International Journal of Power Electronics and Drive System (IJPEDS)
Vol. 17, No. 2, June 2026, pp. 1418~1425
ISSN: 2088-8694, DOI: 10.11591/ijpeds.v17.i2.pp1418-1425

Parameters optimization of solar PV cell using war strategy

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Article Info

Article history:

Received Mar 18, 2025
Revised Mar 29, 2026
Accepted Apr 23, 2026

Keywords:

Metaheuristic algorithm
Parameters extraction
Photovoltaic cells
Root mean square error
Single-diode model
War strategy optimization

ABSTRACT

Enhancing photovoltaic models' performance and dependability requires optimal parameter extraction. This paper presents a practical method for determining these values from experimental current-voltage data: the war strategy optimization algorithm. RTC France, PWP201, and STP6-120/36 are the three PV models to which the war strategy optimization algorithm was successfully applied. According to the findings, the RMSE values for RTC France were 0.0000077298; PWP201 was 0.0020528; and STP6-120/36 was 0.0014253. These results demonstrate the great potential of the warfare strategy optimization (WSO) to improve the accuracy of photovoltaic models and advance photovoltaic technology.

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1. INTRODUCTION

The global transition to sustainable energy systems has highlighted photovoltaic technology as an essential and indispensable element [1], [2]. Conclusively, the performance and efficiency of photovoltaic systems significantly rely on the accuracy of the component models articulated by a set of parameters extracted from a systematic analysis of the experimental current-voltage data of the modules [3], [4]. To properly design, the parameters must be extracted with accuracy and consistency, simulated, and operated on the photovoltaic modules [5], [6]. Unfortunately, the conventional parameter extraction poses stubborn challenges, including initial assumption sensitivity and convergence [7], [8]. The above limitations of past and existing models render them less reliable and efficient in operating photovoltaic systems [9]. It is imperative to devise creative and reliable ways out of the mentioned bottlenecks associated with the traditional extraction methods [10], [11].

Metaheuristic algorithms have become increasingly popular due to their strength in handling complex optimization problems. Metaheuristic algorithms are particularly effective in exploring complex search spaces and avoiding local optima [12], [13]. Among these methods, the warfare strategy optimization algorithm has proven efficient in solving various optimization challenges [14], [15].

In summary, we have achieved exceptional accuracy and reliability utilizing the warfare strategy optimization (WSO) algorithm to extract optimal parameters for three distinct photovoltaic models solely from the available experimental data. Our study is well-structured to facilitate the reader's understanding. Section 2 introduces fundamental photovoltaic models, and section 3 explains our methodology, with the use of the WSO algorithm. In turn, section 4 demonstrates that our use of WSO beats other models, and section 5 concludes the findings, presenting the ramifications for the further study of these most intricate living organisms.

2. MATHEMATICAL FORMULATION OF PV MODELS

Figure 1 illustrates how the single diode model represents the incident flux irradiation using a current source. Two resistances, R_s and R_{sh}, which stand for the leakage current and the ohmic contacts, respectively, and a diode, which symbolizes the P-N junction, are connected in parallel with this source. The output current I is computed using the following [16], [17].

$$I = I_{pv} - I_d - I_{sh} \tag{1}$$

Here, I_d is the diode current as calculated by the Shockley diode equation, I_{pv} is the photo-generated current, and Ish is the current passing through the shunt resistor.

$$I_d = I_0 \left[e^{\left(\frac{q(V+I.R_S)}{nNT}\right)} - 1 \right] \tag{2}$$

$$I_{sh} = \frac{V+I.Rs}{R_{sh}} \tag{3}$$

The cell temperature in this instance is T in Kelvin (K), the electron charge is $q = 1.60217646 \times 10 - 19$ C, the diode ideality factor is n, and the Boltzmann constant is $N = 1.3806503 \times 10 - 23$ J/K. It is possible to represent the output current using (1)-(3).

$$I = I_{pV} - I_0 \left[e^{\left(\frac{q(V+I_L.R_S)}{a\,NT}\right)} - 1 \right] - \frac{V+I.Rs}{R_{sh}} \tag{4}$$

The five unknown parameters are I_{pv}, I_0, R_s, R_{sh}, and n.

