*Rev. Roum. Sci. Techn.– Électrotechn. et Énerg.*
Vol. **70**, *4*, pp. 489–494, Bucarest, 2025

# COMPARISON BETWEEN SEVERAL METHODS OF IDENTIFICATION OF PHOTOVOLTAIC PARAMETERS

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**Keywords: Identification; Artificial intelligence (AI); Photovoltaic (PV); Meta-heuristic; Least squares; Particle swarm; Genetic algorithm.**

**Renewable energy, especially photovoltaic, is a promising solution to combat the depletion of fossil fuels. Using single- and dual-diode models, solar cell modeling can predict the behavior of photovoltaic modules under various environmental conditions, making accurate parameter extraction essential. In this paper, we provide an in-depth comparative analysis of different methods for identifying photovoltaic parameters, including nonlinear least squares, several meta-heuristic algorithms such as genetic algorithm (GA), particle swarm optimization (PSO), and their versions combined with explicit equations (PSOX, GAX), and continuous domain ant colony optimization (ACOR). The performance of these methods is evaluated using experimental data obtained from a SY-M80W polycrystalline photovoltaic panel. Based on the single diode model, the five unknown parameters, namely photovoltaic currents (Iph), saturation currents (Is), series resistance (Rs), parallel resistance (Rsh), and ideality factor (A), can be determined. The objective is to determine the most efficient method in terms of accuracy, convergence speed, and robustness, with a view to guiding the selection of extraction techniques to improve the efficiency and reliability of photovoltaic systems.**

## 1. INTRODUCTION

The use of traditional energy sources continues to grow worldwide. It is important to note, however, that even though these resources are economical, efficient, and easily transportable, their increasing scarcity is gradually harming the ecosystem [1].

In response to these challenges, a significant shift toward green energies has been initiated, such as solar, wind, hydroelectric, biomass, hydrogen, and geothermal energy [2]. Solar energy, and specifically photovoltaic, stands out among other options for its availability, sustainability, reduced environmental impact, ease of installation, and lack of noise pollution. Developing models for photovoltaic systems is essential when designing and improving these systems, as it provides essential information to anticipate the operation of photovoltaic cells in different operational situations [3]. Solar cell models are often used to create graphs characterizing current and voltage (I-V) and power and voltage (P-V), as well as to anticipate the behavior of a real solar cell in different environments.

Most models are based on nonlinear equivalent circuits, such as the single-diode or dual-diode model. However, regardless of the model chosen, it is crucial to accurately extract the essential parameters—photocurrent (Iph), saturation current (Is), series resistance (Rs), parallel resistance (Rsh), and ideality factor (A)—to accurately reproduce the real behavior of photovoltaic panels and optimize system efficiency [4].

Over the past decade, various identification techniques have been proposed. Two types of methods are generally distinguished: traditional numerical techniques, such as the Newton-Raphson method [5] and the least-squares method [6], and metaheuristic optimization algorithms. These include techniques such as genetic algorithm (GA) [7], bee swarm optimization (ABCO) [8], particle swarm optimization (PSO) [9], bee colony algorithm (ABC) [10], Firefly algorithm (FA) [11], ant colony continuous optimization (ACOR) [12], whale optimization algorithm (WOA) [13] and differential evaluation (DE) [14].

This paper proposes a comparative study of various identification techniques implemented on the characteristics of a SY-M80W photovoltaic panel, under standard conditions of 1000 W/m² and a temperature of 30 °C. A model based on explicit equations was initially designed. Subsequently, we applied several optimization methods, such as least squares (LS), genetic algorithms (GA), particle swarm optimization (PSO), hybrid strategies merging explicit equations with (GA) and (PSO), as well as ant colony-based continuous optimization (ACOR).

We compared the effectiveness of each method based on its accuracy, convergence speed, and robustness. The objective of this study is to establish the optimal method for accurately and quickly identifying photovoltaic parameters, a necessary condition for optimizing the performance, diagnosis, and preventive maintenance of photovoltaic systems.

