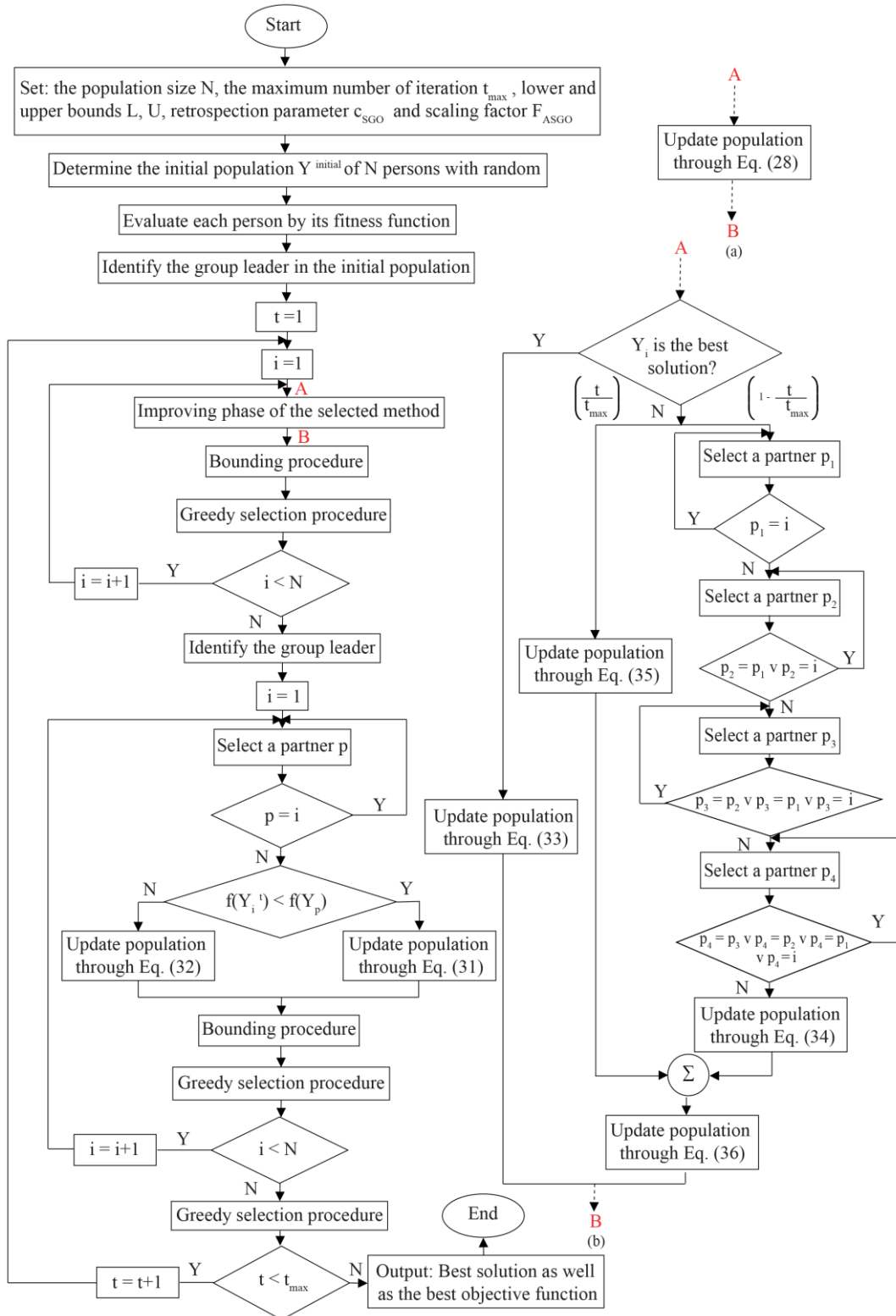


Figure 3. Flowchart of the SGO and ASGO techniques (a): Improving phase of SGO, (b): Improving phase of ASGO

5. Simulation results

Within this section, the performance of SGO and ASGO algorithms in determining the unknown parameters of PV models (SDM and DDM) were evaluated, compared and tested using experimental data obtained from two different case studies.

The RTC France PV cell and the Photowatt PWP PV module were utilized in the first and second case study, respectively. The measured data related to

each case studied were collected from [34]. This latter has been extensively cited in literature in order to verify the effectiveness of any new suggested optimization algorithm in the PV parameter identification task. In all experiments, the controlling settings associated to each technique were defined as: $c_{SGO} = 0.2$ and $F_{ASGO} = 0.8$. Besides that, the values of the upper and the lower bounds for all the used case studies are displayed in Table 1.

Table 1. Parameters limits of SDM and DDM for all the used case studies

Parameters	Case study 1		Case study 2	
	Lower limit	Upper limit	Lower limit	Upper limit
I_{pv} [A]	0	2.Isc ₁	0	2.Isc ₂
I_s [A]	1E-17	1E-03	1E-17	1E-03
a	0.9	6	0.9	6
R_s [Ω]	0.001	0.6	0.001	2
R_{sh} [Ω]	0.001	150	0.001	10000
I_{s1} [A]	1E-17	1E-03	1E-17	1E-03
I_{s2} [A]	1E-17	1E-03	1E-17	1E-03
a_1	0.9	6	0.9	6
a_2	1	6	1	6

All the computations were implemented in MATLAB 2019b computing environment on a laptop possessing the following specifications: Intel® Core™ i7-8750 H with a 2.20 GHz CPU processor speed, 16 GB RAM and Windows 10 Professional 64-bit.

Because the outcomes of a single execution of MHAs are stochastic, each algorithm has been run 50 times before displaying the final results related to each case study. With that in mind, four statistical criteria were used for assessing SGO and ASGO techniques regarding the RMSE: *Min*, *Mean*, *Max* and *Std*. In which, “*Min*” represents the minimum RMSE value, “*Mean*” denotes the average RMSE values, “*Max*” means the maximum RMSE value and “*Std*” refers to standard deviation of RMSEs. They were calculated using the following formulas [29]:

$$Min = \min(O.F_i)_{i=1, \dots, Run} \quad (29)$$

$$Mean = \frac{1}{Run} \times \sum_{i=1}^{Run} O.F_i \quad (30)$$

$$Max = \max(O.F_i)_{i=1, \dots, Run} \quad (31)$$

$$Std = \sqrt{\frac{\sum_{i=1}^{Run} (O.F_i - Mean)^2}{Run - 1}} \quad (32)$$

Where *Run* = 50, which represents how many times each technique is executed, *O.Fi* is the achieved objective function when run number equals to *i*. Needs to say, that the minimum and maximum RMSE corresponds to the best and worst run, respectively and the closer the *Std* value is to zero, the higher reliable and stable is the examined method.

5.1. Accuracy, consistency of solutions, computation time and convergence curves

The aim of this section is to evaluate the accuracy and the stability of the solutions obtained by SGO and ASGO techniques as well as to illustrate the convergence curves and the time taken by each method. In all experiments used in this subsection, 25 individuals were assigned in 2000 iterations for the SDM, whereas 50 agents were allocated in 3000 iterations for the DDM. All the presented values have been represented in long format with 18 decimal digits since model accuracy is highly sensitive to circuit parameter values [24].

5.1.1. Case study 1

In the first case study, 26 pairs of current and voltage were employed to extract the required SDM and DDM parameters for the commercial silicon solar cell RTC France (distinctive with a diameter of

57 mm). These data were measured at a temperature of 33°C and an irradiance of 1000 W/m². Using interpolation [25], one can get the following key points related to this PV cell: $I_{sc1} = 0.7605$ A, $I_{mpp1} = 0.6755$ A, $V_{mpp1} = 0.4590$ V and $V_{oc1} = 0.5722$ V.

5.1.1.1. Case study 1 results with SDM

Table 2 exhibits the estimated SDM parameters for the RTC France achieved by each technique in its best and worst run. It also contains information about the four metrics previously mentioned.

When inspecting each best and worst parameter in Table 2, ASGO findings displayed a strong resemblance between its values; the disparity is estimated at less than 1.28E-5%, whereas those obtained by SGO revealed significant differences, which range in between 6% and 199.87%. Meanwhile, the best-found solutions by both methods were remarkably similar to one other, with a slight difference estimated at less than 0.69%. In regards to RMSE results, the least values reached by SGO and ASGO were 7.73080686937670E-04 and 7.73006268779181E-04, respectively. This means that the latter only provides 9.63E-05 % improvements compared to the former, while their average values were 1.7654406676469715E-01 and 7.73006268779266E-04, consecutively, which signifies that ASGO gives 95.56% improvements against SGO. To further show the distribution of the

final RMSEs for both techniques across all the runs, we use boxplots as depicted in Figure 4. It is obvious from the figure that all the computed values with ASGO were so close to the minimum one. Therefore, it managed to get a tiny *Std* rate of about 3.31E-17 with a tight maximum variation band fewer than 1.81E-16 (see Table 2). By contrast, RMSEs generated by SGO were very distant from the lowest one. Thus, it got a high *Std* rate of about 1.83E-02 with a wide maximum variation band inferior to 0.05.