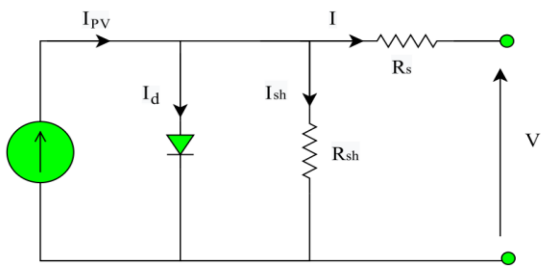


Figure 1. The single diode model's corresponding electric circuit

3. WAR STRATEGY OPTIMIZATION

Ancient kingdoms, which kept military forces made up of many groups to repel enemy incursions, served as the model for the WSO [18]. Each kingdom created tactical strategies to counter enemy troops during battles, and the monarch or commander set up particular coordinating methods to achieve goals. WSO has two main strategies [19]. The first is "attack mode," in which every soldier shifts positions based on where the commander and king are. The soldier who is the most fit is crowned the next king in this mode [20]. Every soldier starts from the same starting point, and their ranks rise when they accomplish their goals:

$$Y_i(t+1) = Y_i(t) + rand.W_i.(C - Y_i(t)) + 2.\rho.(K - Y_{rand}(t)) \tag{5}$$

The new soldier's position is represented by Yi(t + 1), the old soldier by Yi(t), the commander by C, the monarch by K, the weight by Wi, and the threshold value by ρ. The soldier will decide to remain in their present position if the attack power (f_n) of the new one is less than the existing position's fp.

$$Y_i(t+1) = \big(Y_i(t)\big) * (f_n < f_p) + Y_i(t+1) * (f_n \geq f_p) \tag{6}$$

If a soldier can update their location, their rank (Ri) will be increased.

$$R_i = R_i * \big(f_n < f_p\big) + (R_i + 1) * \big(f_n \geq f_p\big) \tag{7}$$

The (8) determines the new weight based on the rank:

$$w_i = w_i \times \left(1 - \frac{R_i}{Max\_iter}\right)^{\alpha} \tag{8}$$

where the maximum number of iterations is Max_iter and α is a configurable parameter. The WSO algorithm's second position update method entails moving the commander, the monarch, and one soldier chosen at random while keeping the initial weight and rank adjustments.

$$Y_i(t+1) = rand.W_i.(C - Y_i(t)) + Y_i(t) + 2.\rho.(K - Y_{rand}(t)) \tag{9}$$

Where X_{rand} is a random soldier's position.

4. THE WSO'S PSEUDO-CODE

The algorithm initializes max iterations (M), dimension (D), and soldiers (N), then deploys soldiers chaotically via a chaos map. For each soldier and each dimension, it computes the fitness (attack) and evaluates overall performance. During t < M, Yi(t+1) is updated according to a random threshold ρ1, then fitness is recalculated, and Wi is updated, with GA crossovers to form new positions. At the end, it identifies the weakest soldier and outputs the king's position and fitness. Figure 2 shows the WSO flowchart, and the following is the pseudo-code for WSO.