## 2. MATHEMATICAL PV MODEL

Figure 1 shows the most frequently used modeling method for a photovoltaic cell directly transforming solar energy into electricity, *i.e.*, an equivalent circuit comprising a current source associated with a diode. To account for dissipative effects, two resistances have been incorporated: the series resistance and the shunt resistance [15].

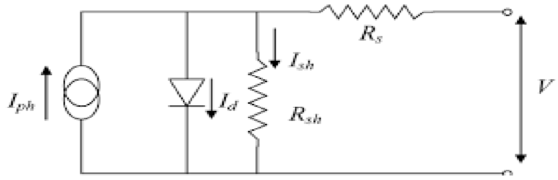


Fig.1 – Equivalent circuit of a PV cell.

The circuit's mathematical representation is:

$$I = I_{ph} - I_s\left(e^{\left(\frac{q(V+R_sI)}{aKT}\right)} - a1\right) - \frac{V + R_sI}{R_{sh}} \quad (1)$$

where: $q$ denotes the charge of an electron, $V$ is the voltage across the diode, K is the Boltzmann constant, $T$ is the factual temperature of the cell (in Kelvin), $A$ is the Ideality Factor, $R_s$ is the series resistance of the diode, $R_{sh}$ is the shunt resistance of the diode, $V_{oc}$, the open circuit voltage of the solar cell; Eg: the band gap energy in the solar cell.

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DOI: 10.59277/RRST-EE.2025.70.4.10

To formulate the model of the photovoltaic module using the information provided in the datasheet, five parameters need to be assessed: $I_{ph}$, $I_s$, a, $R_s$, and $R_{sh}$ [16]:

$$I_{ph} = (I_{ph,n} + K_i \Delta_T)\frac{G}{G_n}. \quad (2)$$

$$\Delta_T = T - T_n \quad (3)$$

where $I_{ph,n}$ [A] is the light-generated current at the nominal condition, the diode saturation current $I_s$ in eq. (7), and $I_{o,n}$ is the nominal saturation current:

$$I_s = I_{o,n}\left(\frac{T_n}{T}\right)^3 e[\frac{qE_g}{aK}\left(\frac{1}{T_n}-\frac{1}{T}\right)], \quad (4)$$

$$I_{o,n} = \frac{I_{sc,n}}{e\left(\frac{V_{oc,n}}{aV_{t,n}}\right)-1}. \quad (5)$$

The saturation current viscosity of the semiconductor (Is, frequently expressed in A/cm$^2$ influences the $I_o$ of the photovoltaic cells. Equation (7) is replaced by the equation below for the purpose of improvement

$$I_s = \frac{I_{sc,n}+K_i\Delta_T}{e\left(\frac{V_{oc,n}+K_i\Delta_T}{aV_t}\right)-1}. \quad (6)$$

The purpose of this modification is to fit the open-circuit voltage of the model to experimental data over a wide temperature range. Equation (6) is derived from eq. (5) by integrating the current/voltage parts, $K_i$, $K_V$ into the equation. The saturation current Io depends exponentially on temperature. This equation simplifies the model and eliminates contiguous model crimes [17].

The expression that represents the series resistance and the ideality factor is

$$R_s = \frac{\frac{N_S AKT}{q} l_n\left(1-\frac{I_m}{I_{cc}}\right)+V_{co}-V_m}{I_m}], \quad (7)$$

$$A = \frac{q(2V_m - V_{co})}{N_S KT[^{I_{cc}}/_{I_{cc}-I_m} + l_n(1-\frac{I_m}{I_{cc}})]}]. \quad (8)$$

To identifier the parameters of various solar cell models from *I-V* and *P-V* data, it is crucial to establish a performance criterion or an objective function using optimization methodologies [18]. The issue can be framed as an optimization challenge that aims to minimize the error between the observed and predicted currents. The root mean square error (RMSE) serves as the objective function (f) where the error function is the variation between the predicted and actual currents, as illustrated in Equation 13. This can be articulated as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} f_i(I_i, V_i, X))^2}. \quad (9)$$

$$f(I, V, X) = 0. \quad (10)$$

The estimation problem is presented in this paper as a nonlinear optimization problem. Algorithms are employed to evaluate the parameters by minimizing a predefined objective function.