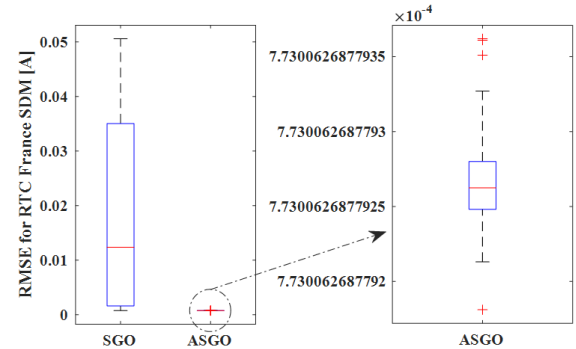


Figure 4. Boxplot of best RMSEs across 50 independent runs of SGO and ASGO for case study N°01 with SDM

An additional boxplot, representing a zoomed view of ASGO, is incorporated to aid in the analysis of the RMSEs values

Table 2. The extracted results for the SDM of the case study N°01 obtained via SGO and ASGO methods (the best values are bolded)

Parameter	Best solutions	Worst solutions	RMSE		Time [s]	
SGO						
I_{pv} [A]	0.760785500227719180	0.807811423833799114	Min	0.000773080868693767	Min	1.0199
I_o [A]	3.128351237402376879E-07	9.997436835341726082E-04	Mean	0.017654406676469715	Mean	1.1281
a	1.477959768319722089	3.262963460444093133	Max	0.050579068185401289	Max	1.3216
R_s [Ω]	0.036516916970748804	0.001000296086951437	Std	0.018287590886430005		
R_p [Ω]	53.038970059656499245	149.996605669866994504				
Parameter	Best solutions	Worst solutions	RMSE		Time [s]	
ASGO						
I_{pv} [A]	0.760787966545731775	0.760787967373472651	Min	0.000773006268779181	Min	1.1437
I_o [A]	3.106845859766879454E-07	3.106846027998150869E-07	Mean	0.000773006268779266	Mean	1.1543
a	1.477267782962302212	1.477267788508413782	Max	0.000773006268779362	Max	1.1658
R_s [Ω]	0.036546945461201366	0.036546945068562153	Std	3.308666760733280401E-17		
R_p [Ω]	52.889789191601934704	52.889782415936103632				

Similarly, the execution time distribution for each method during the different runs is illustrated in Figure 5. From Figure 5 and Table 2, it can be observed that there were no significant differences between the time taken to run each method despite the slight rapidity of SGO over ASGO (see the

average time recorded by each one was 1.1281s and 1.1543s, respectively). This is due to the fact that the ASGO has an additional step in its structure for selecting four random solutions, different from each other, for generating each new member at each cycle.

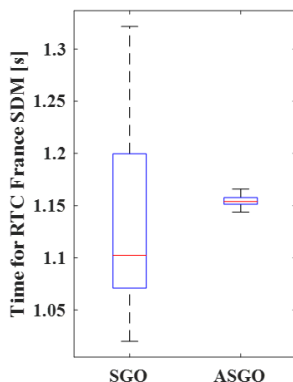


Figure 5. Boxplot of the execution time taken by SGO and ASGO across 50 independent runs for case study N°01 with SDM

Figure 6 portrays the best, mean and worst SDM convergence trends of SGO and ASGO, with an enlarged display of the best convergence curves for both methods. All the values given in DataTips are marked either in blue for SGO or in black for ASGO. In addition, to avoid overcrowding, the best and the worst results are only shown in DataTips (which we will keep in the remaining cases). By comparing the best convergence curves, we find that ASGO advances about more than three times as fast as SGO, even though they both end up with roughly the same final results. As for comparing the worst and the mean curves, we find that SGO always converges towards incorrect regions, in contrast to ASGO, which maintains the same final results, so that its speed in its best curve is about 1.4 times faster than its speed in its worst curve.

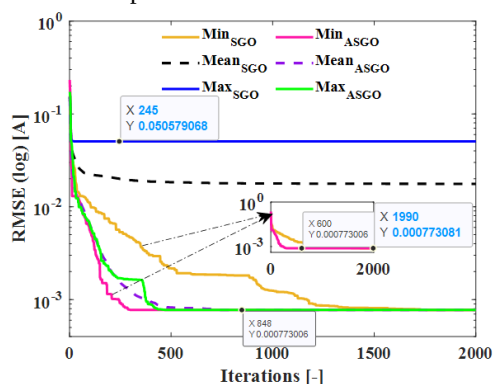


Figure 6. Best, average and worst convergence histories across 50 independent runs of SGO and ASGO for case study N° 01 with SDM

To test the reliability of both methods, one can benefit from the worst parameters values extracted via SGO and ASGO to reconstruct the I-V curve as shown in Figure 7, respectively. Evidently, the

estimated curve via ASGO agrees well with the experimental data used for this case study compared to SGO, which in turn shows significant difference between its estimated curve and the experimental one.

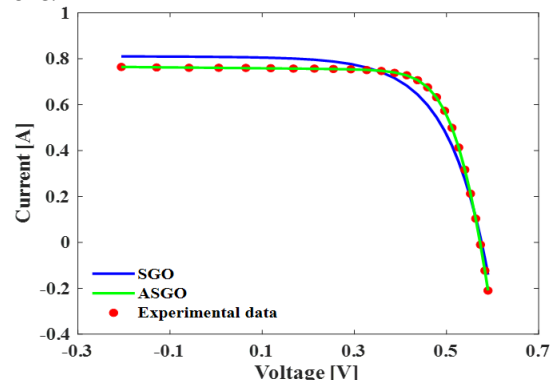


Figure 7. Comparison of the experimental and the computed I-V curves by SGO and ASGO for case study N°01 with SDM, using the worst parameters values

Lastly, to quantify these differences, we recourse to plot the *IAE* for both methods at each measured voltage, as depicted in Figure 8. From the drawn figure, ASGO provides smaller error values than SGO in all voltage points, where the error range for the first is between 1.673E-05 and 0.001585. As for the second, it falls in between 0.006032 and 0.08715. In light of the preceding results shown in Table 2, Figures 4, 6, 7 and 8. ASGO seems to be well-suited to estimate the five unknown parameters of RTC France PV cell.

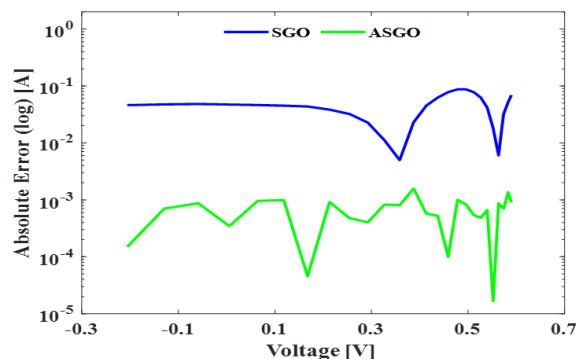


Figure 8. individual absolute error values for current using SGO and ASGO for case study N°01 with SDM, using the worst parameters values

5.1.1.2. Case study 1 results with DDM

Table 3 summarizes the best and the worst DDM parameters for RTC France as well as the variation of the statistical values corresponding to *RMSE* and

the time consumed by SGO and ASGO in the course of runs.

By examining each best and worst parameter in Table 3, we notice that the difference resulting from applying SGO technique amounts to approximately between 6% and 200%. The disparity in ASGO attains least and largest values of 0.011% and 195.56%, respectively. As for the best-found solutions by both methods, the difference varies between 6.51E-4% and 10.11%.

Based on the *RMSE* results exposed in Table 3, we noticed that the smallest values gotten by SGO and ASGO were 6.93235338763384E-4 and

6.92004832875467E-4, respectively, which reveals an enhancement of 10.33% in SGO and 10.48% in ASGO compared to SDM findings. Besides, ASGO produces only 0.18% better than SGO in DDM. As for the mean *RMSEs* achieved by both techniques, they were 5.564799665229263E-3 and 6.95616910766259E-4, respectively. This indicates that ASGO offers an amelioration, in DDM, by 87.50% over SGO and it outperforms itself by 10.01% compared to SDM findings. In fact, even SGO is improved in DDM by 68.48% over its peer in the previous model.

