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Parameter identification of the photovoltaic panel's two-diode model

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ABSTRACT

This work deals with the two-diode model of a photovoltaic (PV) panel. It provides the per-unit energy and current representations in addition to identifying its unknown parameters. Mathematical equations have been proposed and built using the MATLAB/Simulink simulator to achieve this goal. Only one variable has been adjusted to get all the unknown parameters simultaneously at standard test conditions (STC). Three variables have to be adjusted under any other atmospheric conditions. Two different technologies have been used. The accuracy of the proposed mathematical model has been provided using the absolute relative error between the simulated value and the measured one. The biggest values of the absolute relative error are 0.000788%, 0.0006157%, and 0.000616% under STC, nominal cell temperature condition (NOCT), and random daily atmospheric conditions, respectively.

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1. INTRODUCTION

Due to the damage caused to our environment as a result of the widespread use of petroleum factories and cars, attention is turning to the use of renewable and environmentally friendly energies such as solar energy. This latter depends on PV panels to convert sunlight into electricity. The market has many types of PV panels. The difference lies in the material from which it is made and the size, in addition to the number of PV cells used. Each PV panel has its own data sheet, which does not include the values of the photocurrent source, the resistances, nor the quality factors of the diode and its reverse saturation current. These parameters are required to adjust the PV panel models. Three equivalent circuits can be used for the PV panel, namely: the one-diode model, the double-diode model, and the three-diode model. Our work is focused on the two-diode model. Many techniques have been used and developed for the two-diode model of solar cell/module during the last few years. Among these techniques are: the salp swarm algorithm [1], the biogeography-based heterogeneous cuckoo search algorithm [2], the performance-guided JAYA algorithm [3], the hybridized interior search algorithm [4], the sine cosine algorithm [5], the flexible particle swarm optimization algorithm [6], a modified flower algorithm [7], and the Lozi map algorithm [8]. The particle swarm optimization algorithm based on anarchic universal heterogeneous learning [9], the cuckoo search algorithm and grey wolf optimizer [10], the interval branch and bound algorithm [11], a multitask optimization technique that is evolutionary [12], the levy flight backtracking search algorithm [13], the

Nelder-Mead moth-based orthogonal flame technique [14], the farmland fertility optimization algorithm [15], and the differential vectors reusing backtracking search algorithm [16].

The particle swarm optimization algorithm based on multi-swarm spiral leader [17], the algorithm for Laplacian Barnacles mating based on neighborhood strategy [18], a logistic chaotic JAYA algorithm [19], the slime Mould algorithm [20], a differential evolution algorithm based on an ensemble of self-adaptive [21], the salp swarm algorithm based on opposition learning [22], the improved equilibrium optimizer algorithm [23], and the Harris Hawks optimization algorithm [24]. The adaptive teaching-learning algorithm [25], the particle swarm algorithm based on parallel computing of the niches [26], the vertical and horizontal crossover of the Nelder-Mead Simplex and Harris Hawks algorithms [27], the ant lion optimizer algorithm [28], the particle swarm optimization technique based on the ensemble of the fractional chaotic [29], the backtracking search algorithm [30], the JAYA algorithm [31], and an optimization algorithm for generalized normal distribution [32]. The equilibrium optimizer algorithm [33], the distribution algorithm [34], a shuffled frog-leaping algorithm [35], the reinforcement learning differential evolution algorithm [36], the spherical evolution algorithm [37], the supply-demand-based optimization algorithm [38], an improved slime Mould algorithm [39], and the combined self-adapting algorithm with Newton-Raphson method [40]. The non-uniform mutation genetic algorithm [41], the marine predators' algorithm [42], the frog-leaping algorithm [43], the Rao-1 algorithm [44] and its logistic chaotic optimization algorithm [45], an advanced slime Mould algorithm [46], an enhanced algorithm to optimize the adaptation of the butterfly [47], and a combination of two algorithms: experience learning with teaching-learning [48]. The whippy Harris Hawks Optimization Algorithm [49], a combination of two algorithms: the adaptive grey wolf optimizer and its chaotic algorithm [50], a combined shuffled frog leaping algorithm with a driven ensemble by multi-strategy [51], an enhanced gaining-sharing knowledge algorithm [52], an enhanced equilibrium optimization algorithm [53], the Laplace cross search algorithm has been combined with the Nelder-Mead simplex algorithm [54], the improved JAYA algorithm [55], and a combination of two algorithms: gradient-based optimization and random learning [56]. In addition to the arithmetic optimization algorithm [57], the heap-based optimizer algorithm [58], the heterogeneous differential evolution algorithm [59], the bio-inspired metaheuristic algorithms [60], and a combination of two algorithms: Crisscross and Nelder-mead [61]. In this paper, the MATLAB/Simulink simulator has been used to build the proposed mathematical equations for the identification of the parameters of the solar panel. Per-unit representations of the current-voltage and power-voltage characteristics of a PV panel have been represented at and NOCT. Moreover, unknown parameters have been calculated for three atmospheric conditions, namely: STC, NOCT, and random atmospheric conditions.

