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Fotovoltaik Model Parametrelerinin Optimal Tanımlanması için Tazmanya Canavarı Optimizasyonu

Birsen BOYLU AYVAZ[1*], Zafer DOGAN[2]

Öne Çıkanlar:
- Fotovoltaik hücreler
- Parametre tahmini
- Optimizasyon algoritmaları

Anahtar Kelimeler:
- Fotovoltaik hücreler
- Parametre tahmini
- Metasezgisel algoritmalar
- Tazmanya canavarı optimizasyonu
- Optimizasyon

ÖZET:

Dünya genelinde, elektrik üretiminin kaynaklara göre dağılımı incelendiğinde, fotovoltaik (PV) sistemlerin elektrik üretiminde önemli bir paya sahip olduğu görülmektedir. Bu durum göz önüne alındığında, PV sistem verimliliğini artırmak için PV hücresinin akım-gerilim ölçüm verilerine dayalı yüksek doğruluklu modeller geliştirilmelidir. Literatürde, PV hücre modelleri olarak genellikle tek diyotlu ve iki diyotlu devreler kullanılmaktadır. Modellerin hassasiyeti, çoğunlukla karakteristik parametrelerin doğruluğuna bağlıdır. Bu parametrelerin, PV hücresi ölçüm verileri kullanılarak etkili ve doğru bir şekilde tahmin edilmesi gerekmektedir. Tahmini ve deneysel ölçüm verileri arasındaki en iyi uyumu sağlayan optimal parametreleri elde etmek için en çok tercih edilen optimizasyon yöntemleri meta-sezgisel algoritmalardır. Bu çalışma, optimal PV model parametrelerini belirlemek için Tazmanya canavarı optimizasyon (TDO) algoritmasını önermektedir. Önerilen yöntem, literatürde yaygın olarak kullanılan güneş hücrelerine uygulanmıştır. Önerilen yöntemin performansı, literatürdeki diğer yöntemlerle karşılaştırılarak değerlendirilmiştir. Tek diyotlu ve iki diyotlu devreler ile PV modülü için TDO kullanılarak elde edilen PV hücre modellerinin, diğer yöntemlerle elde edilen modellere kıyasla deneysel verilerle daha yüksek doğrulukta eşleşme sağladığı görülmüştür.

Tasmanian devil optimization for optimal identification of photovoltaic model parameters

Highlights:
- Photovoltaic cells
- Parameter estimation
- Optimization algorithms

Keywords:
- Photovoltaic cells
- Parameter estimation
- Metaheuristic algorithms
- Tasmanian devil optimization
- Optimization

ABSTRACT:

In the whole world, when the distribution of electricity generation according to resources is examined, it is seen that photovoltaic (PV) systems constitute an important part of electricity generation. Considering this situation, to improve the PV system efficiency, high-accuracy models for PV cells should be developed depending on the current-voltage measurement data of the PV cell. In literature studies, single-diode and two-diode circuits are often utilized as PV cell models. The precision of the models is frequently determined by the accuracy of the characteristic parameters. These parameters need to be estimated effectively and accurately using PV cell measurement data. To get the optimal parameters that provide the best match between the estimated and experimental measurement data, metaheuristics are the most preferred optimization methods. This study proposed the Tasmanian devil optimization (TDO) algorithm for identifying the optimal PV model parameters. The proposed method is applied to solar cells that are frequently used in literature. The performance of the proposed method is evaluated by comparing it with other literature methods. It is seen that the PV cell models obtained by using TDO for two diode circuits, i.e. single-diode and two-diode, and PV module, demonstrate higher accuracy in matching experimental data compared to other models obtained by different methods.

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INTRODUCTION

All over the world, technological developments form the basis of industrial development. This situation causes the energy demand to increase day by day. Today, most electricity generation is met by fossil fuel-based energy sources, also known as conventional energy sources. The increase in fossil fuel prices, the limited resources, and foreign dependency, as well as the fact that the CO_2 gas released into the atmosphere after the utilization of these sources causes weather anomalies and changes in climate, highlight the significance of utilizing renewable energy resources (Solarin, 2020). Solar energy, a leading type of renewable energy, is increasingly being utilized to address growing energy demands and mitigate the drawbacks of conventional sources (Li et al., 2019).

Solar energy, which is a promising alternative energy source in electricity generation in a clean way, is at the third rank among renewable electrical energy sources in the world after hydro and wind. Considering the advantages of solar systems such as low maintenance costs, easy installation, inexhaustible energy sources, noiseless electricity generation, and flexible dimensions, the use of these systems in electrical energy generation is increasing with each passing day (Kler et al., 2019). In addition, the reduction in costs of electricity generation from solar energy systems and various government incentives, such as energy purchase guarantees direct investors to the solar energy sector (Sahu, 2015).

In photovoltaic (PV) systems, solar PV cells or modules are used to convert solar energy into electrical energy (Izci et al., 2024). These cells are manufactured using p-n semiconductor technology. Modules are formed by connections of individual cells, which can be in parallel or series, or both series and parallel. The PV module output is changed depending on several factors, including the number of cells used, the amount of radiation, and temperature change (Garip, 2023).

According to the literature, there is a huge effort to improve the power provided from the output terminal of the PV device. Accurate modeling and simulation of photovoltaic cells are required for the performance prediction, conception, and evaluation of a PV power generation system. Single-, double-, and three-diode models are utilized as PV cell equivalent circuits in the literature (Abdel-Basset et al., 2020). The most famous ones are the defined circuits of the single diode model (SDM) and the double-diode model (DDM). SDM has five parameters: photocurrent, reverse current of saturation, ideality coefficient of diode, resistance connected in shunt, and resistance connected in series. In addition to the five parameters of SDM, the reverse current of the second diode's saturation and ideality coefficient of the diode are used in modeling the DDM. For a model with high accuracy, these parameters must be determined accurately (Dogan and Boylu Ayvaz, 2022).