Table 3. The estimated results for the DDM of the case study N°01 obtained via SGO and ASGO methods (the best values are bolded)

Parameter	Best solutions	Worst solutions	RMSE		Time [s]	
SGO						
I_{pv} [A]	0.760938344736490024	0.804735291562165167	Min	0.000693235338763384	Min	3.4783
I_{o1} [A]	3.166834277394834848E-04	1.580435188654688848E-08	Mean	0.005564799665229263	Mean	3.8288
a_1	5.999960781716409564	5.624616135942544837	Max	0.049542291645177525	Max	4.4132
I_{o2} [A]	2.193347960018601897E-07	9.435500022489539838E-04	Std	0.011918555258458160		
a_2	1.444078548731312583	3.238002970143198045				
R_s [Ω]	0.037462502909385534	0.001000088331344513				
R_{sh} [Ω]	75.692609190016540310	149.891388062870419162				
ASGO						
I_{pv} [A]	0.760953163331004490	0.760870589527282148	Min	0.000692004832875467	Min	3.9778
I_{o1} [A]	3.503953418493101256E-04	3.931717989348956308E-06	Mean	0.000695616910766259	Mean	4.0827
a_1	5.99999823029767754	2.261819114753836679	Max	0.000726439419194194	Max	4.5727
I_{o2} [A]	2.099509363286433618E-07	1.340013854176605943E-07	Std	7.298456197353460824E-06		
a_2	1.439998686703198638	1.404409598075057497				
R_s [Ω]	0.037562779479991287	0.037771162340425740				
R_{sh} [Ω]	78.966837527590953982	57.804365843070819153				

For more clarity, Figure 9 outlines the distribution of the *RMSEs* for each method considering all the runs. From Figure 9, it seems that the values produced by ASGO were closer to the lowest one compared to SGO, and accordingly it presented a small *Std* rate of about 7.30E-6 with a maximum variation that did not exceed 3.45E-5 (see Table 3). These values are higher than those reported in the prior model. With regards to SGO, the *RMSEs* were scattered in a range that did not surpass 0.05, which is considered narrower than that obtained previously in SDM. Knowing that *Std* value calculated for this method was around 1.20E-2.

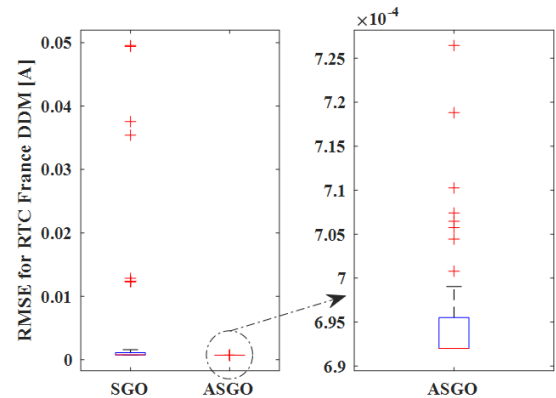


Figure 9. Boxplot of best *RMSEs* across 50 independent runs of SGO and ASGO for case study N°01 with DDM

Zoomed view of ASGO, is incorporated to aid in the analysis of the *RMSEs* values.

Apart from this, the average time expended by SGO and ASGO to perform their tasks were 3.8288s and 4.0827s, respectively. That is, there is an increase of about three times compared to the SDM outcomes. For more details, Figure 10 depicts the execution time distribution for each technique along all the runs.

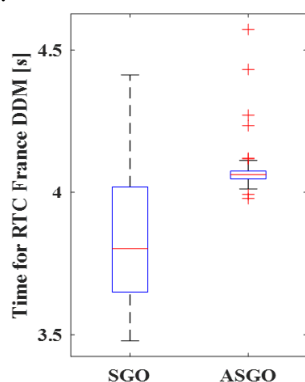


Figure 10. Boxplot of the execution time taken by SGO and ASGO over 50 independent runs for case study N°01 with DDM

Figure 11 illustrates the DDM convergence graphs of SGO and ASGO in their best, mean and worst runs. From Figure 11, it is evident that, ASGO shows superiority than SGO on the convergence speed, where the former converges 1.85 times faster than the latter regarding to their best runs although their final results were close. ASGO in its best run progresses 1.85 times faster than itself in its worst run. As for SGO in its mean and worst runs, it is always stuck into local optimums.

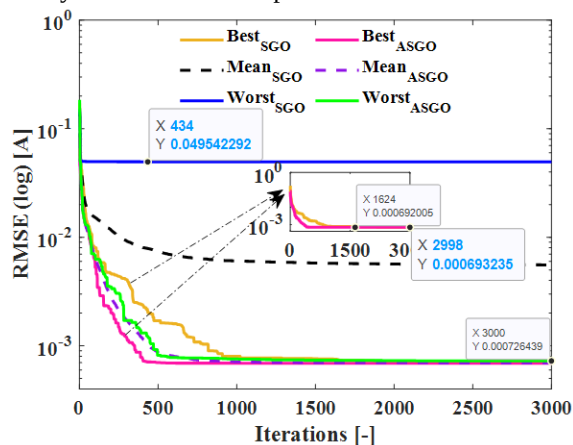


Figure 11. Best, average and worst convergence histories across 50 independent runs of SGO and ASGO for case study N° 01 with DDM

In summary, it is noticed that the computational efforts for both techniques in DDM have been increased compared to what have been found in

SDM. This is expected to happen seeing that model complexity has increased, too (more parameters have been added to be identified).

Additionally, to confirm the reliability of the estimated findings, one can rebuild the I-V characteristic relying on the worst DDM parameters resulted by both techniques, as illustrated in Figure 12. It is apparent from Figure 12 that the simulated curve concurs well with the experimental ones during the entire voltage range for ASGO. As for SGO, its identified curve does not fit the experimental data.

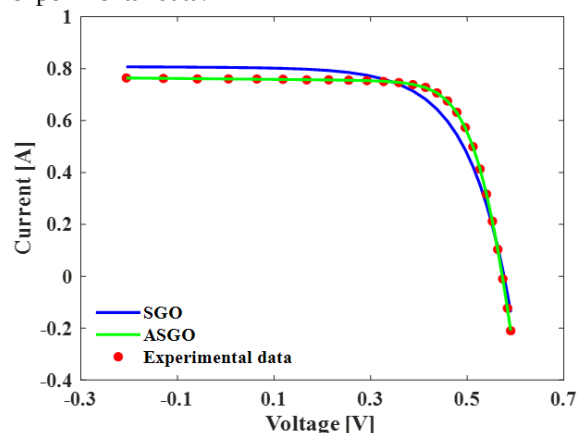


Figure 12. Comparison of the experimental and the computed I-V curves by SGO and ASGO for case study N°01 with DDM, using the worst parameters values

Figure 13 pinpoints the *IAE*, for current, between each method and the experimental data used when considering the worst obtained parameters. It is obvious from the figure that ASGO gets reduced errors values, for all the measured voltage, compared to SGO, the *IAE* values for SGO and ASGO are in the intervals [0.006476, 0.08637] and [6.617E-05, 0.001183], respectively.

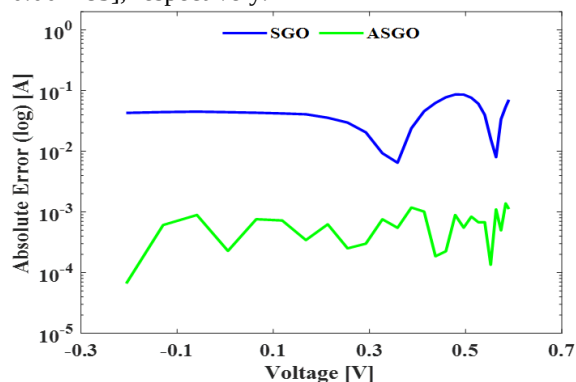


Figure 13. Individual absolute error values for current using SGO and ASGO for case study N°01 with DDM, using the worst parameter values

In view of the outcomes obtained from Table 3, Figures 9, 11, 12 and 13, ASGO prove its effectiveness and robustness against SGO in determining the seven parameters of RTC France PV cell.

5.1.2. Case study 2

The second case study was concerned with Photowatt PWP PV module fabricated from 36 multi-crystalline silicon solar cells, connected in series. As for the number of samples measured on this PV module at an irradiance of 1000 W/m² and a temperature of 45°C were 26. Based on interpolation

[25], the following key points specifications can be obtained related to this PV module: $I_{sc2} = 1.0317$ A, $I_{mpp2} = 0.9120$ A, $V_{mpp2} = 12.6490$ V and $V_{oc2} = 16.7785$ V.

5.1.2.1. Case study 2 results with SDM

The best and the worst five SDM parameters of the Photowatt PWP-201 PV module obtained from SGO and ASGO techniques as well as the corresponding RMSEs and the execution time variation in the course of all runs are tabulated in Table 4.