2. PARAMETER IDENTIFICATION OF PHOTOVOLTAIC PANEL

The basic components of a solar panel are the solar cells. Therefore, the modeling of a solar panel is based on the solar cell's equivalent electrical circuit. Figure 1 represents the equivalent electrical circuit of the two-diode model for a solar panel. This circuit consists of a photocurrent source, I_{phP}, in parallel with the two diodes, $D1$ and $D2$, in addition to the parallel and series resistances, R_{ShP} and R_{SP}, respectively. The characteristic equation of the PV panel's current has been obtained using Kirchhoff's laws with consideration of Shockley's diode equation, as given by (1). This equation has seven unknown parameters: the photocurrent source, I_{PhP}, the two diode reverse saturation currents, I_{OP1} and I_{OP2}, the two thermal voltages, V_{ThP1}, V_{ThP2}, the series resistance, R_{SP}, and the parallel resistance, R_{ShP}. In this paper, MATLAB/Simulink software has been used to implement the proposed mathematical equations for simultaneously calculating these seven unknown parameters at different atmospheric conditions. The thermal voltages can be determined using (2) and (3). n_{P1} and n_{P2} are the quality factors of the two diodes. K_b is the constant of Boltzmann ($1.38065*10^{-23}$J/K), q is the magnitude of the electronic charge ($1.602*10^{-19}$C), T_a is the ambient temperature (K), N_S is the number of solar cells connected in series, and T_{STC} is the temperature at STC (298K).

$$I_P = I_{PhP} - I_{OP1}\left(exp^{\frac{R_{SP}I_P + V_P}{V_{ThP1}}} - 1\right) - I_{OP2}\left(exp^{\frac{R_{SP}I_P + V_P}{V_{ThP2}}} - 1\right) - \frac{V_P + R_{SP}I_P}{R_{ShP}} \quad (1)$$

$$V_{ThP1} = \frac{n_{P1} K_b}{q} T_a \quad N_s \left(\frac{T_{STC}}{T_a}\right) \quad 0.7 \quad (2)$$

$$V_{ThP2} = \frac{n_{P2} K_b}{q} T_a \quad N_s \left(\frac{T_{STC}}{T_a}\right) \quad 0.7 \quad (3)$$

The short-circuit current and the open-circuit voltage can be calculated using (4) and (5), respectively.

$$I_{SCP} = I_{SC}\left[1 + \frac{k_i}{100}\left(T_a\left(\frac{T_{STC}}{T_a}\right)^{-0.125} - T_{STC}\right)\right]\left(\frac{R_{STC}}{R}\right)^{k_{Isc}} \tag{4}$$

$$V_{OCP} = V_{OC}\left[1 + \frac{k_v}{100}\left(T_a\left(\frac{T_{STC}}{T_a}\right)^{1.25} - T_{STC}\right)\right]\left(\frac{IR_{STC}}{IR}\right)^{k_{Voc}} \tag{5}$$

The temperature coefficients of the short-circuit current and the open-circuit voltage, *ki* and *kv*, respectively, are usually given in the data sheet of a PV panel. *IR* is the solar irradiation at an ambient temperature, and IR_{STC} is the solar irradiation at STC (1000 W/m^2). k_{Isc} has to be adjusted to obtain the value of the short circuit current. Moreover, the value of the open circuit voltage can be obtained by varying k_{Voc}. The two saturation currents' values can be calculated using (6) and (7). Moreover, the value of the photocurrent source can be obtained using (8).

$$I_{OP1} = \frac{1}{2} * \frac{I_{SCP} * \left(\frac{R_{SP} + R_{ShP}}{R_{ShP}}\right) - \frac{V_{OCP}}{R_{ShP}}\left(1 - \frac{\left(exp^{\frac{I_{SCP} R_{SP}}{V_{ThP2}}} - 1\right)}{\left(exp^{\frac{V_{OCP}}{V_{ThP1}}} - 1\right)}\right)}{\left(exp^{\frac{V_{OCP}}{V_{ThP1}}} - 1\right) - \left(exp^{\frac{I_{SCP} R_{SP}}{V_{ThP2}}} - 1\right)} \tag{6}$$

$$I_{OP2} = \frac{1}{2} * \frac{I_{SCP}\left(\frac{R_{SP} + R_{ShP}}{R_{ShP}}\right) - \frac{V_{OCP}}{R_{ShP}}\left(1 - \frac{\left(exp^{\frac{I_{SCP} R_{SP}}{V_{ThP1}}} - 1\right)}{\left(exp^{\frac{V_{OCP}}{V_{ThP2}}} - 1\right)}\right)}{\left(exp^{\frac{V_{OCP}}{V_{ThP2}}} - 1\right) - \left(exp^{\frac{I_{SCP} R_{SP}}{V_{ThP1}}} - 1\right)} \tag{7}$$

