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Hybrid ACOR–PSO Approach for The Identification of Photovoltaic Panel Parameters

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ABSTRACT

This paper proposes a hybrid optimization approach combining continuous domain ant colony optimization (ACOR) and particular swarm optimization (PSO) algorithms for the identification of photovoltaic panel parameters. The proposed ACOR-PSO method exploits the exploitation capacity of ACOR to generate relevant candidate solutions, while the swarm optimization (PSO) algorithm intervenes in the local exploitation phase to refine the search for the best solutions.

This collaboration overcomes the constraints specific to each technique, including blocking or anticipated convergence.

The main objective is to optimize the accuracy, consistency and convergence speed in the estimation of the five essential parameters of the diode model (Iph, Is, Rs, RSH, a). Validation was carried out on Matlab using experimental data collected in the field under standard environmental conditions. The results indicate that the hybrid ACOR–PSO approach provides more accurate identification, increased stability, and acceptable convergence time compared to conventional methods, achieving a root mean square error (RMSE) of 1×10^{-3} and stable parameter estimation over multiple runs. Despite its higher computational cost, the proposed approach demonstrates robustness and reliability in identifying PV parameters, making it promising for modeling, simulation, control, and energy optimization applications in the photovoltaic sector.

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النهج الهجين ACOR-PSO لتحديد معاملات الألواح الكهروضوئية

عابد حيزية، بوري سهام

ملخــص: تقترح هذه الورقة نهجًا هجينًا لتحسين الأداء يجمع بين خوارزميتي تحسين مستعمرة النمل في النطاق المستمر (*ACOR*) وتحسين السرب الخاص (*PSO*) لتحديد معلمات الألواح الكهروضوئية. تستغل طريقة *ACOR-PSO* المقترحة قدرة استغلال *ACOR* لتوليد حلول مرشحة مناسبة، بينما تتدخل خوارزمية تحسين السرب (*PSO*) في مرحلة الاستغلال المحلي لتحسين البحث عن أفضل الحلول. يتغلب هذا التعاون على القيود الخاصة بكل تقنية، بما في ذلك الحجب أو التقارب المتوقع. الهدف الرئيسي هو تحسين الدقة والاتساق وسرعة التقارب في تقدير المعلمات الأساسية الخمسة لنموذج الصمام الثنائي (*Iph*، *Is*، *Rs*، *RSH*، *a*). تم التحقق من الصحة باستخدام برنامج *MATLAB* باستخدام بيانات تجريبية جُمعت ميدانيًا في ظل ظروف بيئية قياسية. تشير النتائج إلى أن نهج *ACOR-PSO* الهجين يوفر تحديدًا أكثر دقة، واستقرارًا أعلى، وزمن تقارب مقبولًا مقارنةً بالطرق التقليدية، محققًا خطأ جذر متوسط مربع (*RMSE*) قدره 1×10^{-3} وتقديرًا مستقرًا للمعلمات على مدار عدة عمليات تشغيل. وعلى الرغم من ارتفاع تكلفته الحسابية، يُظهر النهج المقترح متانة وموثوقية في تحديد معلمات الطاقة الكهروضوئية، مما يجعله واعدًا لتطبيقات النمذجة والمحاكاة والتحكم وتحسين الطاقة في قطاع الطاقة الكهروضوئية..

الكلمات المفتاحية: خوارزمية مستعمرة النمل، تحسين السرب الجزيئي، الألواح الكهروضوئية، التحسين، التعريف.

1. INTRODUCTION

Due to technological advances, solar energy, particularly photovoltaic energy, appears to be an essential response to the increasing energy demand, the fight against global warming, the reduction of greenhouse gas emissions and the management of fossil fuel shortages. This form of energy has gained popularity due to its accessibility, sustainability, environmental friendliness and rapid decrease in cost [1, 2].

To ensure the optimal operation of photovoltaic systems, it is essential to improve energy production to maximize their capacity to generate electricity [3]. However, despite significant technological advances, various obstacles persist, largely hindering the adoption of photovoltaic systems [4]. These challenges include fluctuation in solar energy production due to weather conditions, constraints of existing technologies and problems of integrating these systems into conventional electricity grids [5]. Accurate modeling of PV cells is crucial for studying and predicting the performance of photovoltaic systems under various sunlight and temperature conditions. In recent years, several equivalent circuit models have been developed; the most commonly used being the single-diode model (SDM) and the dual-diode model (DDM) [6]. The performance of these models depends primarily on the accurate determination of their electrical parameters. This phase is essential for the simulation, performance analysis, optimized design, and real-time monitoring of photovoltaic systems [7]. Within the context of the single-diode model, five unknown parameters must be accurately determined. The five parameters are the photocurrent (I_{ph}), the reverse saturation current (I_s), the series (R_s) and shunt (R_{sh}) resistances, and the ideality factor (a).