Table 4. The estimated results for the SDM of the case study N°02 obtained via SGO and ASGO method (the best values are bolded)

Parameter	Best solutions	Worst solutions	RMSE		Time [s]	
SGO						
I_{pv} [A]	1.032116805182032859	1.071331237405863446	Min	0.002041919956358257	Min	0.8887
I_o [A]	2.527009981057685278E-06	8.170479533153353086E-04	Mean	0.00887755947695563	Mean	1.0042
$N_s \cdot a$	47.441952350033695041	85.473573393576842250	Max	0.028090775415435334	Max	1.0910
R_s [Ω]	1.240061807110952596	0.113311276876659192	Std	0.009843331690825585		
R_{sh} [Ω]	765.553673744876846285	1345.707368203650275973				
Parameter	Best solutions	Worst solutions	RMSE		Time [s]	
ASGO						
I_{pv} [A]	1.032357595002611816	1.032357593248183214	Min	0.002039992273298329	Min	1.1376
I_o [A]	2.496595829820002391E-06	2.496595192148922664E-06	Mean	0.002039992273298390	Mean	1.1632
$N_s \cdot a$	47.398555237092892867	47.398554301436831793	Max	0.002039992273298588	Max	1.2307
R_s [Ω]	1.240547323604431762	1.240547354349746945	Std	4.779641182807256942E-17		
R_{sh} [Ω]	748.322948651863612213	748.323003774794301535				

When each best and worst parameter are compared in Table 4, one can see that those extracted by ASGO were strikingly similar, such that the disparity is less than 2.55E-5 %, while large discrepancies were found between those provided by SGO, which in some parameters reach 198.77% and 166.51%, while in others they are not less than 3.73%. As for the best solutions produced by both methods, the similarity is less than 9.15E-2% for I_{pv} , a and R_s and is lower than 2.28% for I_o and R_{sh} .
By examining the other findings of this table, it was found that the RMSEs relevant to the optimal solutions obtained by SGO and ASGO were 2.041919956358257E-3 and 2.039992273298329E-3, respectively, which implies that the latter is only 9.44E-2 % better than the former. Additionally, their mean objective function values were 8.887755947695563E-3 and 2.039992273298390E-3, consecutively, meaning that ASGO yields a significant improvement of 77.05 % over SGO.

The detailed RMSEs distribution across all the runs are plotted in Figure 14, where we can clearly see that the RMSEs achieved by ASGO were very adjacent to the best one while those obtained via SGO were far from the smallest one.

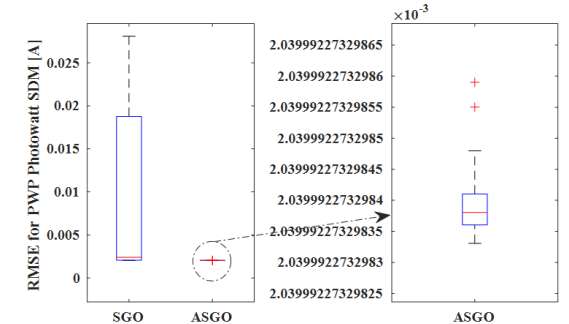


Figure 14. Boxplot of best RMSEs across 50 independent runs of SGO and ASGO for case study N°02 with SDM
An additional boxplot, representing a zoomed view of ASGO, is incorporated to aid in the analysis of the RMSEs values.

This leads to get a very tiny *Std* rate of about $4.78\text{E-}17$ with a narrow maximum variation less than $2.60\text{E-}16$ for the former and a big *Std* value of $9.84\text{E-}3$ with a significant maximum variation less than $2.60\text{E-}2$ for the latter (see Table 4).

Figure 15 displays the running time carried out by each method across all the runs where it turns out that SGO executed slightly lesser time than ASGO (the average time recorded by SGO and ASGO, as shown in Table 4, were 1.0042s and 1.1632s, respectively).

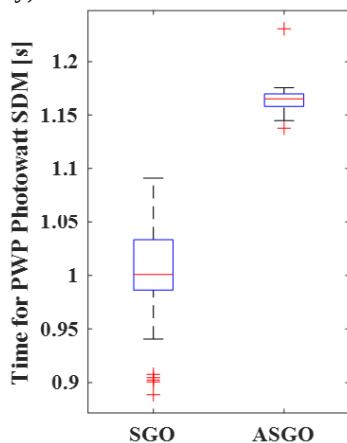


Figure 15. Boxplot of the execution time taken by SGO and ASGO over 50 independent runs for case study N°02 with SDM

The SDM convergence characteristics obtained by SGO and ASGO at their best, average and mean runs are represented in Figure 16. By inspecting Figure 16, one can see that SGO gets trapped into local minima in both its worst and mean runs and subsequently it fails to reach the optimum final solutions, while ASGO always converges to a lower objective function value. It shows that it is 2.88 times faster, on the convergence speed, than SGO when it comes to compare their best runs. ASGO in its best run is quicker than itself in its worst run by 1.4.

By relying on the worst extracted parameters from SGO and ASGO, the I-V curve can be reproduced as shown in Figure 17. It is evident from this figure that the findings retrieved by ASGO method agree well with the experimental data, whereas SGO curve does not match all the measured data.

It is evident from Figure 18, which displays the current IAE values for both methods, that ASGO present a small error band ranging from $1.235\text{E-}05$ to 0.003878 . As for SGO, its error band ranges from 0.002596 to 0.04023 .

The results given in Table 4, Figures 14, 16, 17 and 18 specify that ASGO is a reliable and effective

technique for identifying the required SDM parameters for Photowatt PWP-201 PV module.

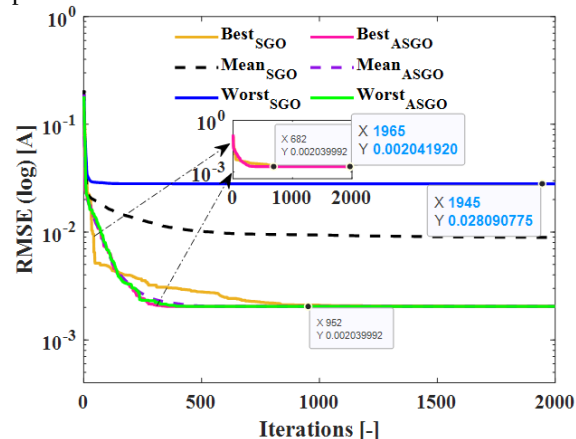


Figure 16. Best, average and worst convergence histories across 50 independent runs of SGO and ASGO for case study N°02 with SDM

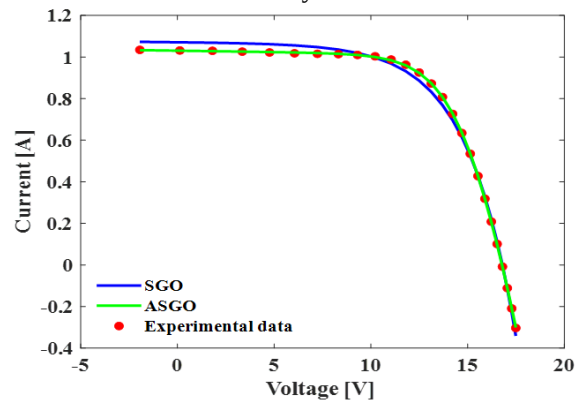


Figure 17. Comparison of the experimental and the computed I-V curves by SGO and ASGO for case study N°02 with SDM, using the worst parameters values

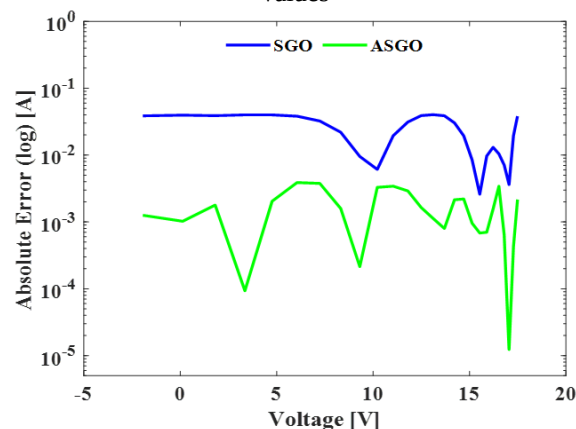


Figure 18. Individual absolute error values for current using SGO and ASGO for case study N°02 with SDM, using the worst parameters values

5.1.2.2. Case study 2 results with DDM

Table 5 reports the optimal and the worst parameters needed for the DDM of the Photowatt PWP-201 PV module got by SGO and ASGO techniques in addition to the corresponding *RMSE* and time variations along all runs. By comparing each best and worst parameter in Table 6, we find that all values obtained via SGO differ from each other, where the disparity is between 2.3% and 200%. Regarding ASGO, there is a high similarity

between I_{pv} , R_s and R_{sh} parameters of less than 4.3E-7%, whereas for the rest of parameters the differences are up to 200%. It should be noted here that although each worst value of a_1 , a_2 , I_{o1} and I_{o2} , in ASGO, is different from its best counterpart, this does not prevent it to obtain the same fitness values in its worst and best runs. As for the best-found solutions by both methods, the difference varies between 1.86E-6 and 200%.