After the mathematical model of the cell equivalent is determined, the parameter estimation phase of the photovoltaic model is started. The aim here is to realize a minimum error between the estimated current-voltage curve of the PV cell model and the measured one obtained from a real PV cell output. Manufacturers perform several tests on their PV modules, in which irradiance is considered 1000 W/m2 while temperature is considered 25 °C, and provide several parameters such as voltage&current values at the maximum power point, short circuit current, open circuit equivalence voltage, and current, voltage, and power temperature coefficients (Chenouard & El-Sehiemy, 2020). In such tests, unknown parameters should be extracted using parameter estimation methods such as optimization methods as proposed in this study.

In recent literature, parameter estimation studies for photovoltaic systems have been carried out using various methods. These are grouped under three headings: analytical methods, numerical methods, and metaheuristic algorithms (Ayvaz, 2022). Although the analytical methods have the advantage of easy implementation, the effectiveness of the analytical solution largely depends on the values of the points determined for the solution process. Despite the advantages of analytical methods, such as ease of application and fast solution mechanism, the approximations and assumptions reduce the accuracy of the results obtained by these methods. On the other hand, the accuracy of the results obtained by numerical methods such as Newton-Raphson depends on the selected initial values. In addition, the non-linearity of the equations when estimating PV parameters complicates and prolongs the solution process in parallel to the rise in the unknown parameters of the PV model.

Metaheuristic methods solve nonlinear and highly constrained problems without the need for excessive mathematical calculations (Ramadan et al., 2021). In addition to the computational simplicity, the fact that a metaheuristic method does not impose any limitations on the formulation of the problem and is suitable for multimodal problems. On the other hand, metaheuristics have a stochastic nature, and this makes the global search ability of these algorithms more than that of analytical and numerical methods. In the past decade, metaheuristics have been utilized frequently in parameter extraction studies in PV cells. Some of the metaheuristic methods used in these studies are cuckoo search (Ma et al., 2013), artificial bee colony (Oliva et al., 2014), improved crayfish optimization algorithm (Chaib et al., 2014), enhanced slime mould algorithm (Devarajah et al., 2024), and war strategy optimization algorithm (Ayyarao & Kumar, 2022). Although these methods give effective results, the search for more accurate and reliable metaheuristic methods is continuing to get better PV cell models. Furthermore, recent metaheuristics demonstrate high potential for achieving effective optimization results, as they are typically validated through comprehensive comparisons with previous methods. Therefore, it is important to try recent metaheuristics in all fields of optimization, like PV parameter estimation in this study.

Recently, a new population-based metaheuristic method called the Tasmanian devil optimization algorithm (TDO) has been developed by Denghani et al. (Dehghani et al., 2022). The design of the method was inspired by Tasmanian devils' foraging behavior in nature. These creatures are fed by hunting in nature or by eating the carcasses of dead animals. The method's performance is examined on twenty-three benchmark objective functions. The obtained results demonstrate that the algorithm's exploitation and exploration performances are high and, to effectively solve the optimization problems, it creates a suitable balance between these two optimization phases. In addition, the results obtained from TDO in the study were compared with eight different methods, and it was seen that TDO has a higher capacity than eight competing algorithms, with its strong performance and is much more competitive.

In this study, TDO is proposed to find the most correct model parameters of SDM/DDM cells and PV modules. The TDO has the advantages of easy implementation, few control parameters, and low computational requirements. Therefore, it has been applied to several engineering problems in recent years, including parameter identification of electric transformers (Wang and Lyu, 2024) and wireless sensor network layout optimization (Rizk-Allah et al., 2024). According to the literature review of the authors, TDO is first applied to the PV parameter identification problem. The TDO's performance in parameter extraction has been tested by comparing it with different optimization methods in the literature. The obtained optimization outcomes confirm that the accuracy of the suggested method in this study is highest, and it can be used as an alternative method in this topic.

The main contributions of this study can be summarized as follows:

- The recently developed Tasmanian devil optimization (TDO) algorithm is proposed to use for estimating the parameters of PV cell/module.

- The proposed method is validated using the experimental data of real-world photovoltaic devices, namely the R.T.C. France solar cell and the STM6-40/36 PV module.
- A further performance analysis of the proposed method under partial shading conditions (PSCs) is performed.
- To evaluate the effectiveness of the TDO algorithm, the results obtained are compared with those of other well-known algorithms, including particle swarm optimization (PSO), African vultures optimization algorithm (AVOA), and jellyfish search (JS).

The rest of the article is organized as follows. Materials and Methods section presents the PV cell models and the PV module used in this study with their mathematical formulations and details the application of the proposed TDO method to the PV parameter estimation problem. The results and discussions of the study are given in Results and Discussion section. Finally, the conclusions of the study are provided in Conclusion section.

MATERIALS AND METHODS

Photovoltaic Models

Photovoltaic models are utilized to characterize the I-V curve of real-world solar cells. It is important to determine the accurate model parameters that are changeable over time due to nonlinear behavior and aging of PV cells (Pourmousa et al., 2019). In this context, the most common PV models, including SDM, DDM, and the PV module model, are considered in this study and described below.

Single-diode model (SDM)

The single-diode model includes a current source, one diode, a shunt resistor, and an additional resistor in series with all these model components, as observed in Figure 1. The current at the output of the equivalent circuit can be mathematically represented as follows:

$$I_L = I_{Ph} - I_D - I_{Sh} \tag{1}$$

where, I_{ph} denotes the current due to photo-generated electrons, I_{sh} is the current flowing in front of the shunt resistor, I_d is the current passing through the diode and formulated using the Shockley equation as follows:

$$I_D = I_{sd} \cdot \exp\left[\frac{(R_S \cdot I_L + V_L) \cdot q}{T \cdot n \cdot k} - 1\right] \tag{2}$$

where I_{sd} is the current of reverse saturation, R_S represents the current of the resistor connected in series, V_L expresses the voltage at the output of the solar cell, q represents the electron charge that equals $1.6021765 \times 10^{-19}$ C, T describes the junction temperature in Kelvin, n denotes the diode's ideality factor in the circuit, and k refers to the Boltzmann coefficient that equals 1.38065×10^{-23} J/K.