$$I_{PhP} = \frac{I_{SCP}\left(\frac{R_{SP} + R_{ShP}}{R_{ShP}}\right) - \frac{\left(exp^{\frac{I_{SCP} R_{SP}}{V_{ThP2}}} - 1\right)\frac{V_{OCP}}{R_{ShP}}}{\left(exp^{\frac{V_{OCP}}{V_{ThP1}}} - 1\right)}}{\left(exp^{\frac{V_{OCP}}{V_{ThP1}}} - 1\right) - \left(exp^{\frac{I_{SCP} R_{SP}}{V_{ThP2}}} - 1\right)} \tag{8}$$

The series and parallel resistances are given by (9) and (10), respectively. The number of the parallel solar cells is *Np*. S is the surface of the solar panel. The resistance r_S must be varied until the maximum power point (MPP) of the solar panel is attained at STC. For any other atmospheric condition, k_{RS} has to be varied to attain the PV panel's MPP.

$$R_{SP} = r_S * \frac{Np}{Ns} * \frac{\left(\frac{P_{max}}{S * IR}\right)}{T_a\left(-\frac{K_p}{100}\right)}\left(\frac{T_{STC}}{T_a} * \frac{IR_{STC}}{IR}\right)^{k_{Rs}} \tag{9}$$

$$R_{ShP} = 25\left[\frac{Ns}{Np} * \frac{\left(\frac{S * IR}{P_{max}}\right) T_a\left(-\frac{K_p}{100}\right)}{\left(\frac{T_{STC}}{T_a} * \frac{IR_{STC}}{IR}\right)}\right] \tag{10}$$

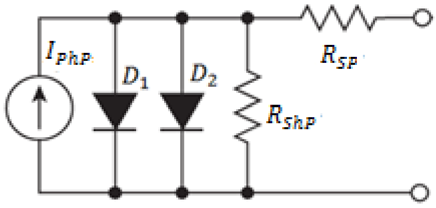


Figure 1. Equivalent electrical circuit of the double-diode model for PV panel

3. RESULTS AND DISCUSSION

In this section, the MATLAB/Simulink simulator has been used to implement (1)–(10). It has the ambient temperature, solar irradiation, and the data sheet as inputs, while its outputs are the current and power of the PV panel. Different sizes of PV panels for different markets have been used, such as Suntech of 50W, SW 85 poly RNA of 85 W, and JAM60S01 of 320 W. The parameters of these PV panels have been obtained at STC and NOCT. Moreover, the parameters of the Suntech PV panel have been obtained under random atmospheric conditions.

3.1. Results at STC and NOCT

We achieved the MPP of each used panel by varying only the value of r_S for the series resistance given by (9) at STC. We adjusted the variable $k_{Rs}$of the series resistance for each used PV panel to achieve its maximum power point under NOCT (Gr = 800 W/m^2, Ta = 20 °C). The data sheets of the used panels are given in Table 1. Table 2 shows the adjusted values of r_S and k_{Rs}in addition to the calculated parameters. Figure 2 shows the per-unit curves of I-V and P-V for the used panels (a) at STC and (b) under NOCT. Pds and Ids are used for the per-unit values of the power and the current, which are given in the data sheet, respectively. There are three highlighted points for each used panel. The per-unit points of the short circuit current and open circuit voltage are equal to one, so their calculated values are equal to the data sheet's values. The third point is the maximum power point. Its per-unit values are very close to one. Therefore, the calculated values are very close to the data sheet values. This closeness is calculated using (11). Table 3 shows the obtained values for the absolute relative error.

$$\Delta e\ \% = \frac{|calculated\ value - data\ sheet\ value|}{data\ sheet\ value} * 100 \qquad (11)$$

Table 1. Values from the data sheet of PV panels

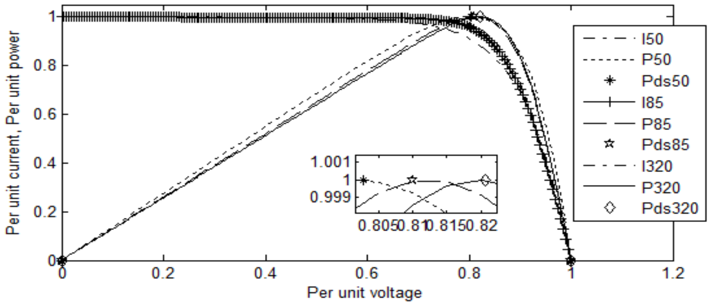
	STC conditions			NOCT conditions		
	50 W	85 W	320 W	50 W	85 W	320 W
P_{max}(W)	50.75	85.204	320.0688	36.192	62.103	235.162
I_{Pmax} (A)	2.9	4.76	9.56	2.32	3.81	7.66
V_{Pmax} (V)	17.5	17.9	33.48	15.6	16.3	30.70
I_{SC}(A)	3.2	5.02	10.5	2.59	4.04	8.05
V_{OC} (V)	21.8	22.1	40.8	19.8	20.1	37.61