Table 5. The estimated results for the DDM of the case study N°02 obtained via SGO and ASGO methods (the best values are bolded)

Parameter	Best solutions	Worst solutions	RMSE		Time [s]	
SGO						
I_{pv} [A]	1.032357614376031796	1.056374822295589544	Min	0.002039992274701181	Min	3.1666
I_{o1} [A]	1.019402035668271652E-17	9.959492931426987966E-04	Mean	0.004538721221980909	Mean	3.5288
N_s, a_1	215.901259601076532135	88.116725876797517003	Max	0.025565674206952799	Max	4.0428
I_{o2} [A]	2.496520835998573946E-06	4.236485277715406333E-10	Std	0.006567488707252704		
N_s, a_2	47.398445663924135829	129.437642437475517454				
R_s [Ω]	1.240550777780805136	0.001001698283010480				
R_{sh} [Ω]	748.315686298898185669	9999.834773224047239637				
Parameter	Best solutions	Worst solutions	RMSE		Time [s]	
ASGO						
I_{pv} [A]	1.032357595148039930	1.032357595060023669	Min	0.002039992273298298	Min	3.9840
I_{o1} [A]	2.496595718440897041E-06	1.000287934858749167E-17	Mean	0.002039992273298348	Mean	4.0246
N_s, a_1	47.398555075782894619	76.759674849348741077	Max	0.002039992273298410	Max	4.0783
I_{o2} [A]	4.638524770973845424E-17	2.496595555426948675E-06	Std	2.277420848015029038E-17		
N_s, a_2	215.982219376013858891	47.398554832905190892				
R_s [Ω]	1.240547327306491310	1.240547332573512573				
R_{sh} [Ω]	748.322927423257965529	748.322922081608794542				

Table 6. Comparative study of population size, the mean exploration, exploitation and diversity on the behaviour of SGO and ASGO for the case study N°02 of the SDM (the best values are bolded)

Case study N°02							
T_{max} , N	1500, 20		1500, 25		1500, 30		
	<u>SGO</u>	<u>ASGO</u>	<u>SGO</u>	<u>ASGO</u>	<u>SGO</u>	<u>ASGO</u>	
Min	0.002065174303141513	0.002039992273298390	0.002045482111043136	0.002039992273298368	0.002044920851493012	0.002039992273298371	
Mean	0.015457470684526707	0.002039992273871290	0.011292287123290310	0.002039992273313077	0.009693913926315707	0.002039992273336571	
Max	0.092232699692465253	0.002039992300046341	0.029617648836703779	0.002039992273526762	0.028352449564584405	0.002039992274488039	
STD	0.015512686233610866	3.77927600685586625E-12	0.010396220408266588	4.111320031116224526E-14	0.010108977425377129	1.738115795876669606E-13	
%XPL	0.340048288674429100	29.610218157188437971	0.298437668732016104	43.517569207387680308	0.331738698749654282	34.209258150273726073	
%XPT	99.659951711325632573	70.389781842811601109	99.701562331268235084	56.482430792612341008	99.668261301250353768	65.790741849726458668	
DIV _{mean}	21.636754891413946922	1735.856318388552153920	20.594863104479479432	2782.417176567340447946	27.802521992677629470	2930.510112215753451892	

RMSE results stated in Table 5 show that the minimal values found by SGO and ASGO were 2.039992274701181E-3 and 2.039992273298384E-3, respectively, indicating that they were slightly

decreased by 9.44E-2% and by 1.51E-14%, respectively compared to their previous analogues ones in SDM. In other words, ASGO retains approximately its value in SDM and did not differ from that obtained by SGO in DDM (only about

6.88E-8%). Also, the decrease in the average *RMSE* value, in DDM, from 0.004538721221980909 for SGO to 0.002039992273298348 for ASGO results in an improvement of the latter against the former by 55.05%. Indeed, ASGO keeps almost the same value as obtained in SDM despite its negligible enhancement of 2.06E-12 %. However, SGO records an outperformance against its counterpart in SDM by 48.93%.

By looking at Figure 19, which plots the distribution of the final *RMSEs* along the different runs for each technique, one can see that ASGO appears to be more stable than SGO since all of its values were very close to each other. This has resulted in obtaining a very tiny *Std* rate of about 2.28E-17 for ASGO, which is lesser than half of its old value in SDM, and they span in a slightly narrower range that did not surpass 1.12E-16. As far as SGO is concerned, *RMSEs* distribution area remains quite high compared to ASGO, even though it has seen a decrease in its variation compared to SDM findings (its height is less than 2.35E-2) with a *Std* rate of about 6.57E-3.

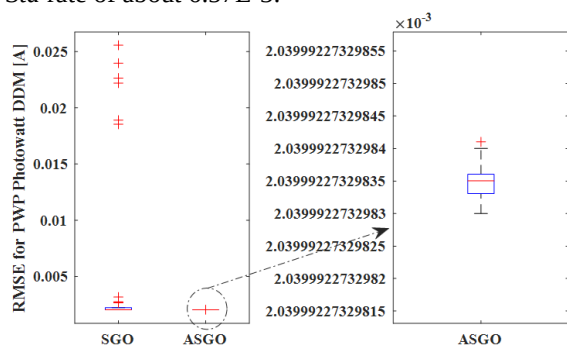


Figure 19. Boxplot of best *RMSEs* across 50 independent runs of SGO and ASGO for case study N°02 with DDM

An additional boxplot, representing a zoomed view of ASGO, is incorporated to aid in the analysis of the *RMSEs* values.

From computational efforts perspective represented by Figure 20, it is found that the average counted time consumed to run SGO and ASGO were 3.5288s and 4.0246s, respectively, which are approximately three times greater than those obtained in SDM (see Table 5 and Figure 20).

The DDM convergence curves carried out by SGO and ASGO during their best, worst and mean runs are provided in Figure 21, we can observe that the quickest convergence speed is achieved by ASGO, wherein it is 2.29 times faster than SGO, at their best runs. The convergence speed of ASGO in its best run exceeds itself by 1.37 times at its worst run. On

the other hand, the SGO curves in its worst and mean runs remain higher than those obtained by ASGO, which means it falls back into the trap of local minima.

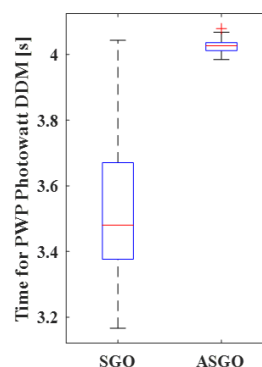


Figure 20. Boxplot of the execution time taken by SGO and ASGO over 50 independent runs for case study N°02 with DDM

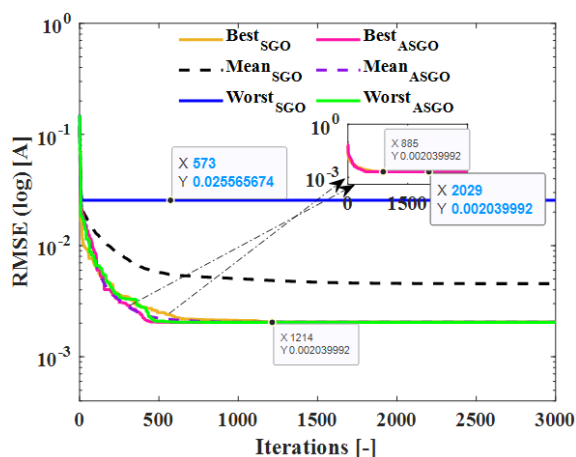


Figure 21. Best, average and worst convergence histories across 50 independent runs of SGO and ASGO for case study N° 02 with DDM

Using the worst solutions acquired by SGO and ASGO, the I-V characteristic can be redrawn together with the experimental data as presented in Figure 22. Outwardly, we find that the computed I-V curve is remarkably homogeneous with the experimental one for ASGO, while difference appears between the calculated and the measured I-V curve for SGO. To quantify these differences more precisely, we propose to draw the *IAE*, for current, for both methods, as depicted in Figure 23, where the errors span from 0.0005537 to 0.04487 for SGO and from 1.235E-05 to 0.003878 for ASGO. It is obvious from Table 5, Figures 19, 21, 22 and 23 that ASGO is a potent technique to extract the needed DDM parameters for Photowatt PWP.

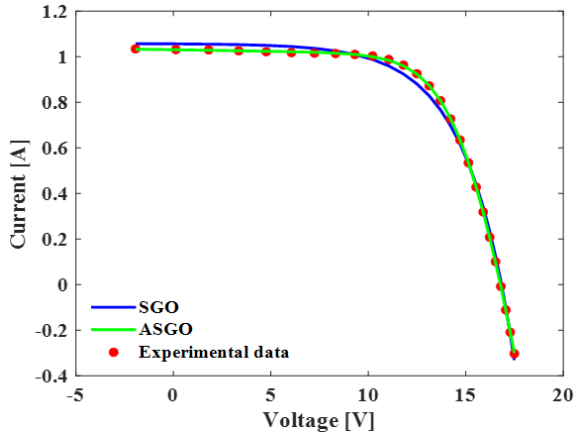


Figure 22. Comparison of the experimental and the computed I-V curves by SGO and ASGO for case study N°02 with DDM, using the worst parameters values

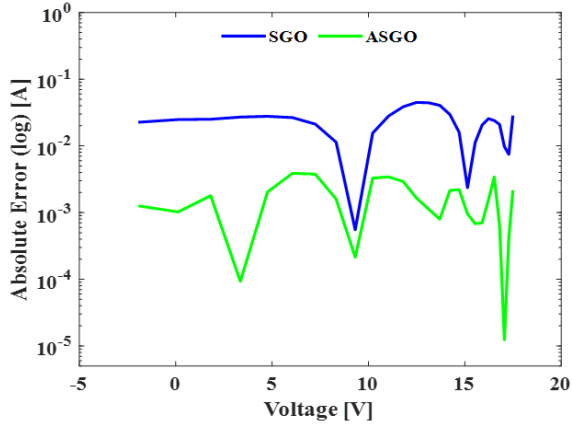


Figure 23. Individual absolute error values for current using SGO and ASGO for case study N°02 with DDM, using the worst parameters values