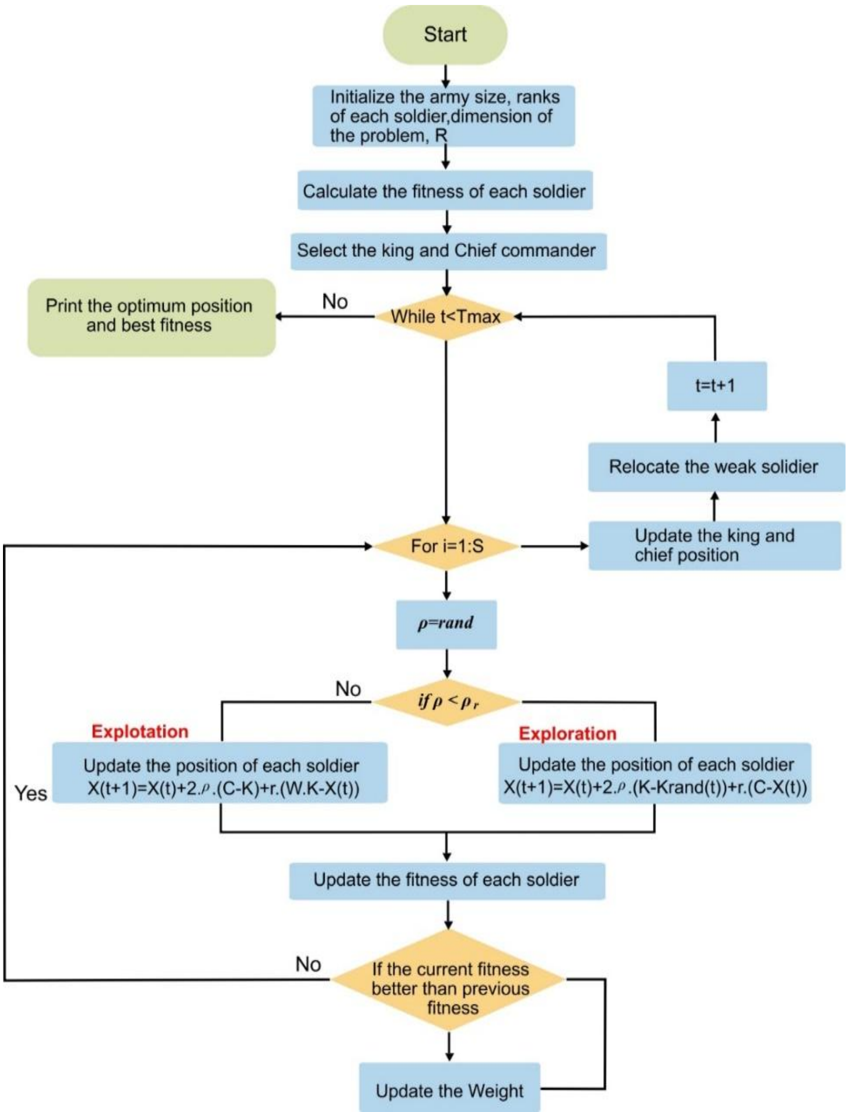


Figure 2. The WSO algorithm's flowchart for the PV parameter extraction use case

Algorithm 1. Pseudocode for WSO
```
Start by setting the maximum number of iterations (M), issue dimension (D), and soldier
size (N).
To evenly and randomly deploy soldiers throughout the battlefield, use chaos mapping.
For k = 1:N
   For i = 1:D
      Determine each soldier's fitness (attack force).
   End
End
Assess each soldier's level of fitness.
While t < M
   For 1:N
        ρ1 = rand
        If ρ > ρ1
            Utilizing (5), update Yi(t + 1)
        Else use(6) to update the Yi(t + 1).
        Final if condition
            Determine each soldier's fitness level.
            Update Yi(t + 1)
            Utilizing (9) update Wi
        The for loop's end
        Determine which soldier is the weakest and least fit. Cross-mutations are added in
        conjunction with genetic algorithms to create the positions of new warriors.
        t = t + 1
When the while loop ends
Show off the king's position and fitness.
```

5. THE WSO PARAMETERS ALGORITHM AND OBJECTIVE FUNCTION

The proposed soft computing method determines five parameters, X = [I_0, I_{ph}, n, R_{sh}, Rs], using an optimization algorithm that minimizes a predefined objective function until a stopping criterion is met. Establishing an appropriate objective function is crucial before optimization, and this research uses the RMSE to define it [20].