Conventional optimization methods often encounter difficulties in providing accurate and satisfactory solutions to these problems due to the high complexity of constraints, strong nonlinearity, and high dimensionality of independent variables [8].

Various approaches have been developed in the literature to extract parameters from

PV photovoltaic models. These approaches can be divided into three categories: analytical, numerical (deterministic and stochastic), and hybrid methods. To address this problem, various traditional methods have been suggested, including analytical approaches based on explicit equations [9], the Newton-RAPHSON method [10], and least-squares techniques [11]. In 2023, Ekinci and al [12] conducted a comparative study of the Gazelle-Nelder–Mead hybrid algorithm for parameter extraction and optimization of solar photovoltaic systems, from their perspective. On their part, M. Abdel-Basset and al suggested a comparative analysis between Lambert's W function and Newton-Raphson method [13], in association with artificial intelligence-based optimization techniques, in order to identify the parameters of photovoltaic models. However, these methods frequently encounter problems when faced with highly multivariate nonlinear functions, and can be reactive to initial conditions, leading to local minima. Due to these constraints, meta-heuristic optimization algorithms have gained popularity. For example, Yang and al [14] employed a Bayesian neural network artificial ecosystem optimization algorithm to efficiently identify the parameters of photovoltaic cells. Furthermore, K. V. and al [15] developed an advanced modeling of the photovoltaic solar module based on adaptive particle swarm optimization to determine the parameters. On their part, Hassan and al [16] introduced a fractional order Kepler optimization algorithm (FO-KOA) for PV cell extraction. Sha Yang and al [17] proposed an improved version of the Whale algorithm for parameter determination. In addition, Abd El-Mageed and al [18] developed a hybrid approach based on the sparrow search algorithm, combined with exponential distribution and differential evolution, for parameter prediction. In 2024, Y. Han and al [19] presented a research focused on exploring and exploiting the multiverse optimizer for parameterization of photovoltaic models. Elshara and al [20] worked with the Coati optimization algorithm to estimate the parameters of photovoltaic cells and modules, in 2024, P. Ashwini and al [21] introduced an adaptive bivariate RAO technique for the accurate extraction of parameters from a solar photovoltaic system.

However, each method has some limitations. Particle swarm optimization (PSO) often suffers from premature convergence to local minima and sensitivity to inertia and acceleration parameters. ACOR, on the other hand, offers better global export, but may experience slow convergence and higher computational load during the local exploitation phase. Moreover, since Meta-heuristic algorithms are probabilistic in nature, their performance may vary from one run to another.

To overcome these drawbacks, we propose a hybrid approach combining ACOR and PSO to improve the identification of PV parameters. The ACOR algorithm allows to efficiently explore the global search space, while PSO refines the convergence around promising solutions provided by ACOR. This coupling allows to benefit from the complementary strengths of both techniques and to avoid the classic pitfalls of stagnation or premature convergence and to reinforce the stability of the results at each run. The performance of the proposed method is evaluated using experimental data from field-collected measurements performed on the SY-M80W photovoltaic module, under environmental conditions (1000 W/m2, 30 °C). The objective is to demonstrate the stability, accuracy, robustness and efficiency of the hybrid ACOR–PSO approach in the context of photovoltaic model identification.

2. MATERIALS AND METHODS

In order to transform solar energy into electrical energy, a solar panel is made up of many photovoltaic cells placed in parallel or in series. Because of its similar functions, the photovoltaic cell is depicted as a p-n junction diode [22]. Although a number of models have been created to depict the I-V properties of solar panels, the single-diode and dual-diode models are the most widely used in practice [23]. A single-diode photovoltaic cell model's electrical circuit is shown in Figure 1. This model uses a basic metallic framework to achieve a suitable balance between accuracy and simplicity. The equivalent schematic of the overall model includes a photocurrent (Iph), a diode, a parallel resistance (R_{sh}) which represents a leakage current, and a series resistance (Rs) attributed to the interconnections between the semiconductors and the metallic elements [24].