The current flowing through the shunt resistor is calculated as follows:

$$I_{Sh} = \frac{R_S \times I_L + V_L}{R_{Sh}} \tag{3}$$

where, R_{Sh} expresses the current of the resistor connected in shunt.

The model of SDM includes some unknown model parameters, which are R_S, R_{Sh}, I_{sd}, I_{Ph}, and n, and they are aimed to be identified in this study.

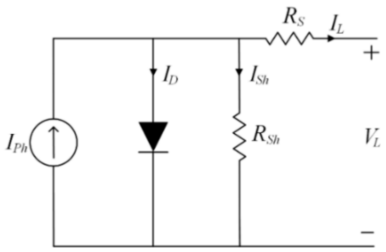


Figure 1. The SDM's equivalent circuit

Double-diode model (DDM)

The model of the double-diode circuit includes an extra diode that contacted in parallel to the existing diode in the SDM model. Figure 2 demonstrates the DDM equivalent model. With this modification, the current at the output terminal of the DDM can be formulated as follows:

$$I_L = I_{Ph} - \left[I_{sd1} \cdot \exp\left[\frac{(R_S \times I_L + V_L)\cdot q}{n_1 \cdot k \cdot T} - 1\right] + I_{sd2} \cdot \exp\left[\frac{(R_S \times I_L + V_L)\cdot q}{n_2 \cdot k \cdot T} - 1\right] + \frac{R_S \times I_L + V_L}{R_{Sh}}\right] \quad (4)$$

where, I_{sd1} and I_{sd2} represent the currents of reverse saturation for the diodes and n_1 and n_2 determine ideality factors of these diodes.

The DDM model's unknown parameters for its equivalent circuit are I_{sd1}, I_{sd2}, n_1, n_2, I_{Ph} R_{Sh}, and R_S.

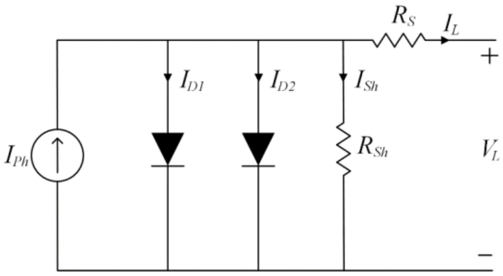


Figure 2. The DDM's equivalent circuit

PV module equivalent circuit

Solar cells are formed to connect with each other in series and/or parallel to compose a PV module. Figure 3 demonstrates a general design of a photovoltaic module equivalent circuit. The current at the output of the model is calculated as follows:

$$I_L = N_P \cdot I_{Ph} - N_P \cdot I_{sd} \times \exp\left[\frac{\left(\frac{R_S \cdot I_L \cdot N_S}{N_P} + V_L\right)\cdot q}{N_S \cdot k \cdot n \cdot T} - 1\right] - \frac{R_S \cdot I_L \cdot N_S + N_P \cdot V_L}{R_{Sh} \cdot N_S} \quad (5)$$

where, N_P and N_S denote the solar cell count connected in parallel and series, respectively. The parameters (I_{Ph}, I_{sd}, n, R_S, and R_{Sh}) are unknown and have to be extracted.

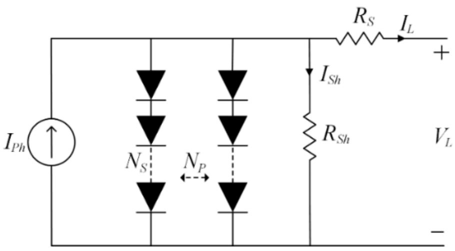


Figure 3. The module's equivalent circuit

Optimization Method and Problem Formulation

In this paper, the Tasmanian devil optimization (TDO) algorithm is proposed to estimate the unknown parameters of PV cells/modules. This section provides the mathematical background of TDO and the optimization problem solved by TDO.

Tasmanian devil optimization (TDO) algorithm

TSO is a recent population-based metaheuristic optimization algorithm developed by Denghani et al. in 2022. The algorithm imitates the foraging behavior of the Tasmanian devil. Tasmanian devil has two options for feeding. One of them is to find and eat carrion in the area, while the other is to hunt and eat prey. The mathematical model of TDO is based on these two behaviors.

As in the first behavior, the Tasmanian devil usually prefers to eat the carrion left by the prey hunted by other predators in the vicinity. This strategy is modeled by Eqs. (6)-(8).

$$C_i = X_k \tag{6}$$

where, X_k is the position of the kth Tasmanian devil followed by ith one to find the best carrion. The position update rule of ith Tasmanian devil is given as follows:

$$X_{i,j}{}^{new,s1} = \begin{cases} X_{i,j} + r \cdot \left(C_{i,j} - I \cdot X_{i,j}\right), & F_{C_i} < F_i; \\ X_{i,j} + r \cdot \left(X_{i,j} - C_{i,j}\right), & otherwise, \end{cases} \tag{7}$$

$$X_i = \begin{cases} X_i{}^{new,s1} \ , & F_i{}^{new,s1} < F_i; \\ X_i \ , & otherwise, \end{cases} \tag{8}$$

where, $X_{i,j}$ and $X_{i,j}{}^{new,s1}$ are the current and new locations of the ith Tasmanian devil, respectively. I is a random number that takes 0 or 1. r is a random number between [0, 1]. In the first strategy, each Tasmanian Devil in the population follows the other to reach the best location for carrion. If the fitness value corresponds to the target location, $F_i{}^{new,s1}$, is lower than the current fitness value obtained by the ith Tasmanian devil, F_i, the position of the ith Tasmanian devil will be updated according to Eq. (7). Otherwise, the position of the ith Tasmanian devil will remain the same for the corresponding iteration of the optimization.