## 1.1 THE LEAST SQUARES METHOD

The least squares method was first suggested by Gauss to evaluate the orbit of an asteroid in 1795 [19]. Its main objective is to ensure the accuracy of a photovoltaic panel's parameters, thereby improving its performance. Due to its simplicity of expression, low computational cost, and robustness against white noise, it is one of the most used methods.

Nowadays, the least squares method finds an extremely wide application in the evaluation of numerical values of parameters, in the fitting of functions to experimental data, and in the estimation of static characteristics of parameters. It is available in various forms and remains a fundamental tool in the analysis of photovoltaic systems.

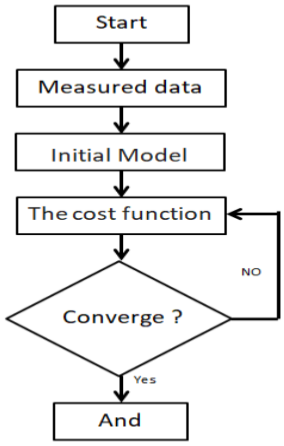


Fig.2 – Flowchart of the least squares method.

The nonlinear least squares approach is a method used to fit an $n$-parameter nonlinear model to m observations ($m > n$). Next, this technique was used in identifying the characteristics of PV modules and further estimating the model parameters from V-I measurements. Indeed, the least squares method is used to reduce the gap between the observed current and that estimated by the mathematical model of the photovoltaic panel [20].

As shown in eq. (1), the generalized equation for current from a photovoltaic module aims to reduce errors present in measured currents compared to those derived from this equation. The nonlinear least squares principle aims to find the minimum of a cost function, which involves the sum of the squares of the errors; measuring the currents $I_{model}(V, x)$ for the voltages $V$, let us consider the modeled currents $\mathrm{I}_{\mathrm{model}}(V, x)$, we obtain the cost function:

$$\mathrm{Cost}(x) = \sum_{i=1}^{N}( I_{mesuré}(V_i) - I_{model}(V_i, x))^2. \quad (11)$$

## 1.2 PARTICLE SWARM OPTIMIZATION (PSO)

Particle swarm optimization, a technique invented by James Kennedy and Russell Eberhart in 1995 [21], is emerging as one of the most widespread strategies for improving the stability of power grids. The PSO approach is a meta-heuristic inspired by the foraging behaviors of fish and the collective movements of flocks of birds navigating a D-dimensional search landscape.

A crucial aspect of the algorithm's effectiveness lies in its topology, specifically how particles interact with each other. It efficiently reaches the optimal value of a function within a reasonable computational time. In this method, the continuous movement of particles in the space of possible solutions reveals each particle as a potential solution. Each particle is associated with a velocity, which is updated using an equation that accounts for both individual and collective experience.

The fundamental idea is to modify each particle's position in space to explore optimal solutions based on its previous personal best position ($P_{Best}$) and the global best position of the swarm ($g_{Best}$). Represented by eq. (13) [22].

At each cycle, an evaluation of the objective function is performed, thus encouraging each particle to readjust itself according to the criteria discussed above.

However, a significant shortcoming of classical PSO is its inclination to get stuck in local optima, which hinders its ability to traverse the search space [23] efficiently.

Mathematically, the update of the ith parameter of the solar cell in relation to the $j^{th}$ particle of the swarm during iteration k+1 is carried out as follows.

$$X_{i.j}^{k+1} = X_{i.j}^{k} + V_{i.j}^{k+1}, \quad (12)$$

where $V_{i,j}^{k+1}$ is the updated velocity vector corresponds.