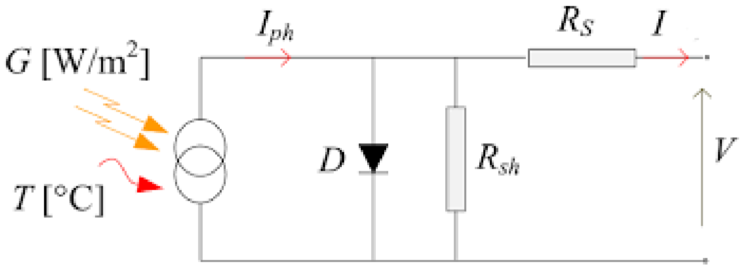


Figure 1: PV cell equivalent circuit

According to the electrical diagram presented in Figure 1, the fundamental equation representing the I-V characteristics of a photovoltaic cell model is expressed according to Kirchhoff's first law and can be formulated as follows [25]:

$$I = I_{ph} - I_s(e^{(\frac{(q(V+R_s I)}{aKT})} - 1) - \frac{V + R_s I}{R_{sh}} \tag{1}$$

Where: I_{ph} is the photocurrent (A), I_s is the saturation current (A), a is the ideality factor R_s (Ω) and R_{sh} (Ω) is the series and shunt resistance, K is the Boltzmann constant (1.3806×10^{-23} J/K), T is the temperature, q the electron charge (1.602×10^{-19} C).

2.1. Parameter identification

The goal of parameter extraction is to define the five unresolved parameters of the single-diode photovoltaic model: the photocurrent Iph, the reverse saturation current Is, the series resistance Rs, the resistance Rsh, and the diode ideality factor a. This is to ensure that the simulated I-V characteristics match the experimental data as closely as possible.

The primary goal of the PV model parameter identification problem is to determine the optimal combination of undefined parameter values to reduce the gap or error between the measured and calculated current data.

This optimization problem can be expressed as the minimization of an error function that measures the gap between the values derived from experiments and those derived from the model. In this research, the cost function used is the root mean square error (RMSE), [26] which is defined as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(I_{exp,i} - I_{mod,i}))^2} \quad (2)$$

Where: $I_{exp,i}$ represents the experimentally measured current for the i^{th} voltage point, $I_{mod,i}$ is the current estimated from the model, N is the total number of measurement points. Optimizing this error allows to obtain an ideal parameterization guaranteeing a precise correspondence between the experimental and simulated curves. In this work, the objective equation (2) is employed in parallel with a hybrid optimization algorithm based on ACOR-PSO.

2.2. Ant Colony Optimization for Continuous Domain (ACOR)

Ant Colony Optimization for Continuous Domain (ACOR) is an adaptation of the Ant Colony Optimization (ACO) algorithm, first presented by Marco DORIGO to address combinatorial problems, such as the traveling salesman problem (TSP) [27]. The first proposal to use ACO to address continuous optimization problems was made by Krzysztof SOCHA and Marco DORIGO (2006) [28]. This approach is particularly relevant for complex real-variable systems such as photovoltaic systems. ACO draws inspiration from the innate feeding habits of ants and their instinctive ability to identify the optimal route from a food source to their colony [29].

We perceive the ant colony-based approach as a swarm meta-heuristic, where each solution is symbolized by an ant navigating in the search space. Ants have the ability to collectively solve complex problems, such as determining the best route between two points in challenging environmental conditions. Therefore, they exchange information indirectly and locally through volatile hormones called pheromones [30]. In their evolutionary process, ants release pheromones and then randomly select their path based on a probability that depends on the number of pheromones previously deposited [31].

In combinatorial optimization, ACO stores pheromone data in a table. At each step, it uses certain aspects of this table as discrete probability distributions to decide which elements to add to the current partial solution. Continuous optimization is not restricted to a limited choice of options. Thus, it is not possible to represent pheromones in a tabular form. Similar to traditional ACOs, we apply the technique of updating the pheromone matrix relative to the components of the appropriate solution [32].

Instead of relying on pheromone evaporation, the pheromones associated with the previous method are removed via a negative update of the pheromone array, thus erasing their impacts.