In the second strategy, the Tasmanian devil hunts the living prey and eats it instead of carrion. The mathematical model of this strategy is given by Eqs. (9)-(11).

$$P_i = X_k \tag{9}$$

where, X_k is the position of the kth Tasmanian devil followed by ith one to get the best position to hunt and eat prey. According to this strategy, the position update rule of ith Tasmanian devil is given as follows:

$$X_{i,j}{}^{new,s2} = \begin{cases} X_{i,j} + r \cdot \left(P_{i,j} - I \cdot X_{i,j}\right), & F_{P_i} < F_i; \\ X_{i,j} + r \cdot \left(X_{i,j} - P_{i,j}\right), & otherwise, \end{cases} \tag{10}$$

$$X_i = \begin{cases} X_i{}^{new,s2} \ , & F_i{}^{new,s2} < F_i; \\ X_i \ , & otherwise, \end{cases} \tag{11}$$

where, $X_i{}^{new,s2}$ and $F_i{}^{new,s2}$ are the new position of the ith Tasmanian devil and the fitness value corresponding to this position, respectively. Similar to the first strategy, the Tasmanian devils update their positions to reach the best location for hunting and eating prey.

Problem formulation

The aim is to identify the most proper PV cell model parameters. To do this, optimization methods are used to minimize the error between the experimental I-V curve, which is provided from a real-world PV cell or module, and the estimated I-V curve obtained from the PV cell or module model. The objective function of the optimization problem for modeling the PV cell/module is given by (12).

$$OF = RMSE(V) = \sqrt{\frac{1}{N_m} \sum_{i=1}^{N_m} \left(I_{L,mea}^{i} - I_{L,est}^{i}\right)^2} \tag{12}$$

where, N_m is the number of measurement points on the experimentally obtained I-V curve, $I_{L,mea}^{i}$ and $I_{L,est}^{i}$ are the measured and extracted cell/module output current values, respectively, for the data point i.

RESULTS AND DISCUSSION

To validate the performance of the proposed method on estimating the PV model parameters, standard test data from a 57 mm diameter R.T.C. France solar cell at the irradiation of 1000 W/m2 and a temperature of 33 °C is used (Askarzadeh and Rezazadeh, 2012). For the PV module, the I-V data of the commercial PV panel named STM6-40/36 is used. STM6-40/36 panel includes 36 cells that are serially connected (Li et al., 2019).

Besides the proposed TDO algorithm, three different algorithms including the PSO algorithm (Kennedy and Eberhart, 1995), AVOA (Adollahzadeh et al., 2021), and JS algorithm (Chou and Truong, 2021) are studied in this paper for a detailed comprehensive analysis.

All the simulation experiments are performed using MATLAB software on a PC with a 2.6 GHz processor speed and 8 GB of random access memory. The optimization parameters, called maximum iteration number and population size, are chosen as 10000 and 60, respectively. To avoid premature convergence to sub-optimal solutions, the optimization process is repeated for 20 independent runs. The upper and lower bounds of the optimization problem are given in Table 1.

Table 1. The upper and lower bounds of the optimization constraints for different PV models

Parameters	Single and double diode models		STM6-40/36 PV module model	
	Upper	Lower	Upper	Lower
R_S	0.5	0	0.36	0
R_{Sh}	100	0	1000	0
I_{Ph}	1	0	2	0
$I_{sd}/I_{sd1}/I_{sd2}$	1×10^{-6}	0	50	0
$n/n_1/n_2$	2	1	60	1

SDM and DDM Models

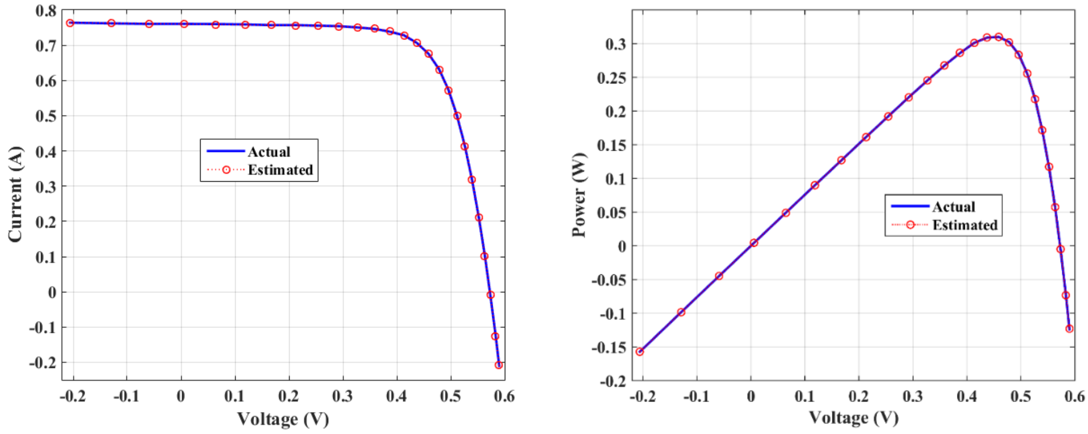
The results for the SDM model are tabulated in Table 2. It is seen that the RMSE values obtained by the TDO and JS algorithms are equal. These two algorithms outperform the other considered algorithms, i.e. AVOA and PSO. The RMSE value obtained via PSO is considerably close to those obtained via TDO and JS while that of AVOA is relatively higher than all the other results. Figure 4 demonstrates the extracted I-V and P-V curves obtained via the proposed TDO algorithm and the actual curves for the SDM model. It is seen that the actual and estimated curves overlap each other quite well.