The speed update associated with each solar cell parameter is given by the following equation:

$$V_{i.j}^{k+1} = wV_{i.j}^{k} + C_1 r_{i.j}^{k}(P_{i.best}^{k} - X_{i.j}^{k}) + C_2 r_{2.j}^{k}(P_{i.gbest}^{k} - X_{i.j}^{k}), \quad (13)$$

where $V_{i,j}^{k}$ is the velocity of the $i^{th}$ particle; $X_{i.j}^{k}$ is the position of the ith particle; $P_{i.best}^{k}$ is the best known position of the particle; $P_{i.gbest}^{k}$ is the best known position found by all particles; $r_{i.j}^{k}$ and $r_{2,j}^{k}$ represent random numbers varying between [0, 1]; $w$ is the inertia factor, $C_1$ and $C_2$ are the social acceleration constant [24].

We also used a modified PSO algorithm (Algorithm 1) by combining it with explicit equations. Using this hybrid method improves convergence efficiency and parameter identification accuracy by leveraging the advantages of PSO, such as its ability to explore a wide range of solutions, while integrating explicit equations to better steer exploitation toward relevant domains.

The use of explicit eq. (2) to (8) adds dynamics to the algorithm, allowing it to overcome potential strategies and accelerate solution search, while integrating explicit equations to better steer exploitation toward relevant domains.

**Algorithm 1:** Particle Swarm Optimization with defined equations (PSOX)
Input: l, u, it_max, n
Output: A swarm S comprising n particles and their ultimate locations
1. Initialize S of size n at random positions within u and l;
2. Assign velocities to particles V of size n with arbitrary values.
3. Determine $\boldsymbol{G_{Best}}$ and individual best position $\boldsymbol{P_{Best}}$
5. Start iteration, it = 1; 6. Set convergence to false;
While it ≤ it_max
For each particle in S do
- Adjust the velocity V and position utilizing (12) (13)
Employ defined equations to enhance the position.
-Update P_Best if the new position surpasses
End, End

## 1.3 GENETIC ALGORITHM (GA)

In 1975, Holland introduced the genetic algorithm, one of the most famous evolutionary techniques for dealing with constrained and unconstrained optimization problems, inspired by natural selection and genetics. They have an extremely broad scope. These algorithms are classified as stochastic optimization algorithms. They have been implemented to solve optimization problems in the fields of engineering and science. Their methods rely on the process of natural selection to tackle complex optimization problems [25].

The algorithm uses chromosomes to represent decision variables and uses fitness values to estimate and choose between the seed and the parents. Individuals are called search result sets, which are consecutively modified by three mechanisms: selection, crossover, and mutation [26].

Selection: First, produce the population P in the given search interval; second, estimate the population using the fitness value. Finally, estimate the chromosome fitness value to obtain the next generation.

Crossover is the emulsion of two parents to produce offspring for the next generation.

Mutation is the arbitrary operation of variations on individual parents to produce offspring. Like the previous particle swarm optimization algorithm, we also used a modified version of GA combined with explicit equations, as illustrated in Algorithm 2.

This combination allows us to exploit the robustness of the GA to find globally optimal solutions, while leveraging the explicit equations to efficiently guide the exploration of potential solutions.

The explicit equations increase the diversity of solutions produced by the GA and prevent premature convergence.

The use of this hybrid method strikes a balance between global exploration and local exploitation, resulting in more accurate and faster parameter identification.

**Algorithm 2:** Genetic Algorithm with explicit equation (GAX)
Input: l, u, Pop_size, it_max, P_m, P_c
Output: An optimal solution drawn from the final population
1. Generate a population P of size Pop_size with random individuals within the upper and lower limits u and l;
2. Assess the fitness of each existent in the population;
3. Set iteration to it = 1;
While it ≤ it_max
DO choose parents for reproduction using a selection strategy
Create offspring, Implement mutation
Utilize explicit equations on the offspring's
Assess, Replace, Increment, Verify convergence
End, End

## 1.4 ANT COLONY IN THE CONTINUOUS DOMAIN

Ant colony optimization is a population-based metaheuristic inspired by ant conditioning and their natural ability to create the most efficient path to connect a food source to their habitat. In ACO, introductory creatures called ants construct a search result for a combinatorial optimization problem by creating pheromone trails that serve as a means of communication between ants [27].