Each solution in the archive is assigned a weight (Equation 3), generally defined by a decreasing function of the solution's rank l. Equation 4 provides the formula for calculating the probability p(l) of producing a new solution.

$$w(l) = \frac{1}{qk\sqrt{2\pi}} e^{\frac{(l-1)^2}{2q^2k^2}} \quad (3)$$

Where k is the archive size and q is the intensification coefficient controlling the selection pressure.

$$P(l) = \frac{W(l)}{\sum_{j}^{k} W(j)} \quad (4)$$

A new solution is sampled from a Gaussian distribution with mean μ_l^i and standard deviation σ_l^i for each variable i of solution l [33]:

$$\sigma = \frac{z}{k-1} \sum_{r=1}^{k} \left| \mu_l^i - \mu_r^i \right| \quad (5)$$

Where: Z is a fixed parameter that controls the width of the Gaussian distribution. It defines the balance between exploration and exploitation: higher Z values encourage exploration, while lower Z values promote local search.

2.3. Particle swarm optimization (PSO)

Particle swarm optimization is a meta-heuristic that draws inspiration from the way fish feed and how birds travel collectively around a D-dimensional area. Kennedy and Eberhart created this technique in 1995 [34].

Each particle in the swarm represents a possible solution to the problem, moving through the search space by modifying its speed and position based on its own experience and that of neighboring particles [35]. It is particularly effective for optimization problems in continuous, multidimensional, and nonlinear search environments.

The key concept is to adjust the position of each particle in space to discover optimal solutions, based on its previous best individual position (P_{Best}) and the global optimal position of the swarm (g_{Best}). Represented by Equation 7 [36]. During each iteration, an objective function check is performed, thus encouraging each particle to reconfigure itself in accordance with the standards mentioned earlier.

However, a significant drawback of traditional OSP is its propensity to fixate on local optima, which limits its ability to efficiently navigate the search space [37].

Mathematically, updating the ith parameter of the solar cell based on the j^{th}particle in the swarm during iteration k+1 is performed as follows.

$$X_{i,j}^{k+1} = X_{i,j}^{k} + V_{i,j}^{k+1} \quad (6)$$

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

The following formula provides the speed update for each solar cell parameter:

$$V_{i,j}^{k+1} = wV_{i,j}^{k} + C_1 r_{i,j}^{k} (P_{i,best}^{k} - X_{i,j}^{k}) + C_2 r_{i,j}^{k} (P_{i,Gbest}^{k} - X_{i,j}^{k}) \quad (7)$$

Where: $V_{i,j}^{k}$: the velocity of the ith particle;$X_{i.j}^{k}$: the position of the ith particle; $P_{i.best}^{k}$: best known position of the particle;$P_{i.gbest}^{k}$: 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: the inertia factor, C1 and C2 : the social acceleration constant [38].

2.4. Hybrid approach

Accurately determining the parameters of a photovoltaic (PV) panel is crucial to ensure accurate modeling, thus improving energy yield predictions, identifying anomalies, and adjusting device operation.

With this in mind, we propose a hybrid approach combining the Ant Colony Optimization for Continuous Domains (ACOR) algorithm with the Particle Swarm Optimization (PSO) algorithm to leverage both the global exploration capability of ACOR and the convergence speed of PSO.

Thanks to its probabilistic system and dynamic archive management, the ACOR algorithm offers remarkable global exploration capability of the search space. However, its convergence can be slower in the final stages. Conversely, the PSO algorithm quickly reaches an optimal solution but risks getting trapped in local optima if particle diversity decreases. The concept of this hybrid approach is to exploit the initial diversity of ACOR to create high-quality initial solutions, and then use PSO analysis to refine these solutions locally, thus increasing the accuracy and stability of parameter identification. The procedure follows the phases illustrated in the diagram in Figure 2. And can be summarized as follows:

The ACOR algorithm produces a collection of candidate solutions based on pheromone-driven probabilities. Overall evaluation (ACOR); Candidate proposals are judged based on the objective function. The pheromone archive is continuously updated to guide the search toward promising areas. When ACOR reaches a convergence criterion (such as a maximum number of iterations, a minimum improvement in the objective function, or an RMSE threshold), the optimal solutions are passed to PSO. Particles are then configured based on ACOR's optimal solutions. PSO gradually adjusts particle speeds and positions to locally optimize the search space, which accelerates convergence toward the optimal PV parameters. Finally, the hybrid algorithm terminates when PSO reaches its termination criteria (maximum number of iterations or a minimum change in the objective function). The best option is selected as the identified PV parameters.