Table 2. Optimal parameter values found by different methods for the SDM model

Parameters	PSO	AVOA	JS	TDO
R_S	0.03641	0.03660	0.03638	0.03638
R_{Sh}	54.13895	52.14737	53.71850	53.71977
I_{Ph}	0.76078	0.76081	0.76078	0.76078
I_{sd}	3.2357×10^{-7}	3.0506×10^{-7}	3.2302×10^{-7}	3.2303×10^{-7}
n	1.48134	1.47545	1.48118	1.48119
RMSE	9.8813×10^{-4}	9.9202×10^{-4}	9.8602×10^{-4}	9.8602×10^{-4}

The optimization results obtained via different methods for the DDM model are given in Table 3. According to the results, the proposed TDO shows a superior performance in estimating the DDM model parameters. The RMSE value obtained via TDO is lower than those obtained via the other methods. On the other hand, the obtained results for the DDM model show that the JS algorithm yields 9.8553×10^{-4}

results, while the TDO algorithm yields 9.8355×10^{-4}. Although the TDO and JS algorithms produced similar results for the single diode model, the TDO algorithm outperforms the JS method for the DDM model. The actual and estimated curves for the DDM model are shown in Figure 5. Figure 5 illustrates that the estimated curves obtained via the proposed TDO follow the actual curves perfectly.



(a) (b)

Figure 4. The actual and estimated (a) *I-V* and (b) *P-V* curves for the single diode model

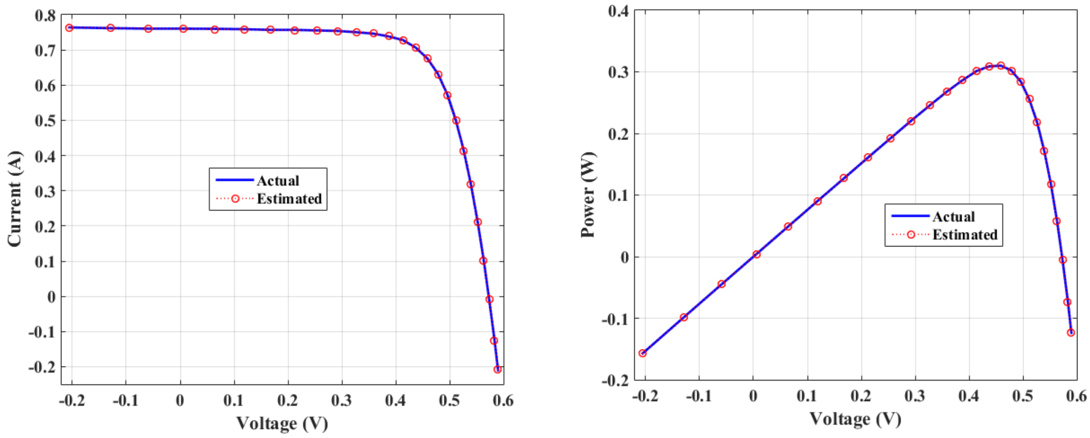
Table 3. Optimal parameter values found by different methods for the DDM model

Parameters	PSO	AVOA	JS	TDO
R_S (Ω)	0.03619	0.03597	0.03639	0.03659
R_{Sh} (Ω)	58.43644	56.80241	53.91421	54.96412
I_{Ph} (A)	0.76055	0.76072	0.76078	0.76074
I_{sd1} (A)	2.192×10^{-7}	3.581×10^{-7}	3.130×10^{-7}	4.223×10^{-7}
I_{sd2} (A)	2.354×10^{-7}	8.265×10^{-13}	7.708×10^{-8}	2.637×10^{-7}
n_1	1.45882	1.49165	1.47860	1.99381
n_2	1.65933	1.12386	1.97828	1.46394
RMSE	10.0604×10^{-4}	10.0531×10^{-4}	9.8553×10^{-4}	9.8355×10^{-4}

On the other hand, the statistical results for the DDM model are given in Table 4. The results are obtained for PSO, AVOA, JS, and TDO methods over 20 independent runs. The TDO method provides the best results in terms of maximum, minimum, average, and standard deviation values. These results, particularly considering the competition between the JS and TDO algorithms, indicate that the TDO algorithm is more stable and consistent compared to the JS algorithm. In addition, although the PSO algorithm performed better for the SDM model than the AVOA algorithm, it yielded worse results for the DDM model. At this point, it can be said that the performance of the PSO algorithm decreases as the unknown parameters increase. Furthermore, the TDO method is the fastest method among the other considered methods. The average time consumed in the CPU is 21.1279 sec for the optimization process performed by the TDO method. On the other hand, it is also evident that the PSO method leads to a significantly higher computational burden compared to the JS and TDO algorithms. In Figure 6, the convergence curves obtained for different methods in estimating the DDM model parameters are illustrated. The TDO method has the fastest convergence performance in comparison to the other methods. Here, it is observed that the TDO and JS algorithms show similar performance up to around the 1150th iteration, but after this period, the TDO algorithm exhibits better convergence performance than its competitors. This also means that good results can be achieved with the TDO algorithm even at low maximum iteration numbers.

Table 4. Statistical optimization results for different methods for the DDM model

Method	Maximum	Minimum	Average	Standard deviation	Average time consumed in CPU (sec)
PSO	13.9617×10^{-4}	10.0604×10^{-4}	11.2059×10^{-4}	1.0904×10^{-4}	51.4683
AVOA	22.6733×10^{-4}	10.0531×10^{-4}	14.4767×10^{-4}	4.3278×10^{-4}	27.5819
JS	9.8730×10^{-4}	9.8553×10^{-4}	9.8578×10^{-4}	3.7556×10^{-7}	21.4398
TDO	9.8603×10^{-4}	9.8355×10^{-4}	9.8545×10^{-4}	2.0784×10^{-7}	21.1279



(a) (b)

Figure. 5. The actual and estimated (a) *I-V* and (b) *P-V* curves for the double diode model