Initially, ants explore several routes. The most efficient one eventually accumulates a significant amount of pheromones, attracting more and more ants. Eventually, all ants meet on the same route. ACO algorithms have generally been applied to solve any discrete optimization problem; later, they have been applied to solve continuous problems. The pheromone framework of the ACOR algorithm consists of a collection of k results, called a solution archive, which the algorithm maintains. The result archive begins with a set of generated answers, and the algorithm progressively improves the archived result by generating m new results and retaining only the best *k* results among the k m available options. The main design of ACOR is to replace the distinct probability distributions used in ACO for the continuous domain with the probability viscosity function [28, 29].

First, we apply the pheromone table rationalization scheme based on the factors of the applicable result.

Generally, in ACO, the result discovered by the ant is excluded during the pheromone table update process. Rather than performing pheromone evaporation, a negative update scheme is applied. To cancel the pheromones associated with the previous result, the weight of each solution is calculated according to:

$$w(l) = \frac{1}{qk\sqrt{2\pi}} e^{\frac{(l-1)^2}{2q^2k^2}}. \quad (14)$$

Each match is handled individually during the result development process. Initially, it selects an archived result based on a probability that is proportional to its weight.

$$p(l) = \frac{w(l)}{\sum_j^k w(j)}. \quad (15)$$

Furthermore, the algorithm samples around the result element named $S_l^i$ using a Gaussian with $\mu_l^i = S_l^i$ . The Gaussian kernel for match i is

$$\sigma = \xi \sum_{r=1}^{k} \frac{|S_r^i - S_l^i|}{k-1} \quad (16)$$

with ξ a constant parameter analogous to the pheromone evaporation rate.

## 3. SIMULATION RESULT

In this study, we evaluated the performance of the SY-M80W photovoltaic panel under standard conditions (STC): an irradiance of 1000 W/m² and a temperature of 30°C. The main electrical characteristics of the panel are summarized in Table 1.

*Table 1*

PV-250-P60 photovoltaic parameters.

| Parameter | $V_{ocn}$ | $I_{scn}$ | $V_{mp}$ | $I_{mp}$ | $P_m$ |
|---|---|---|---|---|---|
| | 22 V | 4.85 A | 17.4 V | 4.61 A | 80 W |

To estimate the unknown parameters of the panel, several identification methods were applied and compared: LS, PSO, GA, as well as their improved variants (PSOX, GAX), and finally ACOR. The configuration parameters of these algorithms are detailed in Table 2.

*Table 2*

Parameters of the three algorithms: PSO, GA, and ACOR.

| PSOX | GAX | ACOR |
|---|---|---|
| Population size:100 | Population size:1000 | Ant = 100 |
| C1: 1.5 | Selection: uniform stochastic | Q = 0.3 |
| C2: 2 | Crossover: random | Z =1 |
| W: 0.9 | Mutation: Gaussian | |
| iteration:5000 | iterations :5000 | iterations :5000 |

The simulation results obtained using the different methods are presented in Table 3.

*Table 3*

Simulation result

| | PSO | PSOX | GA | GAX | LS | ACOR |
|---|---|---|---|---|---|---|
| $I_{ph}$ (A) | 4.561 | 4.543 | 4.569 | 4.574 | 4.57 | 4.552 |
| $I_s$ (A) | 9.47e-5 | 0.0001 | 0.0002 | 9.82e-5 | 6.96e-8 | 7.731e-5 |
| $R_s$ (Ω) | 0.2293 | 0,032 | 0.17662 | 0,0311 | 0.1571 | 0.2433 |
| $R_{sh}$ (Ω) | 422.45 | | 522.226 | | 1000 | 501.6 |
| $A$ | 1.9245 | 1.971 | 1.26008 | 1.9323 | 1.206 | 1.890 |
| RMSE | 0.0084 | 0.0014 | 0.00555 | 0.0034 | | 0.0008 |

Analysis of the results shows that all methods yield similar values for the photocurrent $I_{ph}$, around 4.56 A, indicating overall consistency in the determination of this key parameter. The reverse saturation current, $I$, is particularly low with the least-squares method, which may reflect increased accuracy. The root-mean-square error (RMSE) is minimal for the ACOR algorithm (0.0008), highlighting its superior ability to estimate parameters with high accuracy.