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} f(I_e, V, X_i)^2} \tag{10}$$

Where xi denotes the vector of unknown parameters shown as $X_i = \left[I_0\ I_{pv}\ n\ R_{sh}\ R_s\right]$. The $f(I_{pv}, V, x_i)$ is shown as (11) and (12).

$$f\left(I_{pv}, V, x_i\right) = \frac{V+R_S I_{pv}}{R_{sh}} + I_e - \left(I_{ph} - I_0 \times \left\{e^{\left[\frac{q(V+R_S I_{pv})}{nKTN_S}\right]} - 1\right\}\right) \tag{11}$$

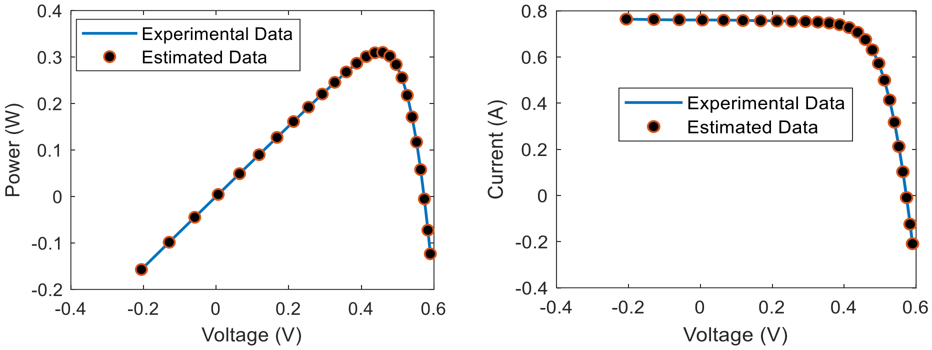
$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left\{I_{exp} - \left(I_{ph} - I_0 \times \left\{e^{\left[\frac{q(V+R_S I_{pv})}{nKTN_S}\right]} - 1\right\} - \frac{V+R_S I_{pv}}{R_{sh}}\right)\right\}^2} \tag{12}$$

In the above objective functions, V and I_e are the experimental values of the voltage and current of the solar module, respectively.

6. RESULTS AND DISCUSSION

First, by forecasting the unknown parameters of the basic model, the suggested WSO method's accuracy, precision, and dependability are validated. To validate the proposed method, four sets of experimental data were selected: a commercial silicon solar panel with a diameter of 57 mm, called RTC France, which operates at 33 °C with a solar irradiance of 1000 W/m²; a photowatt-PWP-201 solar module, consisting of 36 polycrystalline silicon cells operating in series at 45 °C with an irradiance of 1000 W/m²; and a commercial module of type STP6-120/36, consisting of 36 polycrystalline silicon cells operating in series at 55 °C [21]. The I(V) and P(V) curves derived from the WSO algorithm show remarkable consistency with real data, as illustrated in Figures 3(a) and 3(b). A strong correlation is indicative of the high accuracy and reliability of our modeling approach. As shown in Table 1, the RMSE values demonstrate how our suggested method performs relatively better with a RMSE of 7.7298×10^{-4}. For the fact that the RMSE values for the GAMNU method [22] and the PHHO method [23] are 9.8618×10^{-4} and 8.4043×10^{-4}

respectively. These values confirm the proposed model's superiority over the other optimization approaches. Furthermore, the WSO approach and other optimization techniques cited in the literature were used to determine the ideal values of the parameters, which are shown in Table 1. The correctness and resilience of our optimization approach for simulating the performance of RTC France's silicon cells are further supported by the favorable RMSE values and the concordance between the simulated and real data.