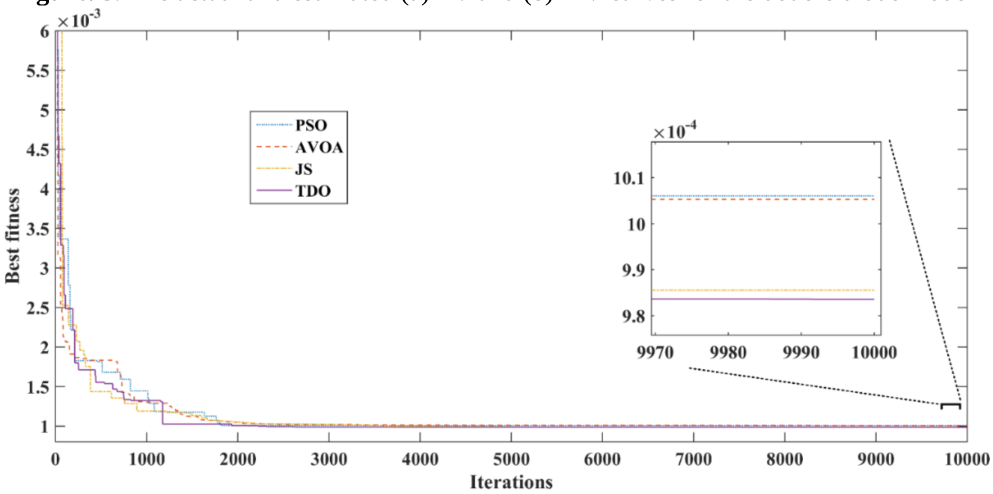


Figure 6. Convergence curves obtained for different methods

PV Module Model

Table 5 provides the optimal parameters of the PV module model and the corresponding RMSE values obtained for different methods. Similar to the SDM model, TDO and JS methods give the lowest RMSE value. AVOA method gives the second-best RMSE value following the TDO and JS methods. Compared to these algorithms, it is also shown that the PSO method performs quite poorly with a result of 6.8218×10^{-2}. From Figure 7, it is seen that the estimated I-V and P-V curves obtained via the TDO method have a good match with the actual I-V and P-V curves.

The results confirm that the TDO method is a powerful optimization algorithm for extracting the PV cell model parameters as well as the PV module model parameters.

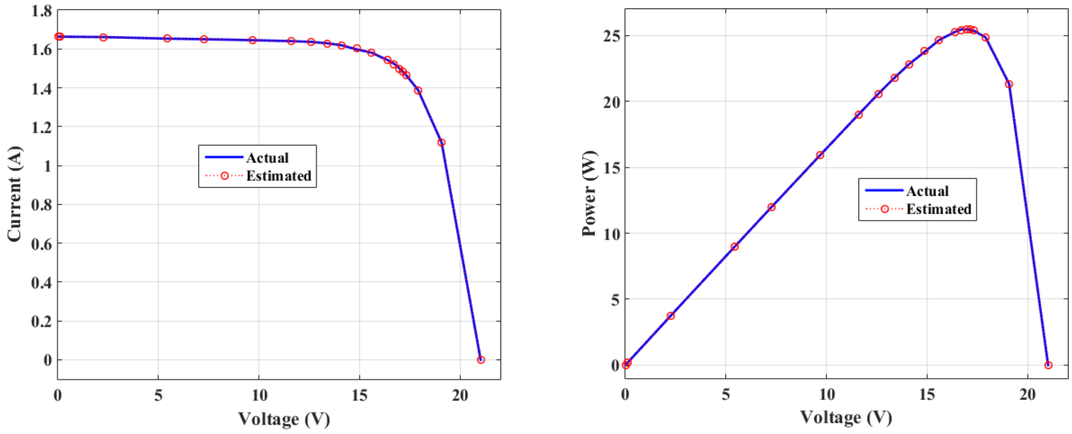
Table 5. Optimal parameter values found by different methods for STM6-40/36 PV module

Parameters	PSO	AVOA	JS	TDO
R_S	0	2.1730×10^{-4}	0.00427	0.00427

R_{Sh}	505.5154	25.66667	15.92868	15.92689
I_{Ph}	0.84106	1.66040	1.66391	1.66391
I_{sd}	1.5126×10^{-3}	5.833×10^{-6}	1.739×10^{-6}	1.738×10^{-6}
n	3.49690	1.65757	1.52032	1.52028
RMSE	6.8218×10^{-2}	32.5303×10^{-4}	17.2981×10^{-4}	17.2981×10^{-4}

Performance analysis of the proposed method under partial shading conditions

In photovoltaic (PV) modules, each region or cell may not always receive equal solar irradiance due to environmental factors, leading to a phenomenon known as partial shading conditions. This condition significantly affects both the performance and the efficiency of PV systems. Therefore, in addition to standard operating conditions, it is essential to model PV behavior accurately under PSC as well.



(a) (b)

Figure 7. The actual and estimated (a) *I-V* and (b) *P-V* curves for STM6-40/36 PV module

Under partial shading, the shaded portions of the module act like electrical loads, dissipating power in the form of heat, which is an undesirable effect that can lead to hot spots and potential damage. To mitigate this issue, the most widely adopted solution in the literature is the integration of bypass diodes. With the inclusion of bypass diodes, the PV equivalent circuit can be mathematically modeled as given in the work of Nunes et al. (2019). In this context, the present study models the behavior of PV modules under partial shading conditions, considering both the SDM and DDM separately. The experimental data for the voltage and current measurements are taken from the work of Wu et al. (2025). The simulation results are presented in Table 6 and Figure 8.

According to the results presented in Table 6, the TDO algorithm provides the most accurate modeling performance under partial shading conditions for both the SDM and DDM models. Furthermore, the DDM-based model using the TDO algorithm provides more accurate estimations than the SDM-based model. As illustrated in Figure 8, the estimated curves obtained using the TDO algorithm closely match the actual values for both SDM and DDM models.