Table 2. Calculated parameters of PV panels

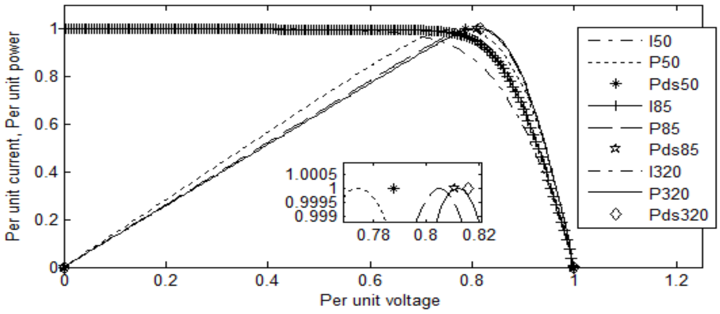
	STC conditions			NOCT conditions		
	50 W	85 W	320 W	50 W	85 W	320 W
k_{Isc}	/	/	/	0.92687	0.9571	0.98245
k_{Voc}	/	/	/	0.5875	0.5858	0.495585
k_{Rs}	/	/	/	-2.8505	0.17839	0.1520
r_s(Ω)	6.645	10.0085	9.6265	6.645	10.0085	9.6265
V_{thM1}(V)	1.6827176	0.8737	1.4022	1.3235872	0.68724723	1.102989
V_{thM2}(V)	1.6827176	0.8737	1.4022	1.3235872	0.68724723	1.102989
Isc (A)	3.2	5.02	10.05	2.59000257	4.04006589	8.0500727
Iph (A)	3.20016593	5.0220	10.0540	2.590746323	4.04249936	8.0547659
Voc(V)	21.8	22.1	40.8	19.800792	20.10003	37.6100062
Rs (mΩ)	92.40804	323.22097	309.8726	515.244988	466.28187	452.784478
Rsh(Ω)	1797.7331	774.12	776.6496	1797.73315	774.1221	776.6496
I_{sat1}(10^{-6}A)	3.76797	$25.84*\ 10^{-6}$	$1.1558*10^{-6}$	0.4106987	$3.9896936*10^{-7}$	$6.2190.3391*10^{-9}$
I_{sat2}(10^{-6}A)	3.76797	$25.84*10^{-6}$	$1.1558*10^{-6}$	0.4106987	$3.9896936*10^{-7}$	$6.2190.3391*10^{-9}$
I_{Mmax}(A)	2.91	4.748	9.5669	2.3604	3.8334	7.7003
V_{Mmax}(V)	17.44	17.9452	33.456	15.3329	16.2006	30.5393
P_{Mmax}(W)	50.7504	85.2038096	320.0702	36.19177716	62.10338004	235.16177179

Table 3. Absolute relative errors of PV panels

	STC conditions			NOCT conditions		
	50 W	85 W	320 W	50 W	85 W	320 W
Δe_{Isc} %	0	0	0	0.0000995	0.00163094	0.0009031
Δe_{Voc} %	0	0	0	0.004	0.00014925	0.00001648
Δe_{Imax} %	0.34482	0.2521	0.072175	1.741379	0.61417	0.52610966
Δe_{Vmax} %	0.34285	0.2525	0.071684	1.722179	0.6131288	0.52345
Δe_{Pmax} %	0.000788	0.000223	0.0004	0.0006157	0.00061195	0.00009704374



(a)



(b)

Figure 2. Per-unit curves of I-V and P-V for the used PV panels: (a) at STC and (b) under NOCT

3.2. Results at arbitrary atmospheric conditions

One experiment had been done at the university using a Suntech PV panel. The atmospheric temperature was 17 °C and the solar irradiation was 1176 W/m^2. By taking atmospheric circumstances into account, we adjusted the variables, $k_{Rs}k_{Voc}$ and k_{Isc}, to make the characteristic curves as close as possible to the measured curves. Therefore, the parameters are obtained simultaneously. Figure 3 shows the characteristic curves of the Suntech panel at arbitrary atmospheric conditions. The adjusted values of the variables and calculated parameters are given in Table 4. The measured and calculated data for the three points, in addition to the resulting absolute relative error, are given in Table 5.