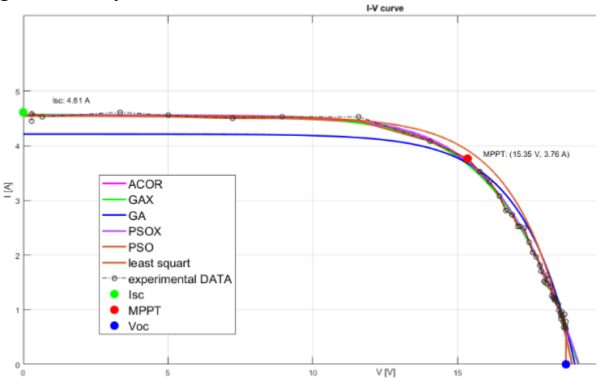


Fig. 3 – Comparison between several methods for the I-V curve.

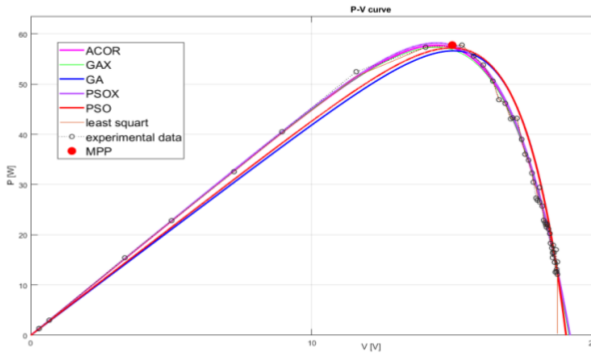


Fig. 4 – Comparison between several methods for the P-V curve.

Figures 3 and 4 present the *I-V* and *P-V* characteristic curves obtained by each method, compared to the experimental data. These graphs provide a visualization of the goodness-of-fit of each method.

Figure 3 (*I-V* Curve) presents several curves representing the different methods for identifying photovoltaic parameters. In the quasi-constant current region (at low voltage), most methods provide good accuracy, confirming their reliability in the standard operating range, but significant variations are observed in the rapidly decaying current region (at high voltage) (Fig. 5), where some methods (such as ACOR and PSOX) appear to be better suited.

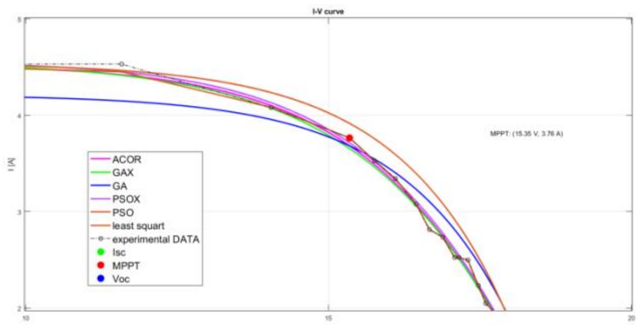


Fig. 5 – Zoom on comparative I-V curve figures.

For Fig. 4 (*P-V* Curve): The graphs fit well in the power ramp-up region (for low voltages), but slight discrepancies appear near the power peak and in the fast decay region (Fig. 6), where the power drops sharply. The ACOR and PSOX methods show excellent correspondence with the experimental data, especially at the power peak and in the fast decay phase. This confirms their better accuracy in modeling the real behavior of the photovoltaic panel under normal conditions.

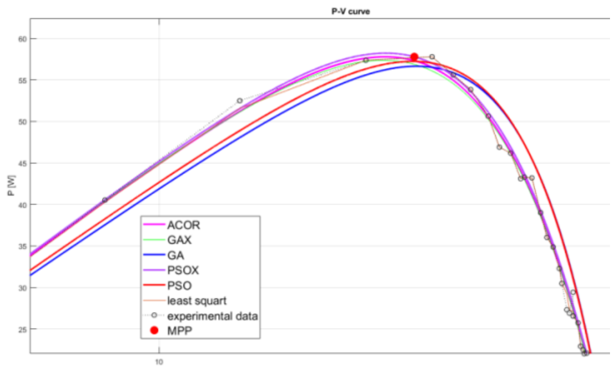


Fig. 6 – Zoom on the comparative P-V curve figure.