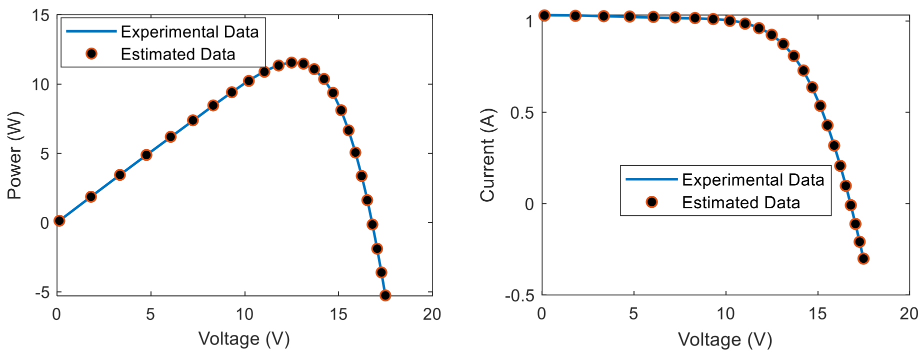
(a) (b)

Figure 3. Comparative evaluation of simulated and experimental data for RTC France: (a) P(V) and (b) I(V) features

Table 1. RTC France's estimated parameters and RMSE values

Algorithms	I_{pv} (A)	Rs (Ω)	N	I0 (A)	Rsh (Ω)	RMSE
Proposed	0.76078	0.0365	1.47727	0.31069	52.8899	7.7298×10^{-4}
GAMNU [22]	0.760774	0.0363	1.482096	0.3255954	53.896860	9.8618×10^{-4}
PHHO [23]	0.76643	0.0304	1.57916	7.91×10^{-7}	24.38538	8.404323×10^{-4}

Figures 4(a) and 4(b) illustrate the striking agreement between the I(V) and P(V) curves produced from data simulated using the WSO algorithm and real experimental data. This resilient and accurate optimization method for solar cell modeling is demonstrated by this strong correlation. The efficiency of our suggested approach is further demonstrated in Table 2, which obtains the lowest RMSE of the approaches examined, 0.205×10^{-3}. For instance, the dichotomy technique [24] has a marginally higher RMSE of 2.225×10^{-3} compared to 2.081×10^{-3} for the DONR method [25]. Other widely used techniques, including PMFO [23] and GAMNU [22], have RMSE values of 2.05×10^{-3} and 2.382×10^{-3} respectively. Additionally, the RMSE for AGDE [26] is 2.42×10^{-3}. It is evident from these comparisons that our suggested approach performs noticeably better than alternative optimization strategies. The ideal values of the parameters determined by WSO and other optimization techniques from the literature are also shown in Table 2. Together with the positive RMSE values. The accuracy of our approach in accurately simulating photovoltaic system performance is further supported by the alignment of the simulated findings with real data.



(a) (b)

Figure 4. Comparative evaluation of simulated and experimental data for Photowatt-PWP201: (a) P(V) and (b) I(V) features

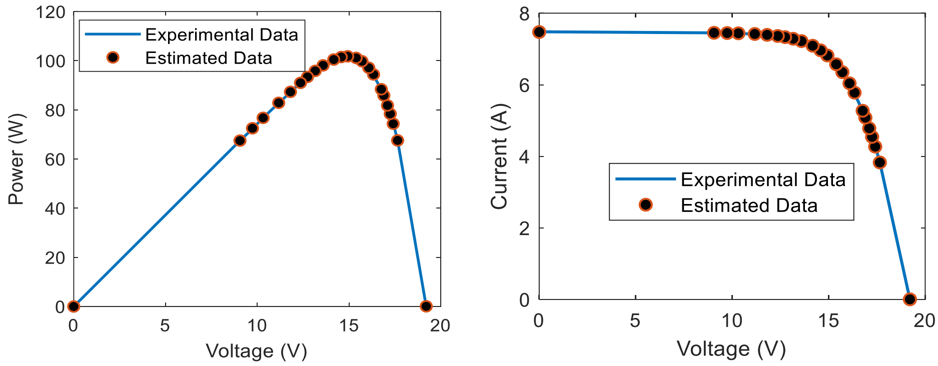
Figures 5(a) and 5(b) demonstrate the striking similarity between the P(V) and I(V) curves derived from data simulated using WSO and actual data. This demonstrates how well the WSO approach may mimic the actual behavior of the system. The RMSE values for various optimization techniques are shown in Table 3. Compared to the GAMNU [22] technique (2.382×10^{-3}) and the TAPSO [27] method (2.077×10^{-3}), the suggested method's RMSE of 1.4253×10^{-3} is substantially lower. These results demonstrate that the proposed method performs more accurately than existing optimization techniques. Table 3 also shows the optimal values of the undisclosed parameters as determined by WSO and as obtained from several optimization methods in the literature. This illustrates the effectiveness of the WSO approach in accurately optimizing these important model parameters.