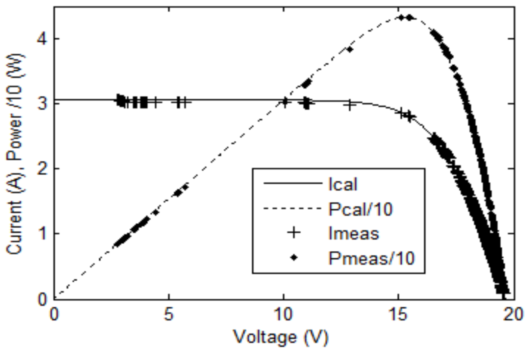


Figure 3. Suntech solar panel: I-V and P-V characteristics at arbitrary atmospheric conditions

Table 4. Calculated parameters at arbitrary atmospheric conditions

The parameter	Calculated value	The parameter	Calculated value
k_{Isc}	-0.22	V_{thM1} (V)	1.1135299
k_{Voc}	-0.95	V_{thM2} (V)	1.1135299
k_{Rs}	-6.7444	I_{sat1} (nA)	32.7536
Rs (mΩ)	521.87354	I_{sat2} (nA)	32.7536
Rsh (Ω)	3109.020864	Iph (A)	3.0651783

Table 5. PV panel under random atmospheric conditions

	I_{SC}(A)	V_{OC} (V)	I_{Pmax} (A)	V_{Pmax} (V)	P_{max}(W)
Measured data	-	-	2.811	15.408	43.311888
Calculated data	3.0646637	19.663987	2.8321	15.2933	43.31215493
Δe %	-	-	0.7506	0.7444	0.000616

4. CONCLUSION

The goal of this paper is the calculation of the parameters for the photovoltaic panel with a two-diode model. Therefore, mathematical equations have been proposed and implemented using the MATLAB/Simulink simulator. Per-unit representations of the current and power of the solar panel with comparisons were obtained for STC as well as NOCT. Moreover, comparisons have been made under arbitrary meteorological circumstances. For the three cases, the absolute relative error of the MPP did not reach 0.0008%.

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REFERENCES

[1] R. Abbassi, A. Abbassi, A. A. Heidari, and S. Mirjalili, "An efficient salp swarm-inspired algorithm for parameters identification of photovoltaic cell models," *Energy Conversion and Management*, vol. 179, pp. 362–372, 2019, doi: 10.1016/j.enconman.2018.10.069.

[2] X. Chen and K. Yu, "Hybridizing cuckoo search algorithm with biogeography-based optimization for estimating photovoltaic model parameters," *Solar Energy*, vol. 180, pp. 192–206, 2019, doi: 10.1016/j.solener.2019.01.025.

[3] K. Yu, B. Qu, C. Yue, S. Ge, X. Chen, and J. Liang, "A performance-guided JAYA algorithm for parameters identification of photovoltaic cell and module," *Applied Energy*, vol. 237, pp. 241–257, 2019, doi: 10.1016/j.apenergy.2019.01.008.

[4] D. Kler, Y. Goswami, K. P. S. Rana, and V. Kumar, "A novel approach to parameter estimation of photovoltaic systems using hybridized optimizer," *Energy Conversion and Management*, vol. 187, pp. 486–511, 2019, doi: 10.1016/j.enconman.2019.01.102.

[5] H. Chen, S. Jiao, A. A. Heidari, M. Wang, X. Chen, and X. Zhao, "An opposition-based sine cosine approach with local search for parameter estimation of photovoltaic models," *Energy Conversion and Management*, vol. 195, pp. 927–942, 2019, doi: 10.1016/j.enconman.2019.05.057.

[6] S. M. Ebrahimi, E. Salahshour, M. Malekzadeh, and Francisco Gordillo, "Parameters identification of PV solar cells and modules using flexible particle swarm optimization algorithm," *Energy*, vol. 179, pp. 358–372, 2019, doi: 10.1016/j.energy.2019.04.218.

[7] R. Benkercha, S. Moulahoum, and B. Taghezouit, "Extraction of the PV modules parameters with MPP estimation using the modified flower algorithm," *Renewable Energy*, vol. 143, pp. 1698–1709, 2019, doi: 10.1016/j.renene.2019.05.107.

[8] N. Pourmousa, S. M. Ebrahimi, M. Malekzadeh, and M. Alizadeh, "Parameter estimation of photovoltaic cells using improved Lozi map based chaotic optimization Algorithm," *Solar Energy*, vol. 180, pp. 180–191, 2019, doi: 10.1016/j.solener.2019.01.026.

[9] D. Yousri, D. Allam, M. B. Eteiba, and P. N. Suganthan, "Static and dynamic photovoltaic models' parameters identification using Chaotic Heterogeneous Comprehensive Learning Particle Swarm Optimizer variants," *Energy Conversion and Management*, vol. 182, pp. 546–563, 2019, doi: 10.1016/j.enconman.2018.12.022.