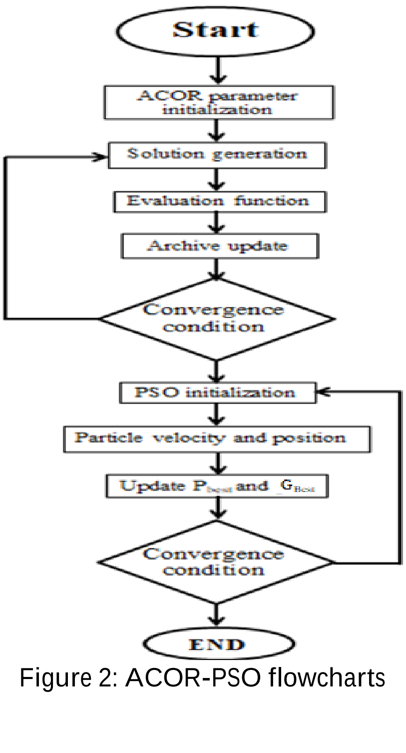


Figure 2: ACOR-PSO flowcharts

This hybrid approach combines the exploration strength of ACOR with the fast convergence of PSO, reducing the risk of getting stuck in local optima while ensuring high accuracy and stability of the results. However, it has some drawbacks: it requires more computation than a single algorithm, which can make the execution time significant, especially when the number of PV parameters or the population size is large. Moreover, incorrect parameter settings can lead to slow convergence or suboptimal solutions.

3. RESULTS

This paper proposes the hybrid ACOR +PSO technique for the identification of photovoltaic parameters. The panel studied is the SY-M80W, whose electrical specifications are summarized in Table 1

Table 1: PV Module SY-M80W

Parameter	Value
Open-circuit voltage (Voc)	22 V
Short circuit current (Isc)	4.85 A
Voltage at Pmax (Vmp)	17.4 V
Current at Pmax (Imp)	4.61 A
Maximum Power (Pmax)	80 W
Max System Voltage	600 V
Tolerance	5%

The experimental data used for verification were collected during experiments conducted in April at the University of Tlemcen (Algeria). The solar panel was installed under real-world conditions and evaluated using a data collection system. Electrical parameters (voltage and current) were evaluated, while irradiance and temperature were monitored using a Solari Meter (AK9635D) and a thermocouple, respectively.

These empirical data were used as benchmarks to assess the accuracy, stability, and robustness of the proposed hybrid identification method (ACOR–PSO).

The search limits used for the single-diode model parameters are shown in Table 2. These values were selected to cover a wide range of physical conditions.

Table 2: Boundaries Range for SY-M80W Module

Parameter	Lower Bound	Upper Bound
Iph (A)	0	6
Io (μA)	0	1
Rs (Ω)	0	1
Rsh (Ω)	0	3000
a	0	2

Table 3. The algorithm parameter

ACOR		*PSO*	
Iteration	*1000*	*Iteration*	*100*
ants	*100*	*population*	*30*
Q	*0.3*	*w*	*0.7*
Z	*0.7*	*C1, C2*	*1.5*

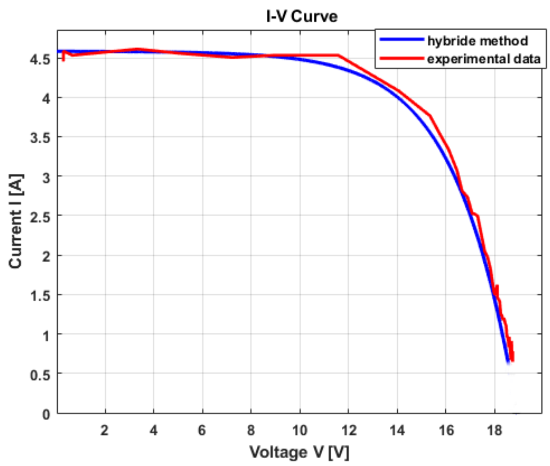
Table 3 illustrates the parameters used to train the ACOR and PSO algorithms.

The approximate values of the photovoltaic model parameters, obtained through three consecutive runs of the same hybrid algorithm, are presented in Table 4 below. The following parameters were evaluated: saturation current (Iph), leakage current (Io), series resistance (Rs), shunt resistance (Rsh) and also the ideality factor (a). For each run, the RMSE is also provided to judge the accuracy of the fit.