Table 2. Photowatt-PWP201's estimated parameters and RMSE values

Algorithms	Ipv(A)	Rs(Ω)	A	I0(A)	Rsh(Ω)	RMSE
Proposed	1.031	1.2356	47.598	2.63796	821.609	0.205×10^{-3}
DONR [25]	1.030	1.2179	48.195	3.09×10^{-6}	952.867	2.081×10^{-3}
Dichotomy method [24]	1.033	1.2375	1.3250	2.70×10^{-6}	710.39	2.225×10^{-3}
GAMNU [22]	-	-	-	-	-	2.382×10^{-3}
PMFO [25]	1.0314	1.23563	1.322	2.64×10^{-6}	821.647	2.05×10^{-3}
AGDE [26]	1.0304	1.1979	48.784	3.61×10^{-6}	1021.173	2.42×10^{-3}

Table 3. STP6-120/36 's estimated parameters and RMSE values

Algorithms	Ipv(A)	Rs(Ω)	N	I0(A)	Rsh(Ω)	RMSE
Proposed	7.47528	0.16891	44.80118	1.93134	570.42878	1.4253×10^{-3}
GAMNU [22]	-	-	-	-	-	2.382×10^{-3}
TAPSO [27]	1.03176	1.22412	47.81345	2.79331	793.86532	2.077×10^{-3}



(a) (b)

Figure 5. Comparative evaluation of simulated and experimental data for STP6-120/36: (a) P(V) and (b) I(V) features

7. CONCLUSION

The results of this study confirm the effectiveness of the warfare strategy optimization approach in accurately determining the parameters of photovoltaic cells. Offering a new perspective on parameter optimization, the WSO method was rigorously evaluated using experimental data from three different PV cells: STP6-120/36, Photowatt-PWP201, and RTC France. A comparative analysis based on RMSE demonstrated that the WSO method achieves exceptionally low RMSE values, demonstrating its superior accuracy and alignment with experimental data compared to other optimization techniques. These results not only validate the performance of the WSO method for photovoltaic parameter estimation but also highlight its potential for broader applications, such as improving MPPT in photovoltaic systems and addressing challenges related to optimal power flow in electrical networks. This research contributes to the advancement of the field by providing a robust and accurate tool for photovoltaic system optimization and opens up avenues for future exploration.

FUNDING INFORMATION

This work is supported by the URL 7 grant from the CNRST-Morocco.

AUTHOR CONTRIBUTIONS STATEMENT

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Radouan Gouaamar	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓
Seddik Bri	✓	✓	✓		✓	✓		✓	✓	✓	✓	✓	✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflicts of interest regarding the research, authorship, and publication of this article.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available upon request from the corresponding author.

REFERENCES

[1] H. Bakır, "Comparative performance analysis of metaheuristic search algorithms in parameter extraction for various solar cell models," *Environmental Challenges*, vol. 11, p. 100720, Apr. 2023, doi: 10.1016/j.envc.2023.100720.

[2] C. Qin, J. Li, C. Yang, B. Ai, and Y. Zhou, "Comparative study of parameter extraction from a solar cell or a photovoltaic module by combining metaheuristic algorithms with different simulation current calculation methods," *Energies*, vol. 17, no. 10, p. 2284, May 2024, doi: 10.3390/en17102284.

[3] R. Gouaamar, S. Bri, and Z. Mekrini, "Comparative Analysis between Proportional-Integral and Artificial Neural Network Control of a Grid-Connected PV System," *E3S Web of Conferences*, vol. 469, p. 00003, Dec. 2023, doi: 10.1051/e3sconf/202346900003.