5.2. Population size effect, diversity, exploration and exploitation analysis

This subsection covers two parts, the first part dealing with the effect of changing the population size on the performance of SGO and ASGO techniques when using the three cases previously studied. Six separate populations (N) of 20, 25, 30 for SDM and of 30, 35 and 40 for DDM are assessed, whilst retaining the same number of iterations, $t_{max, SDM} = 1500$ and $t_{max, DDM} = 2500$, for each population size considered. Each algorithm was run 50 times for each population size separately and the statistical findings of this experiment with regard to minimum RMSE (Min), average RMSE ($Mean$), maximum RMSE (Max) and standard deviation of RMSEs (Std) of the case study N°02 are listed in Table 6 for SDM and in Table 7 for DDM. It should

be noted here that only the results of case study N°02 were displayed in order to avoid overcrowding

The aim of the second part is to evaluate the diversity as well as the explorative and the exploitative abilities of SGO and ASGO techniques relying on the dimension-wise diversity suggested in [35] for each population size employed in the first part. The following is the definition of the population diversity under this method:

$$Div_j = \frac{1}{N} \cdot \sum_{i=1}^N |median(Y^j) - Y_i^j| \quad (33)$$

$$Div = \frac{1}{h} \cdot \sum_{j=1}^h Div_j \quad (34)$$

Where $median(Y^j)$ symbolizes the overall population median of dimension j . Y_i^j represents the dimension j of the person i . N corresponds to the population size, while h denotes the number of the design variables of the optimization problem.

In each dimension j , the average diversity Div_j at each iteration is the distance between each individual i and the median of that dimension. By taking the average of each Div_j for each dimension, the total population's diversity at each iteration is calculated in Div .

Once the group's diversity has been recorded for each iteration. Now, it is feasible to compute the ratio of exploration and exploitation in SGO and ASGO for each iteration employing Eqs. (35) and (36) [35].

$$\%XPL = \left(\frac{Div}{Div_{max}} \right) \times 100 \quad (35)$$

$$\%XPT = \left(\frac{|Div - Div_{max}|}{Div_{max}} \right) \times 100 \quad (36)$$

In Eqs. (35) and (36), Div_{max} represents the maximum diversity across all cycles, $\%XPL$ and $\%XPT$ are the exploration and the exploitation ratios for each iteration, respectively.

Tables 6 and 7 also denotes the mean percentage of diversification $\%XPL$, the mean percentage of intensification $\%XPT$ and the mean diversity Div calculated in the worst run among the 50 runs performed on SDM and DDM, respectively.

By examining the first findings of Tables 6 and 7, it can be observed that whatever the population size adopted, ASGO always outperforms SGO in obtaining the lowest results for the best, worst and average errors in both SDM and DDM. Regarding ASGO itself, and when comparing the effect of

population size, we find that it is not necessary for the population size to be high to obtain the accurate results. In SDM and DDM, the lowest results for the worst, best and mean objective functions were found when $N = 25$ and $N = 35$, respectively. In addition,

the difference among the worst errors of the highest, middle and lowest population size is less than $1.30E-06\%$ for SDM and is lower than $5.86E-08\%$ for DDM.

Table 7. Comparative study of population size, the mean exploration, exploitation and diversity on the behaviour of SGO and ASGO for all the case study N°02 of the DDM (the best values are bolded)

Case study N°02						
T _{max} , N	2500, 30		2500, 35		2500, 40	
	SGO	ASGO	SGO	ASGO	SGO	ASGO
Min	0.002040060532507111	0.002039992273298318	0.002040008108969204	0.002039992273298318	0.002039993053805512	0.002039992273298318
Mean	0.008508655625558380	0.002039992273324874	0.007011234835991835	0.002039992273298382	0.005462420879294826	0.002039992273303665
Max	0.026312213172889100	0.002039992274494179	0.025842363007413247	0.002039992273298698	0.025363646965564344	0.002039992273427100
STD	0.009275096887677775	1.696997144174501836E-13	0.008262829633817100	6.275489366457534024E-17	0.007513754391811428	2.537322573271662071E-14
%XPL	0.164734576642779851	41.066603787630675981	0.401900941858416072	42.137040567523669665	0.384099528977913107	24.232236524003859301
%XPT	99.83526542335582121	58.933396212369295597	99.598099058141883688	57.862959432476337440	99.615900471023493878	75.767763475996318334
DIV _{mean}	15.18488427836212828	3313.262399657831338118	39.080956403349993877	3875.750489731418383599	36.650335126944867170	2966.710545733511025901
	5					

Figures 24 and 25 exhibit visual evidence of diversification, intensification and population

diversity obtained by the worst parameters of SGO and ASGO through all iterations, when population size for is equal to 30 for case study N°02.

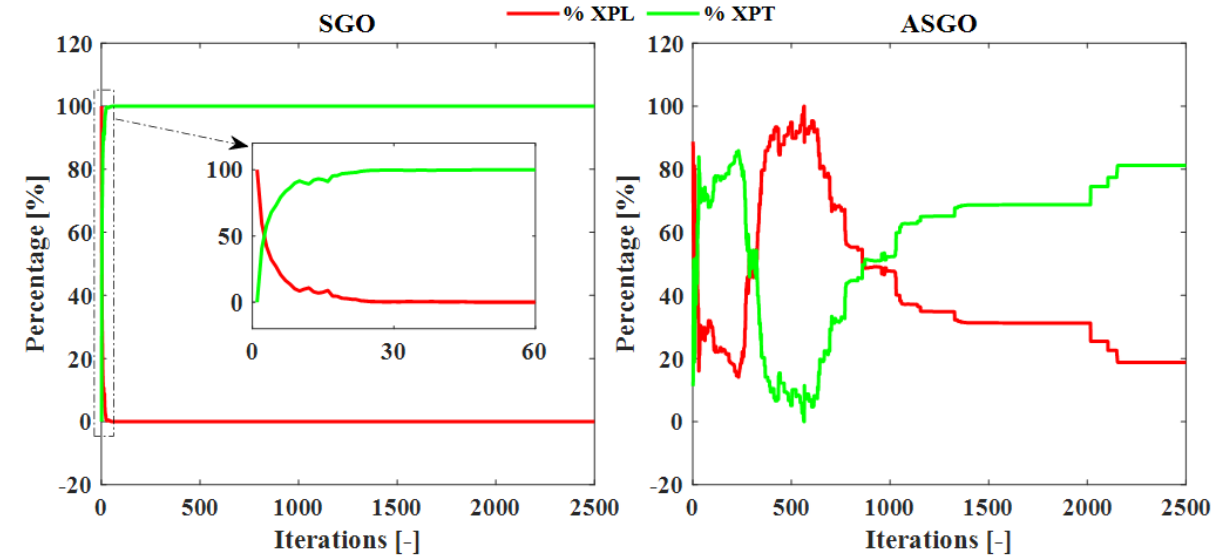


Figure 24. Exploration and exploitation of SGO and ASGO techniques along the iterations on case study N°02, considering the worst run for the DDM

As per Tables 6 and 7, SGO intensified the search area by an average of 99.68% and spent only 0.32% of the time exploring. Figures 24 and 25 confirm

that SGO takes a very short period to explore the entire search space, while still exploiting the search strategy in the majority of iterations.

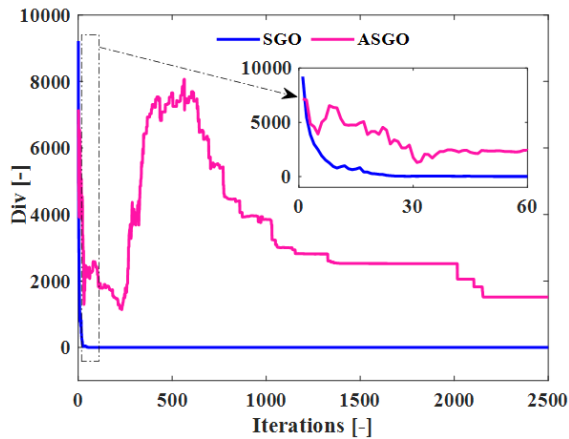


Figure 25. Diversity performance of SGO and ASGO techniques along the iterations on case study N°02, considering the worst run for the DDM

It displays a balance closest to 50% between exploration and exploitation at earlier iterations, which does not exceed the value 6. Before reaching this iteration, the exploration rate is at its high level and after it; the exploitation effect begins to clearly take hold with no trace of exploration to mention. Figures 24 and 25 show a steep decline in the diversity among individuals across first iterations, which in turn are consistent with Figures 24 and 25. This means that the diversity in the newly generated solutions, at the worst run, rely heavily on the random initialization adopted at the beginning of the algorithm. The effect of which quickly decreases while the stochastic impact of the search mechanism is not significant. The latter could be due to the solutions being close to each other or that the best individual found, so far, is not in a feasible region and thus the ease with which SGO falls into the trap of local minima. This is confirmed by the mediocre results shown at the worst calculated errors (see Tables 6 and 7).