Table 6. Comparison of the RMSE values for the partial shading condition

Method	PSO	AVOA	JS	TDO
SDM	21.5841×10^{-2}	3.0165×10^{-2}	2.2375×10^{-2}	2.2260×10^{-2}
DDM	23.5491×10^{-2}	3.0895×10^{-2}	2.4027×10^{-2}	2.2175×10^{-2}

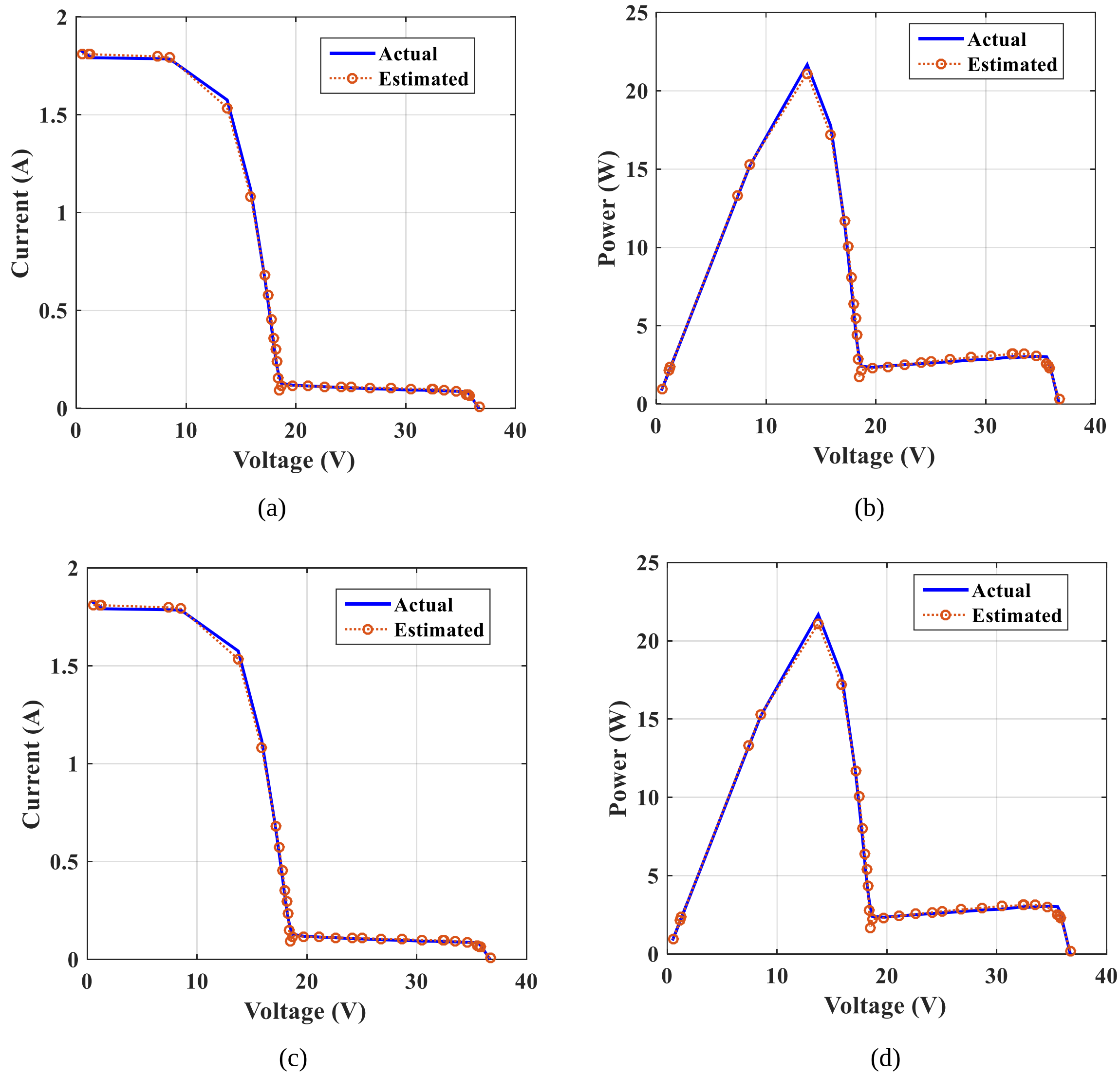


Figure 8. The actual and estimated I–V and P–V curves under partial shading conditions, obtained using the TDO algorithm, for the SDM model in (a) and (b), and for the DDM model in (c) and (d), respectively

Evaluation of the Proposed Method

In this study, the TDO method is used to identify PV model parameters, yielding effective results compared to the PSO and AVOA optimization methods. Although the JS and TDO algorithms yield similar results in SDM and PV module estimation, the TDO algorithm provides a lower error rate in the DDM model compared to JS. While these two algorithms are strong competitors in terms of providing effective results, they also show comparable performance in terms of computational efficiency. However, considering both the obtained statistical optimization results and the CPU time spent, it can be said that the proposed TDO algorithm is a step ahead of JS in accurately estimating PV model parameters. It is clear that the TDO algorithm is an effective method for estimating the parameters of PV models.

On the other hand, according to the statistical optimization results obtained in the study, the TDO algorithm provides the most effective outcomes in terms of maximum, minimum, average, and standard deviation in comparison to other algorithms. This confirms that the TDO algorithm is a stable and consistent method for PV model parameter extraction.

One of the potential limitations of the proposed method is the algorithm parameter determination. This problem is valid for all metaheuristic-based methods. In this study, the trial-and-error procedure is performed to define the TDO control parameters, and the recommended settings given in the original study (Denghani et al., 2022) are found suitable for the problem considered in this study. In the process of determining algorithm parameters, it may be necessary to evaluate the value of each parameter individually or together within a wide search space, which often results in a significant computational burden. However, it is important to emphasize that in the TDO algorithm, the number of control parameters is low, making this process relatively easier compared to many other algorithms. On the other hand, similar to most studies in the literature, RMSE is considered the objective function in this study. Testing other objective functions, such as the sum of square error (SSE) and the sum of absolute error (SAE), could yield different results in model simulation. This is planned for future studies.