[4] R. Gouaamar, S. Bri, and Z. Mekrini, "Improvements the direct torque control performance for an induction machine using fuzzy logic controller," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 14, no. 1, p. 1, Feb. 2024, doi: 10.11591/ijece.v14i1.pp1-11.

[5] U. Chauhan, H. Chhabra, P. Jain, A. Dev, N. Chauhan, and B. Kumar, "Chaos inspired invasive weed optimization algorithm for parameter estimation of solar PV models," *IFAC Journal of Systems and Control*, vol. 27, p. 100239, Mar. 2024, doi: 10.1016/j.ifacsc.2023.100239.

[6] R. Gouaamar, C. EL-Yazami, A. EL Fadl, and S. Bri, "Enhancing artificial neural network-based direct torque control of a double-fed induction generator," *International Journal of Electronics Letters*, vol. 14, no. 1, pp. 13–25, Jan. 2026, doi: 10.1080/21681724.2025.2559249.

[7] S. Lidaighbi, M. Elyaqouti, D. Ben Hmamou, D. Saadaoui, K. Assalaou, and E. Arjdal, "A new hybrid method to estimate the single-diode model parameters of solar photovoltaic panel," *Energy Conversion and Management: X*, vol. 15, p. 100234, Aug. 2022, doi: 10.1016/j.ecmx.2022.100234.

[8] M. Eslami, E. Akbari, S. T. Seyed Sadr, and B. F. Ibrahim, "A novel hybrid algorithm based on rat swarm optimization and pattern search for parameter extraction of solar photovoltaic models," *Energy Science & Engineering*, vol. 10, no. 8, pp. 2689–2713, Aug. 2022, doi: 10.1002/ese3.1160.

[9] R. Gouaamar, A. El Fadl, S. Bri, and Z. Mekrini, "Higher performance enhancement of direct torque control by using Space Vector Modulation for doubly fed induction machine," *E3S Web of Conferences*, vol. 601, p. 00016, Jan. 2025, doi: 10.1051/e3sconf/202560100016.

[10] L. Peng *et al.*, "Information sharing search boosted whale optimizer with Nelder-Mead simplex for parameter estimation of photovoltaic models," *Energy Conversion and Management*, vol. 270, p. 116246, Oct. 2022, doi: 10.1016/j.enconman.2022.116246.

[11] S. Tajjour, S. S. Chandel, H. Malik, M. A. Alotaibi, and T. S. Ustun, "A novel metaheuristic approach for solar photovoltaic parameter extraction using manufacturer data," *Photonics*, vol. 9, no. 11, p. 858, Nov. 2022, doi: 10.3390/photonics9110858.

[12] S. Ekinci, D. Izci, and A. G. Hussien, "Comparative analysis of the hybrid gazelle-Nelder–Mead algorithm for parameter extraction and optimization of solar photovoltaic systems," *IET Renewable Power Generation*, vol. 18, no. 6, pp. 959–978, Apr. 2024, doi: 10.1049/rpg2.12974.

[13] A. Sharma, A. Dasgotra, S. K. Tiwari, A. Sharma, V. Jately, and B. Azzopardi, "Parameter extraction of photovoltaic module using tunicate swarm algorithm," *Electronics*, vol. 10, no. 8, p. 878, Apr. 2021, doi: 10.3390/electronics10080878.