On the other side, ASGO shows a significant increase in the exploration ratio versus a decrease in the exploitation ratio compared to what was obtained via SGO. As Figures 24 and 25, the exploration effect of ASGO lasts up to advanced iterations even though it is mostly concerned with exploitation. In DDM, it reaches the 2500th iteration with exploration rate equals to 18.81%, respectively.

It is also noticed that there are several exploratory peaks throughout the ASGO optimization process, interspersed with several equilibrium points close to 50% between exploration and exploitation, which are far removed from those presented only at the beginning of SGO. The appearance of Figure 25 is similar to that obtained by the exploration

percentage graphs of Figure 24 where the highest values of diversity are found in the most explored iterations. On the overall, the diversity in ASGO is higher than that in SGO, which permit jumping in various regions, thus escaping as much as possible from the trap of local optima and get good quality of solutions. This is confirmed by the high performance of ASGO to get close error results between the best, worst and the mean values. It is worth mentioning to say that the reason for which the exploitation is mostly prevalent in ASGO, despite the noticeable increase in the exploration rates, is its search strategy reliance on attracting operators toward the most optimal global solution.

5.3. Comparison with various MHAs

In this subsection, the accuracy and the performance of SGO and ASGO in identifying the needed parameters for SDM and DDM are compared with other MHAs recently published in various research papers for the previously stated cases from 01 to 03 using the following metrics:

- Minimum *RMSE* and *Std*.
- Absolute error (*AE*).
- Mean absolute error (*MAI*).
- Sum squared error (*SSE*).

It is worth noting that the last three metrics are calculated based on the best PV parameters found by SGO and ASGO since the provided metrics for the other methods used in comparison are also calculated on this basis.

Additionally, this section presents the SGO and ASGO results using a maximum number of iterations of 1500 and a population size of 20 for SDM. Consequently, the number of function evaluations (NFE's) allocated is 75000 (due to the presence of greedy selection in the improving and acquiring phases). As for DDM, the maximum number of iterations is set to 2500 and the population size is fixed to 30, which allocates 150000 NFE's. On that basis, the methods used for comparison were those that employed a larger or equal NFE's than that proposed by our approach.

5.3.1. Case study 1 results with SDM

Table 8 compares the accuracy and the performance of ASGO to a number of metaheuristic techniques that have been published in literature for the SDM. As per Table 8, the outcomes provided by ASGO match those stated in TVAPSO and ELPSO in terms of getting the best value of the minimum RMSE (7.7301E-04) if we consider four digits.

When it comes to robustness, it is observed that ASGO obtained the tiniest Std value amongst all methods that have achieved the best minimum RMSE, which reflects how close the solutions are to each other after each run of the algorithm. We note

that SGO obtained a larger RMSE value than ASGO, TVAPSO and ELPSO. All those outcomes confirm ASGO stability, reliability and suitability for extracting the optimal parameters of SDM for PV cells.

Table 8. Comparison of error results of SGO and ASGO methods with other techniques in literature for the SDM (case study N°01)

Method	min RMSE $\pm$ Std	ξ	AE	MAE	SSE
ASGO	7.73006269E-04 $\pm$ 1.97761449E-14	1.01644480E-03	1.76327395E-02	6.78182287E-04	1.55360060E-05
TVACPSO [26]	7.7301E-04 $\pm$ 5.5805E-10	1.0164E-03	-	-	-
ELPSO [32]	7.7301E-04 $\pm$ 3.4508E-07	1.0164E-03	-	-	-
NSCSO [36]	7.7421E-04 $\pm$ 9.9034E-05	1.0180E-03	-	-	-
SGO	7.76414717E-04 $\pm$ 1.90699280E-02	1.02092665E-03	1.76689578E-02	6.79575301E-04	1.56733151E-05
BO [37]	9.8249E-04 $\pm$ 2.9500E-06	1.2919E-03	-	-	-
IHBA [38]	9.8262E-04 $\pm$ 3.7091E-04	1.2921E-03	-	-	-
INFO [39]	9.8602E-04 $\pm$ 5.0987E-17	1.2965E-03	-	-	-
PSA [40]	9.8602E-04 $\pm$ 1.005550E-03	1.2965E-03	-	-	-
FPSO [41]	9.8602E-04 $\pm$ 2.0142E-08	1.2965E-03	-	6.8090E-04	-
IMFOL [42]	9.8602E-04 $\pm$ 1.0207E-06	1.2965E-03	-	-	-
IBO [43]	9.86021878E-04 $\pm$ 8.57137311E-14	1.29654422E-03	-	-	-
IEO [44]	9.860219E-04 $\pm$ -	1.296544E-03	-	-	-
CapSA [45]	9.86022E-04 $\pm$ -	1.29654E-03	-	-	-

5.3.2. Case study 1 results with DDM

Table 9 evaluates the effectiveness and the precision of ASGO to a number of approaches described in literature for the DDM. Based on the results given in Table 9, the application of ASGO allows to get the highest precision of RMSE, ξ , AE, MAE and SSE in comparison to other methods since it attained the smallest values of these metrics. Therefore, it can be said again that ASGO can be relied upon to ensure accurate parameters capable of describing the real behaviour of a PV cell. It is also noticeable that SGO came in second place immediately after ASGO regarding obtaining the best accuracy of the aforementioned metrics.

5.3.3. Case study 2 results with SDM

When compared to other methods described in literature, Table 10 displays the effectiveness and precision of ASGO in relation to the SDM. Table 10) highlights the superiority of ASGO over its peers in finding the lowest values of RMSE, AE, MAE and SSE. The closest competitors to ASGO, regarding these metrics, were, WDOWOAPSO and GCP SO. From the other hand, Table 10 demonstrates the strength of ASGO to reach almost

the same values of the objective function and that is through getting the smallest Std amongst the best competitors. This would, in turn, confirms the effectiveness of ASGO in obtaining the appropriate SDM parameters for a PV module.

As for SGO, it dropped to fifth place in terms of getting the best minimum RMSE with a larger STD.

5.3.4. Case study 2 results with DDM

In comparison to other techniques recorded in literature, Table 11 shows the performance and accuracy of ASGO when identifying the DDM parameters. From Table 11, it transpires that ASGO achieves the first place with regards to most statistical metrics related to accuracy and robustness followed by SGO, WDOWOAPSO and GCP SO. In fact, among the previous algorithms, only SGO has remarkably recorded an improvement in the minimum RMSE compared to SDM while the rest maintain the same previous values. As a result, it reached the same values as ASGO regarding this metric and ξ . Also, it is noticed when calculating AE, SGO slightly outperforms ASGO with 9.14E-4 %.

Table 9. Comparison of error results of SGO and ASGO methods with other techniques in literature for the DDM (case study N°01)

Method	RMSE $\pm$ Std	ξ	AE	MAE	SSE
ASGO	6.92004863E-04 $\pm$ 2.23404344E-05	9.09934074E-04	1.57337410E-02	6.05143884E-04	1.24506390E-05
SGO	6.93817015E-04 $\pm$ 1.76007809E-02	9.12316916E-04	1.60025198E-02	6.15481531E-04	1.25159333E-05
PSA [40]	9.7078E-04 $\pm$ 9.900088E-04	1.27650E-03	-	-	-
IBO [43]	9.77088322E-04 $\pm$ 4.51183566E-04	1.28467902E-03	-	-	-
IHBA [38]	9.8163E-04 $\pm$ 3.1091E-04	1.2908E-03	-	-	-
INFO [39]	9.8248E-04 $\pm$ 1.6966E-06	1.2919E-03	-	-	-
CapSA [45]	9.8248E-04 $\pm$ -	1.2919E-03	-	-	-
IEO [44]	9.8248E-04 $\pm$ -	1.291893E-03	-	-	-
FPSO [41]	9.8253E-04 $\pm$ 3.1469E-08	1.2919E-03	-	6.8720E-04	-
BMOA [46]	5.6269E-03 $\pm$ -	7.3989E-03	-	4.6059E-03	-

Table 10. Comparison of error results of SGO and ASGO methods with other techniques in literature for the SDM (case study N°02)

Method	RMSE $\pm$ Std	ξ	AE	MAE	SSE
ASGO	2.03999227E-03 $\pm$ 3.77927601E-12	1.97731150E-03	4.37563524E-02	1.6829366E-03	1.0820078E-04
WDOWOAPSO [47]	2.046535E-03 $\pm$ 1.267273E-12	1.983653E-03	4.400033E-02	-	-
GCP SO [24]	2.046535E-03 $\pm$ 1.105194E-10	1.983653E-03	4.400032E-02	1.692320E-03	-
TVACPSO [26]	2.0530E-03 $\pm$ 1.3400E-07	1.9899E-03	-	-	-
SGO	2.06517430E-03 $\pm$ 1.1551269E-02	2.00171978E-03	4.37907612E-02	1.6842600E-03	1.1088857E-04
NSCSO [36]	2.1928E-03 $\pm$ 1.8665E-04	2.1254E-03	-	-	-
INFO [39]	2.3860E-03 $\pm$ 3.3230E-17	2.3127E-03	-	-	-
CapSA [45]	2.42507E-03 $\pm$ -	2.35056E-03	-	-	-
IEO [44]	2.425074E-03 $\pm$ -	2.350561E-03	-	-	-

5.4. Non-parametric test

A statistical analysis test based on Wilcoxon's rank sum, at a 5% confidence level, has been applied to case study N°01 and 02 to show the significance difference between SGO and ASGO techniques. The test outcomes are summarized in Table 12. The effects of change in population size and number of iterations were taken into account in measuring this value. The findings illustrate that ASGO is statistically better than SGO in all cases since p is much lower than 0.05.