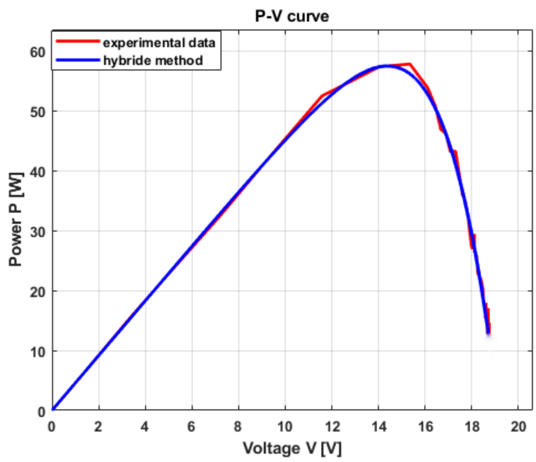
Table 4 : Simulation results

parameters	Value 1	Value 2	Value 3
Iph (A)	4.589193	4.588490	4.588363
Io	0.001329	0.001313	0.001282
Rs (Ω)	0.046261	0.035239	0.037912
Rsh (Ω)	2875.4548	2877.256	2897.8272
A	1.522330	1.520218	1.515834
RMSE	0.0078474	0.0078476	0.0078483

Figures 3 below demonstrate a concordance between the experimental data and those derived from the model using the hybrid approach.



(a)



(b)

Figure 3. I–V and P–V Characteristics of the Single Diode Model; (a) Comparison of I–V characteristics of the single diode model; (b) Comparison of P–V characteristics of the single diode model

These results illustrate the accuracy of the approach used to simulate the operation of the photovoltaic system. Indeed, the current-voltage (I-V) and power-voltage (P-V) characteristic curves of the experimental data, thus confirming the model's ability to identify the photovoltaic parameters of our panel.

Figure 4 represents the convergence curve of our hybrid techniques, where the convergence curves for ACOR and PSO are added. We note that the hybrid approach offers a lower cost, while displaying faster convergence and superior stability compared to the ACOR and PSO methods. This performance improvement demonstrates that combining the two algorithms optimizes the search process, making it more efficient while providing a more accurate and reliable solution.

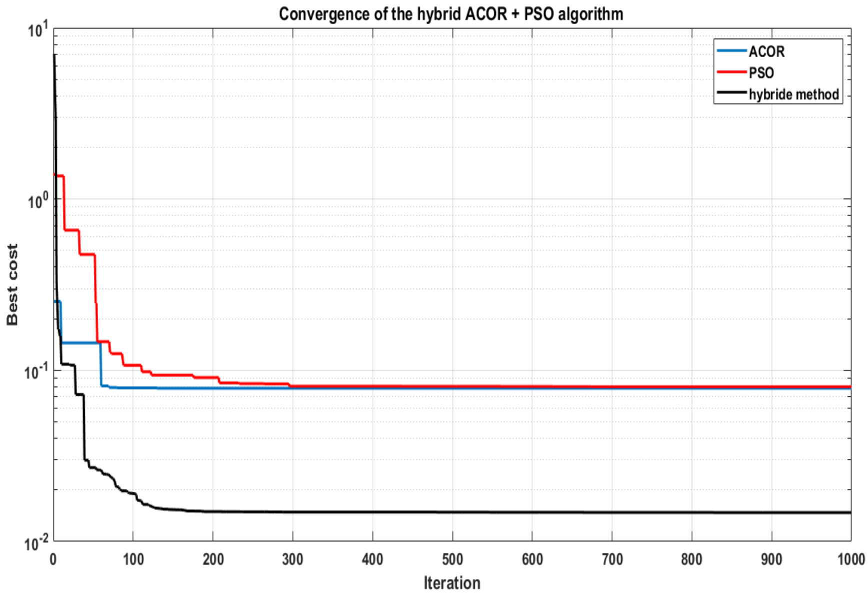


Figure 4: Convergence graph

To further confirm the effectiveness of the suggested hybrid method, the obtained results were compared with the individual ACOR and PSO algorithms (see Table 5). Each algorithm was run three times under the same conditions to identify the five parameters of the SY-M80W photovoltaic module. The results indicate that the ACOR–PSO hybrid method offers the lowest RMSE level, thus demonstrating the best accuracy compared to all the techniques compared. It also offers greater convergence and improved stability between each run, although this results in additional computational time.