[10] W. Long, S. Cai, J. Jiao, M. Xu, and T. Wu, "A new hybrid algorithm based on grey wolf optimizer and cuckoo search for parameter extraction of solar photovoltaic models," *Energy Conversion and Management*, vol. 203, 2020, doi: 10.1016/j.enconman.2019.112243.

[11] R. Chenouard and R. A. El-Sehiemy, "An interval branch and bound global optimization algorithm for parameter estimation of three photovoltaic models," *Energy Conversion and Management*, vol. 205, 2020, doi: 10.1016/j.enconman.2019.112400.

[12] J. Liang *et al.*, "Evolutionary multi-task optimization for parameters extraction of photovoltaic models," *Energy Conversion and Management*, vol. 207, 2020, doi: 10.1016/j.enconman.2020.112509.

[13] Y. Zhang, Z. Jin, X. Zhao, and Q. Yang, "Backtracking search algorithm with Lévy flight for estimating parameters of photovoltaic models," *Energy Conversion and Management*, vol. 208, 2020, doi: 10.1016/j.enconman.2020.112615.

[14] H. Zhang, A. A. Heidari, M. Wang, L. Zhang, H. Chen, and C. Li, "Orthogonal Nelder-Mead moth flame method for parameters identification of photovoltaic modules," *Energy Conversion and Management*, vol. 211, 2020, doi: 10.1016/j.enconman.2020.112764.

[15] A. M. Agwa, A. A. El-Fergany, and H. A. Maksoud, "Electrical characterization of photovoltaic modules using farmland fertility optimizer," *Energy Conversion and Management*, vol. 217, 2020, doi: 10.1016/j.enconman.2020.112990.

[16] Y. Zhang, C. Huang, and Z. Jin, "Backtracking search algorithm with reusing differential vectors for parameter identification of photovoltaic models," *Energy Conversion and Management*, vol. 223, 2020, doi: 10.1016/j.enconman.2020.113266.

[17] H. G. G. Nunes, P. N. C. Silva, J. A. N. Pombo, S. J. P. S. Mariano, and M. R. A. Calado, "Multiswarm spiral leader particle swarm optimisation algorithm for PV parameter identification," *Energy Conversion and Management*, vol. 225, 2020, doi: 10.1016/j.enconman.2020.113388.

[18] R. M. Rizk-Allah and A. A. El-Fergany, "Conscious neighborhood scheme-based Laplacian barnacles mating algorithm for parameters optimization of photovoltaic single- and double-diode models," *Energy Conversion and Management*, vol. 226, 2020, doi: 10.1016/j.enconman.2020.113522.

[19] X. Jian and Z. Weng, "A logistic chaotic JAYA algorithm for parameters identification of photovoltaic cell and module models," *Optik*, vol. 203, 2020, doi: 10.1016/j.ijleo.2019.164041.

[20] M. Mostafa, H. Rezk, M. Aly, and E. M. Ahmed, "A new strategy based on slime mould algorithm to extract the optimal model parameters of solar PV panel," *Sustainable Energy Technologies and Assessments*, vol. 42, 2020, doi: 10.1016/j.seta.2020.100849.