5.5. ASGO parameter tuning

One of the primary strengths of ASGO is its dependency on a single controlling setting parameter

(F_{ASGO}). In all the aforesaid simulations, its value was set at 0.8. In this section, we propose to study the effect of changing this parameter on the performance of ASGO. This test was applied to case study N°02, where F_{ASGO} was adjusted from 0.1 to 0.9; at each value, 50 runs were performed for four times. The heat map shown in Figure 26 was used to display the mean RMSEs. According to figure 26, at values lower than 0.6, ASGO generates fluctuating RMSEs where the values of RMSEs is confined between 0.01 and 0.0021. At values greater than 0.6, the RMSEs remains approximately constant where the STD is nearly between 1.98E-16 and 9.79E-17. Therefore, we conclude that any value for F_{ASGO} between 0.6 and 0.9 is appropriate to get better results with ASGO.

Table 11. Comparison of error results of SGO and ASGO methods with other techniques in literature for the DDM (case study N°02)

Method	RMSE $\pm$ Std	ξ	AE	MAE	SSE
ASGO	2.0399922E-03 $\pm$ 1.696997144E-13	1.97731150E-03	4.37563507E-02	1.68293656E-03	1.08200780E-04
SGO	2.040060E-03 $\pm$ 1.696997144E-03	1.97737766E-03	4.37537998E-02	1.68283846E-03	1.08208021E-04
GCP SO [24]	2.046535E-03 $\pm$ 1.673103E-10	1.983653E-03	4.400032E-02	1.692320E-03	-
WDOWOAPSO [47]	2.046535E-03 $\pm$ 7.083742E-06	1.983653E-03	4.400033E-02	-	-
CapSA [45]	2.3306E-03	2.2590E-03	-	-	-
INFO [39]	2.3860E-03 $\pm$ 5.8990E-17	2.3127E-03	-	-	-

Table 12. Statistical test findings based on Wilcoxon’s rank sum

Case study N°01								
PV model		SDM				DDM		
N/t _{max}	25/2000	20/1500	25/1500	30/1500	50/3000	2500/30	2500/35	2500/40
p-value (ASGO vs SGO)	7.049 E-18	7.063E-18	7.042E-18	7.055E-18	1.241E-15	3.695E-17	1.801E-16	1.241E-15
Case study N°02								
PV model		SDM				DDM		
N/t _{max}	25/2000	20/1500	25/1500	30/1500	50/3000	2500/30	2500/35	2500/40
p-value (ASGO vs SGO)	6.591E-18	7.052E-18	7.055E-18	7.026E-18	6.330E-18	6.645E-18	6.465E-18	6.659E-18

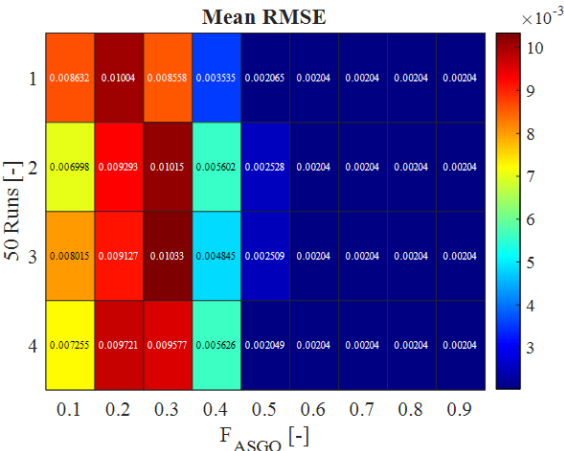


Figure 26. Heatmap for F_{ASGO} variation

6. Conclusion

This study proposed ASGO for parameter estimation in single- and double-diode photovoltaic models by incorporating Gaussian mutation, adaptive current-to-best/2 mutations, and local search into SGO. Evaluation on two benchmark devices showed improved repeatability and lower mean and worst fitting errors, whereas best-run accuracy was often comparable to SGO. Worst-run curve reconstruction and population diversity analysis supported these findings, alongside faster convergence in iterations and modest runtime differences. However, validation was restricted to small, publicly available datasets, and literature-based comparisons involved potentially different evaluation conditions. Sensitivity to parameter bounds and performance under noisy or incomplete I–V measurements remain unexplored. Future work will address these limitations through larger independent experimental datasets, parameter bounds sensitivity analysis, and comparisons under a common evaluation protocol. Controlled noise and missing-data tests, together with enhanced exploration during later iterations, will further assess

and improve ASGO’s robustness for practical PV applications.

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Nomenclature

%XPL	Exploration ratio
%XPT	Exploitation ratio
$a/a_1/a_2$	Ideality factor for SDM and DDM
AE	Absolute error (A)
ASGO	Ameliorated social group optimization algorithm
b	Standard deviation of the Gaussian probability distribution
c_{SGO}	Self-introspection coefficient
DDM	Double diode model
DE	Differential evolution
Div	Diversity
F_{ASGO}	Scaling factor
G	Solar radiation (W/m ²)
h	Number of traits
I	Output current (A)
I_0	Reverse saturation current (A)
I_{01}	Diffusion current (A)
I_{02}	Recombination current (A)

$I_{est}(V_j, z)$	Estimated output current (A)
I_{mpp}	Maximum power point current (A)
$Index_1/index_2$	Location corresponding to the best member in the improving phase/acquiring phase
I_{pv}	Photogenerated current (A)
I_{sc}	Short circuit current (A)
k	Boltzman's constant (J/K)
L	Lower limit
M	Length of experimental pairs
MAE	Mean absolute error (A)
Max	Maximum of RMSEs
$Mean$	Average of RMSEs
$MHAs$	Metaheuristic-based algorithms
Min	Minimum RMSEs
$MPPT$	Maximum power point tracking
N	Polulation size
$NFE's$	Number of function evaluations
p, p_1, p_2, p_3, p_4	Different patterns
PV	Photovoltaic
$p-value$	Output value calculated by Wilcoxon rank sum
q	Electron's charge (C)
$R, R_1, R_2, R_3,$	Random numbers
R_4	
$RMSE$	Root mean square error
R_s	Series resistance (Ω)
R_{sh}	Shunt resistance (Ω))
SDM	Single diode model
SSE	Sum squared error (A)
Std	Standard deviation of RMSEs
T	Cell operating temperature ($^{\circ}C$ or K)
t	Iteration
t_{max}	Maximum number of iterations
U	Upper limit
V	Output voltage (V)
V_j, I_j	Experimental current-voltage pairs
V_{mpp}	Maximum power point voltage (V)

V_{oc}	Open circuit voltage (V)
Y_i	Candidate solution
ζ	Weighted RMSE

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Appendix

Table 1.A. General comparison of different techniques used in PV parameter extraction

Algorithm	DE	TVAPSO	ELPSO	SGO	ASGO
Controlling setting parameter	F, Cr	ω , C_1 , C_2	ω_f , ω_s , C_1 , C_2 , a , F , s	c_{SGO}	F_{ASGO}
Iteration dependent	No	Yes	Yes	No	Yes
Core operators	Mutation & crossover	Velocity update & time varying C_1 and C_2	Velocity update & leader multistage update	Improving & acquiring phases	Improving phase: Mutations and adaptive local search
Mutation operators	DE/rand/1	-	Cauchy & Gaussian	-	Adaptive current- to best/2 & Gaussian
Leader mutation update	No	-	Yes	-	Yes
Other members mutation update	Yes	-	No	-	Yes
Implications	Strong exploration, weak exploitation & leader is not used in mutation	Balanced exploration-exploitation &	Strong leader influence & parameter sensitivity	Less parameter tuning & aggressive exploitation may increases the likelihood of reaching local minima	Less parameter tuning & cooperation between the leader and other members to raise the exploration while maintaining the exploitation

Iteration runtime

To clarify the time consumed per iteration -which differs significantly from the times listed in Tables 2 trough (representing the total time consumed for all iterations in each model)- a new simulation for case study N°01 (SDM) was conducted and is presented in Table A.2. The latter details the average time per iteration for both methods, considering 50 new runs. Moreover, the times taken by the four randomly selected members and the local search utilized in the ASGO.

Table 2. A. Runtime for SGO and ASGO

Method	Iteration time [s]	Four partners time [s]	Local search time in [s]
SGO	0.00066331	-	-
ASGO	0.00070782	4.9738E-06	0.00030953

As shown in Table 2. A, there is a slight difference between both methods, with SGO holding an advantage. This is due to the time consumed by the local search and the choice for finding the four partners.