Table 5. Comparison between PSO, ACOR and ACOR–PSO

Algorithm		Iph (A)	Io	Rs (Ω)	Rsh (Ω)	a	RMSE
PSO	Essai 1	4.594548	3.4785e−5	0.16223	2845.083	1.636191	0.065012
	Essai 2	4.682633	3.47854e−5	0.194967	2911.638	1.555685	0.057228
	Essai 3	4.48578	1.15081e−6	0.041757	2865.859	1.89	0.08816
ACOR	Essai 1	4.491527	1.6269e−5	0.07987	2890.258	1.8801	0.080851
	Essai 2	4.479446	1.8922e−6	0.18	2980.56	1.608	0.0561
	Essai 3	4.5032	4.10253e−6	0.1456	2910.40	1.6966	0.067
ACOR-PSO	Essai 1	4.589193	0.001329	0.046261	2875.455	1.522330	0.0078474
	Essai 2	4.588490	0.001313	0.035239	2877.256	1.520218	0.0078476
	Essai 3	4.588363	0.001282	0.037912	2897.827	1.515834	0.0078483

4. DISCUSSION:

This research focuses on developing an intelligent technique for identifying photovoltaic parameters, based on a SY-M80W photovoltaic panel model. ACOR is well known to be a probabilistic algorithm, which means that the optimal results obtained can fluctuate with each program execution, even when starting from the same initial conditions. This variability can be an obstacle when aiming for reproducibility and consistency of results.

To address this problem, a hybrid technique was developed, combining continuous domain ant colony optimization (ACOR) with specific swarm optimization (PSO). The idea is to overcome the constraints of deterministic techniques and leverage the benefits of both approaches. The ACOR algorithm provides efficient exploration of the global search space, while the PSO improves convergence toward the promising solutions proposed by ACOR. This combination offers the opportunity to exploit the distinct advantages of both methods while avoiding the common pitfalls of stagnation or early convergence, frequently observed in optimization algorithms.

The effectiveness of the suggested technique is evaluated using experimental data. The method's flowchart (Figure 2) follows a structured order: parameter initialization, solution generation using ACOR, stabilization using PSO, evaluation of the objective function (RMSE reduction), and then recording of the best-performing solutions. The curves (Figures 3 and 4) produced from the detected parameters show a close correspondence with the curves resulting from the experiment, presenting minimal deviations (RMSE, MAE) on the I-V and P-V characteristics.

Table 5 presents the results collected from several consecutive attempts. Although ACOR is random in nature, the variation between code iterations is always below 0.01, indicating remarkable consistency and reproducibility of the results. Compared to basic algorithms, PSO ensures fast convergence, but there is a significant risk of getting stuck in a local optimum; conversely, ACOR allows efficient global exploration, although it is associated with slower convergence. The hybrid ACOR-PSO method capitalizes on the advantages of both algorithms: deep exploration thanks to ACOR and fast and reliable convergence thanks to PSO. Consequently, the hybrid approach significantly decreases the identification error and improves stability between different executions, highlighting its robustness and efficiency in determining the PV parameters. However, it is important to mention that this approach requires somewhat higher computation time than basic algorithms, due to the collaboration between ACOR and PSO. However, this additional computational cost is considered an acceptable trade-off given the improvements in accuracy, stability, and reliability.

In conclusion, incorporating a hybrid ACOR-PSO method into the process of determining photovoltaic module parameters helps significantly reduce the difference between experimental and modeled curves, while ensuring high stability and reproducibility of the results. This feature is crucial for real-world applications where reliability and consistency of results are of major importance.

5. CONCLUSIONS:

This research led to the design, simulation, and validation of a hybrid and intelligent method for determining the parameters of a photovoltaic panel, based on the strategic use of ant colony optimization algorithms in the continuous ACOR framework and specific PSO swarm optimization. Tests conducted on the SY-M80W solar panel under normal environmental conditions demonstrated that the hybrid ACOR+PSO model produced results that were accurate, consistent, and robust.

This method aims to overcome the constraints of conventional techniques and meta-heuristics taken separately. The ACOR algorithm offers efficient exploration of the global search space, while the PSO improves convergence toward the promising solutions proposed by ACOR. This combination leverages the complementary advantages of both methods while avoiding the common pitfalls of stagnation or early convergence. The simulations performed demonstrate that this hybrid approach allows for more accurate identification, displaying acceptable convergence times and appreciable stability of the results. The suggested approach offers an efficient way to model photovoltaic systems, and could also be used for their incorporation into control, simulation or energy optimization systems.

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Conflicts of Interest: The authors declare that they have no conflict of interest.

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