[21] J. Liang *et al.*, "Parameters estimation of solar photovoltaic models via a self-adaptive ensemble-based differential evolution," *Solar Energy*, vol. 207, pp. 336–346, 2020, doi: 10.1016/j.solener.2020.06.100.
[22] A. Abbassi *et al.*, "Parameters identification of photovoltaic cell models using enhanced exploratory salp chains-based approach," *Energy*, vol. 198, 2020, doi: 10.1016/j.energy.2020.117333.
[23] M. Abdel-Basset, R. Mohamed, S. Mirjalili, R. K. Chakrabortty, and M. J. Ryan, "Solar photovoltaic parameter estimation using an improved equilibrium optimizer," *Solar Energy*, vol. 209, pp. 694–708, 2020, doi: 10.1016/j.solener.2020.09.032.
[24] S. Jiao *et al.*, "Orthogonally adapted Harris hawks optimization for parameter estimation of photovoltaic models," *Energy*, vol. 203, 2020, doi: 10.1016/j.energy.2020.117804.
[25] S. Li, W. Gong, L. Wang, X. Yan, and C. Hu, "A hybrid adaptive teaching–learning-based optimization and differential evolution for parameter identification of photovoltaic models," *Energy Conversion and Management*, vol. 225, 2020, doi: 10.1016/j.enconman.2020.113474.
[26] X. Lin and Y. Wu, "Parameters identification of photovoltaic models using niche-based particle swarm optimization in parallel computing architecture," *Energy*, vol. 196, 2020, doi: 10.1016/j.energy.2020.117054.
[27] Y. Liu *et al.*, "Horizontal and vertical crossover of Harris hawk optimizer with Nelder-Mead simplex for parameter estimation of photovoltaic models," *Energy Conversion and Management*, vol. 223, 2020, doi: 10.1016/j.enconman.2020.113211.
[28] M. Wang, X. Zhao, A. A. Heidari, and H. Chen, "Evaluation of constraint in photovoltaic models by exploiting an enhanced ant lion optimizer," *Solar Energy*, vol. 211, pp. 503–521, 2020, doi: 10.1016/j.solener.2020.09.080.
[29] D. Yousri, S. B. Thanikanti, D. Allam, V. K. Ramachandaramurthy, and M. B. Eteiba, "Fractional chaotic ensemble particle swarm optimizer for identifying the single, double, and three diode photovoltaic models' parameters," *Energy*, vol. 195, 2020, doi: 10.1016/j.energy.2020.116979.
[30] Y. Zhang, M. Ma, and Z. Jin, "Backtracking search algorithm with competitive learning for identification of unknown parameters of photovoltaic systems," *Expert Systems with Applications*, vol. 160, 2020, doi: 10.1016/j.eswa.2020.113750.
[31] Y. Zhang, M. Ma, and Z. Jin, "Comprehensive learning Jaya algorithm for parameter extraction of photovoltaic models," *Energy*, vol. 211, 2020, doi: 10.1016/j.energy.2020.118644.
[32] Y. Zhang, Z. Jin, and S. Mirjalili, "Generalized normal distribution optimization and its applications in parameter extraction of photovoltaic models," *Energy Conversion and Management*, vol. 224, 2020, doi: 10.1016/j.enconman.2020.113301.
[33] F. E. Ndi, S. N. Perabi, S. E. Ndjakomo, G. Ondoua Abessolo, and G. Mengounou Mengata, "Estimation of single-diode and two diode solar cell parameters by equilibrium optimizer method," *Energy Reports*, vol. 7, pp. 4761–4768, 2021, doi: 10.1016/j.egyr.2021.07.025.
[34] B. P. Chandran, A. I. Selvakumar, G. S. Let, and S. P. Sathiyan, "Optimal model parameter estimation of solar and fuel cells using improved estimation of distribution algorithm," *Ain Shams Engineering Journal*, vol. 12, no. 2, pp. 1693–1700, 2021.
[35] Y. Liu *et al.*, "Evolutionary shuffled frog leaping with memory pool for parameter optimization," *Energy Reports*, vol. 7, pp. 584–606, 2021, doi: 10.1016/j.egyr.2021.01.001.
[36] Z. Hu, W. Gong, and S. Li, "Reinforcement learning-based differential evolution for parameters extraction of photovoltaic models," *Energy Reports*, vol. 7, pp. 916–928, 2021, doi: 10.1016/j.egyr.2021.01.096.
[37] W. Zhou *et al.*, "Metaphor-free dynamic spherical evolution for parameter estimation of photovoltaic modules," *Energy Reports*, vol. 7, pp. 5175–5202, 2021, doi: 10.1016/j.egyr.2021.07.041.
[38] A. R. Ginidi, A. M. Shaheen, R. A. El-Sehiemy, and E. Elattar, "Supply demand optimization algorithm for parameter extraction of various solar cell models," *Energy Reports*, vol. 7, pp. 5772–5794, 2021, doi: 10.1016/j.egyr.2021.08.188.
[39] X. Weng, A. A. Heidari, G. Liang, H. Chen, and X. Ma, "An evolutionary Nelder–Mead slime mould algorithm with random learning for efficient design of photovoltaic models," *Energy Reports*, vol. 7, pp. 8784–8804, 2021, doi: 10.1016/j.egyr.2021.11.019.
[40] P. J. Gnetchejo, S. Ndjakomo Essiane, A. Dadjé, and P. Ele, "A combination of Newton-Raphson method and heuristics algorithms for parameter estimation in photovoltaic modules," *Heliyon*, vol. 7, no. 4, 2021, doi: 10.1016/j.heliyon.2021.e06673.
[41] D. Saadaoui, M. Elyaqouti, K. Assalaou, D. Ben hmamou, 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, 2021, doi: 10.1016/j.ecmx.2021.100129.
[42] M. Abdel-Basset, D. El-Shahat, R. K. Chakrabortty, and M. Ryan, "Parameter estimation of photovoltaic models using an improved marine predators algorithm," *Energy Conversion and Management*, vol. 227, 2021, doi: 10.1016/j.enconman.2020.113491.
[43] Y. Fan, P. Wang, A. A. Heidari, X. Zhao, H. Turabieh, and H. Chen, "Delayed dynamic step shuffling frog-leaping algorithm for optimal design of photovoltaic models," *Energy Reports*, vol. 7, pp. 228–246, 2021, doi: 10.1016/j.egyr.2020.12.013.
[44] X. Jian and Y. Zhu, "Parameters identification of photovoltaic models using modified Rao-1 optimization algorithm," *Optik*, vol. 231, 2021, doi: 10.1016/j.ijleo.2021.166439.
[45] B. Lekouaghet, A. Boukabou, and C. Boubakir, "Estimation of the photovoltaic cells/modules parameters using an improved Rao-based chaotic optimization technique," *Energy Conversion and Management*, vol. 229, 2021, doi: 10.1016/j.enconman.2020.113722.
[46] Y. Liu, A. A. Heidari, X. Ye, G. Liang, H. Chen, and C. He, "Boosting slime mould algorithm for parameter identification of photovoltaic models," *Energy*, vol. 234, 2021, doi: 10.1016/j.energy.2021.121164.
[47] W. Long, T. Wu, M. Xu, M. Tang, and S. Cai, "Parameters identification of photovoltaic models by using an enhanced adaptive butterfly optimization algorithm," *Energy*, vol. 229, 2021, doi: 10.1016/j.energy.2021.120750.
[48] X. Mi, Z. Liao, S. Li, and Q. Gu, "Adaptive teaching–learning-based optimization with experience learning to identify photovoltaic cell parameters," *Energy Reports*, vol. 7, pp. 4114–4125, 2021, doi: 10.1016/j.egyr.2021.06.097.
[49] 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, 2021, doi: 10.1016/j.egyr.2021.06.085.
[50] J. Pan *et al.*, "Parameters identification of photovoltaic cells using improved version of the chaotic grey wolf optimizer," *Optik*, vol. 242, 2021, doi: 10.1016/j.ijleo.2021.167150.
[51] M. Wang, Q. Zhang, H. Chen, A. A. Heidari, M. Mafarja, and H. Turabieh, "Evaluation of constraint in photovoltaic cells using ensemble multi-strategy shuffled frog leading algorithms," *Energy Conversion and Management*, vol. 244, 2021, doi: 10.1016/j.enconman.2021.114484.
[52] K. M. Sallam, M. A. Hossain, R. K. Chakrabortty, and M. J. Ryan, "An improved gaining-sharing knowledge algorithm for parameter extraction of photovoltaic models," *Energy Conversion and Management*, vol. 237, 2021, doi: 10.1016/j.enconman.2021.114030.