## 4. DISCUSSION

This research aims to determine the parameters of a photovoltaic (PV) panel using different identification methods. These methods were chosen for their ability to find global solutions in complex parametric environments, particularly in the context of photovoltaic systems, characterized by high nonlinearity. Optimization algorithms inspired by nature, such as particle swarm optimization (PSO), genetic algorithm (GA), continuous domain ant colony optimization (ACOR), and their variants (GAX, PSOX) [30], were compared with conventional least-squares approaches.

ACOR, PSOX, and least-squares methods are particularly effective for fitting *I-V* and *P-V* curves in areas where the nonlinear character of solar panels is most pronounced, particularly at low voltages. These techniques are more adaptable to experimental data, more effectively capturing the nonlinearity of PV cells. However, significant disparities appear in high-voltage areas, where power and current drop rapidly.

PV curves highlight the importance of the maximum power point (MPP), which is crucial for assessing system efficiency. ACOR, PSOX, and least squares provide a better fit near the MPP, which is essential for fine-tuning the efficiency of photovoltaic systems. However, techniques such as GA and PSO, despite their large-scale effectiveness, are slower and require more computational resources.

Hybrid techniques, which combine PSO and GA with explicit equations, take advantage of the global exploration offered by evolutionary algorithms while benefiting from more efficient local exploitation thanks to these equations. By incorporating explicit equations, PSOX and GAX optimize the convergence of PSO and GA, thus providing more accurate and timely answers.

Regarding the influence of experimental data on the accuracy of results, the quality of current and voltage measurements is paramount. Algorithms and the accuracy of estimated parameters can be significantly influenced by measurement errors or noise in the data. Inaccurate estimation of starting values, especially for traditional methods such as least squares, can lead to incorrect results. Therefore, accurate and methodical measurements are crucial.

Although the ACOR algorithm is effective in navigating complex search spaces, its use requires precise parameter tuning and additional computational time. It is crucial to maintain a balance between solution accuracy and required computational resources.

Mixed approaches that combine ACOR with other optimization methods or the incorporation of explicit models, such as PSOX and GAX, demonstrate solid performance in determining photovoltaic system parameters. However, their effectiveness depends on the accuracy of experimental data and the selection of initial parameters.

## 5. CONCLUSION

In conclusion, the comparison of different techniques for identifying photovoltaic parameters, such as the least squares method, the single and combined particle swarm optimization (PSO) algorithm (PSOX), the single and combined genetic algorithm (GA) (GAX), and the continuous domain ant colony algorithm (ACOR), highlights the specific strengths and limitations of each approach. According to the results, although the LS method is recognized for its effectiveness in exploring the search space and is presented as a robust and easy-to-implement approach, it remains vulnerable to measurement errors and environmental fluctuations.

However, the PSOX and GAX algorithms stand out for their ability to probe the search space efficiently, providing accurate and consistent parameter estimates. Furthermore, ACOR offers the advantage of improved execution speed and optimal convergence towards the ideal solution. Each approach offers specific advantages depending on the priorities of the targeted application (accuracy, speed, stability, or ease of implementation). It is therefore necessary to select the identification method taking into account the specific requirements of the photovoltaic system under investigation. For future research, it would be wise to explore hybrid methods that combine these techniques, with the aim of leveraging their individual benefits, further refining identification accuracy, and improving the overall performance of photovoltaic systems.

## CREDIT AUTHORSHIP CONTRIBUTION

Hizia Abed: formal analysis, investigation, data acquisition and organization, software development, visualization, validation, writing – original manuscript preparation.
Sihem Bouri: conceptualization, methodology, project supervision, project administration, writing – review and editing, validation, and visualization.
Hassan Benariba: project administration, visualization,

*Received on 29 November 2024*

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