[14] A. Elhammoudy *et al.*, "Dandelion optimizer algorithm-based method for accurate photovoltaic model parameter identification," *Energy Conversion and Management: X*, vol. 19, p. 100405, Jul. 2023, doi: 10.1016/j.ecmx.2023.100405.
[15] A. Elhammoudy *et al.*, "A novel numerical method for estimation the photovoltaic cells/modules parameters based on dichotomy method," *Results in Optics*, vol. 12, p. 100445, Jul. 2023, doi: 10.1016/j.rio.2023.100445.
[16] D. Saadaoui, M. Elyaqouti, K. Assalaou, D. Ben Hammou, and S. Lidaighbi, "Parameters optimization of solar PV cell/module using genetic algorithm based on non-uniform mutation," *Energy Conversion and Management: X*, vol. 12, p. 100129, Dec. 2021, doi: 10.1016/j.ecmx.2021.100129.
[17] M. Abdel-Basset, R. Mohamed, M. Abouhawwash, Y. Nam, and A. El-Fergany, "Recent meta-heuristic algorithms with a novel premature convergence method for determining the parameters of PV cells and modules," *Electronics*, vol. 10, no. 15, p. 1846, Jul. 2021, doi: 10.3390/electronics10151846.
[18] X. Yang and W. Gong, "Opposition-based JAYA with population reduction for parameter estimation of photovoltaic solar cells and modules," *Applied Soft Computing*, vol. 104, p. 107218, Jun. 2021, doi: 10.1016/j.asoc.2021.107218.
[19] X. Xia *et al.*, "Triple archives particle swarm optimization," *IEEE Transactions on Cybernetics*, vol. 50, no. 12, pp. 4862–4875, Dec. 2020, doi: 10.1109/TCYB.2019.2943928.
[20] A. Kumar, R. K. Misra, D. Singh, S. Mishra, and S. Das, "The spherical search algorithm for bound-constrained global optimization problems," *Applied Soft Computing*, vol. 85, p. 105734, Dec. 2019, doi: 10.1016/j.asoc.2019.105734.
[21] T. Easwarakhanthan, J. Bottin, I. Bouhouch, and C. Boutrit, "Nonlinear minimization algorithm for determining the solar cell parameters with microcomputers," *International Journal of Solar Energy*, vol. 4, no. 1, pp. 1–12, Jan. 1986, doi: 10.1080/01425918608909835.
[22] W. A. E. M. Ahmed, H. M. A. Mageed, S. A. Mohamed, and A. A. Saleh, "Fractional order Darwinian particle swarm optimization for parameters identification of solar PV cells and modules," *Alexandria Engineering Journal*, vol. 61, no. 2, pp. 1249–1263, Feb. 2022, doi: 10.1016/j.aej.2021.06.019.
[23] K. V. Shihabudheen, G. Dileep, and S. M. Sulthan, "Adaptive particle swarm optimization-based improved modeling of solar photovoltaic module for parameter determination," *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, vol. 8, p. 100621, Jun. 2024, doi: 10.1016/j.prime.2024.100621.
[24] M. Naeijian, A. Rahimnejad, S. M. Ebrahimi, N. Pourmousa, and S. A. Gadsden, "Parameter estimation of PV solar cells and modules using Whippy Harris Hawks Optimization Algorithm," *Energy Reports*, vol. 7, pp. 4047–4063, Nov. 2021, doi: 10.1016/j.egyr.2021.06.085.
[25] M. Abdel-Basset, R. Mohamed, M. Sharawi, L. Abdel-Fatah, M. Abouhawwash, and K. Sallam, "A comparative study of optimization algorithms for parameter estimation of PV solar cells and modules: Analysis and case studies," *Energy Reports*, vol. 8, pp. 13047–13065, Nov. 2022, doi: 10.1016/j.egyr.2022.09.193.
[26] C. Chermite and M. Rachid Douiri, "Hybrid tiki taka and mean differential evolution based Weibull distribution: A comprehensive approach for solar PV modules parameter extraction with Newton-Raphson optimization," *Energy Conversion and Management*, vol. 314, p. 118705, Aug. 2024, doi: 10.1016/j.enconman.2024.118705.
[27] Y. Han, W. Chen, A. A. Heidari, H. Chen, and X. Zhang, "Balancing exploration–exploitation of multi-verse optimizer for parameter extraction on photovoltaic models," *Journal of Bionic Engineering*, vol. 21, no. 2, pp. 1022–1054, Mar. 2024, doi: 10.1007/s42235-024-00479-6.

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