[53] J. Wang *et al.*, "Photovoltaic cell parameter estimation based on improved equilibrium optimizer algorithm," *Energy Conversion and Management*, vol. 236, 2021, doi: 10.1016/j.enconman.2021.114051.
[54] X. Weng *et al.*, "Laplacian Nelder-Mead spherical evolution for parameter estimation of photovoltaic models," *Energy Conversion and Management*, vol. 243, 2021, doi: 10.1016/j.enconman.2021.114223.
[55] 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, 2021, doi: 10.1016/j.asoc.2021.107218.
[56] W. Zhou, P. Wang, A. A. Heidari, X. Zhao, H. Turabieh, and H. Chen, "Random learning gradient based optimization for efficient design of photovoltaic models," *Energy Conversion and Management*, vol. 230, 2021, doi: 10.1016/j.enconman.2020.113751.
[57] M. F. Mahmoud, A. T. Mohamed, R. A. Swief, L. A. Said, and A. G. Radwan, "Arithmetic optimization approach for parameters identification of different PV diode models with FOPI-MPPT," *Ain Shams Engineering Journal*, vol. 13, no. 3, 2022, doi: 10.1016/j.asej.2021.10.007.
[58] D. S. AbdElminaam, E. H. Houssein, M. Said, D. Oliva, and A. Nabil, "An Efficient Heap-Based Optimizer for Parameters Identification of Modified Photovoltaic Models," *Ain Shams Engineering Journal*, vol. 13, no. 5, 2022, doi: 10.1016/j.asej.2022.101728.
[59] D. Wang, X. Sun, H. Kang, Y. Shen, and Q. Chen, "Heterogeneous differential evolution algorithm for parameter estimation of solar photovoltaic models," *Energy Reports*, vol. 8, pp. 4724–4746, Nov. 2022, doi: 10.1016/j.egyr.2022.03.144.
[60] A. Younis, A. Bakhit, M. Onsa, and M. Hashim, "A comprehensive and critical review of bio-inspired metaheuristic frameworks for extracting parameters of solar cell single and double diode models," *Energy Reports*, vol. 8, pp. 7085–7106, 2022, doi: 10.1016/j.egyr.2022.05.160.
[61] M. Premkumar *et al.*, "An enhanced Gradient-based Optimizer for parameter estimation of various solar photovoltaic models," *Energy Reports*, vol. 8, pp. 15249–15285, 2022, doi: 10.1016/j.egyr.2022.11.092.

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