In future work, the authors plan to apply the proposed TDO algorithm to different commercial PV cell/modules and use different error functions besides the RMSE considered in this study.

CONCLUSION

This study introduces the TDO algorithm for estimating the parameters of PV cell and module models. Three models are examined: the single-diode and double-diode PV cell models, as well as a PV module model. The parameter extraction is performed using real-world photovoltaic devices, specifically the R.T.C. France solar cell and the STM6-40/36 PV module. In addition, the partial shading condition is also considered. To evaluate the effectiveness of the TDO method, its performance is compared with three other optimization algorithms: PSO, AVOA, and JS.

The findings indicate that the proposed TDO method performs exceptionally well in estimating the model parameters of PV cells and modules. Among all the evaluated models, TDO achieves the lowest error between the estimated and actual I-V and P-V curves. The results obtained using JS are similar to those of TDO. However, for the double-diode model, TDO stands out as the only method that achieves the minimum RMSE value. In the PV module modeling, it is observed that the R_S and R_{Sh} values estimated by the PSO algorithm differ significantly from those obtained by the other algorithms, resulting in a higher RMSE value. These parameters significantly affect the accuracy and efficiency of PV system modeling. A lower R_S value minimizes internal power losses and improves the fill factor and output efficiency, while a higher Rsh value reduces leakage currents and contributes to a more ideal I-V characteristic, particularly under low irradiance conditions. The TDO algorithm yields balanced and realistic R_S and R_{Sh} values across different PV models, which leads to more accurate model estimation and reduced RMSE. These results confirm that TDO is a highly effective alternative approach for determining the parameters of PV cells and modules.

Conflict of Interest

The article authors declare that there is no conflict of interest between them.

Author's Contributions

The authors declare that they have contributed equally to the article.

REFERENCES

Abdel-Basset, M., Mohamed, R., Mirjalili, S., Chakrabortty, R. K., & Ryan, M. J. (2020). Solar photovoltaic parameter estimation using an improved equilibrium optimizer. *Solar Energy*, 209, 694-708. https://doi.org/10.1016/j.solener.2020.09.032.

Abdollahzadeh, B., Gharehchopogh, F. S., & Mirjalili, S. (2021). African vultures optimization algorithm: A new nature-inspired metaheuristic algorithm for global optimization problems. *Computers & Industrial Engineering*, 158, 107408.

Askarzadeh, A., & Rezazadeh, A. (2012). Parameter identification for solar cell models using harmony search-based algorithms. *Solar Energy*, 86(11), 3241-3249.

Ayyarao, T. S., & Kumar, P. P. (2022). Parameter estimation of solar PV models with a new proposed war strategy optimization algorithm. *International Journal of Energy Research*, 46(6), 7215-7238.

Ayvaz, A. (2022). An improved chicken swarm optimization algorithm for extracting the optimal parameters of proton exchange membrane fuel cells. *International Journal of Energy Research*, 46(11), 15081-15098.

Chaib, L., Tadj, M., Choucha, A., Khemili, F. Z., & Attia, E. F. (2024). Improved crayfish optimization algorithm for parameters estimation of photovoltaic models. *Energy Conversion and Management*, 313, 118627.

Chenouard, R., & El-Sehiemy, R. A. (2020). An interval branch and bound global optimization algorithm for parameter estimation of three photovoltaic models. *Energy Conversion and Management*, 205, 112400.

Chou, J. S., & Truong, D. N. (2021). A novel metaheuristic optimizer inspired by behavior of jellyfish in ocean. *Applied Mathematics and Computation*, 389, 125535.

Dehghani, M., Hubálovský, Š., & Trojovský, P. (2022). Tasmanian devil optimization: a new bio-inspired optimization algorithm for solving optimization algorithm. *IEEE Access*, 10, 19599-19620.

Devarajah, L. A., Ahmad, M. A., & Jui, J. J. (2024). Identifying and estimating solar cell parameters using an enhanced slime mould algorithm. *Optik*, 171890.

Dogan, Z. & Boylu Ayvaz, B. (2022). A comprehensive comparison of different meta-heuristic methods for estimating the optimal parameters of photovoltaic cell model. *5th International Symposium on Innovative Approaches in Smart Technologies,* 28-29 May 2022, Turkey.

Garip, Z. (2023). Parameters estimation of three-diode photovoltaic model using fractional-order Harris Hawks optimization algorithm. *Optik*, 272, 170391.

Izci, D., Ekinci, S., & Hussien, A. G. (2024). Efficient parameter extraction of photovoltaic models with a novel enhanced prairie dog optimization algorithm. *Scientific Reports*, 14(1), 7945.

Kennedy, J., & Eberhart, R. (1995, November). Particle swarm optimization. *In Proceedings of ICNN'95-international conference on neural networks* (Vol. 4, pp. 1942-1948). IEEE.

Kler, D., Goswami, Y., Rana, K. P. S., & Kumar, V. (2019). A novel approach to parameter estimation of photovoltaic systems using hybridized optimizer. *Energy Conversion and Management*, 187, 486-511.

Li, S., Gong, W., Yan, X., Hu, C., Bai, D., & Wang, L. (2019). Parameter estimation of photovoltaic models with memetic adaptive differential evolution. *Solar Energy*, 190, 465-474.

Ma, J., Ting, T. O., Man, K. L., Zhang, N., Guan, S. U., & Wong, P. W. (2013). Parameter estimation of photovoltaic models via cuckoo search. *Journal of applied mathematics*, 2013.

Nunes, H. G. G., Pombo, J. A. N., Bento, P. M. R., Mariano, S. J. P. S., & Calado, M. R. A. (2019). Collaborative swarm intelligence to estimate PV parameters. *Energy Conversion and Management*, 185, 866-890.

Oliva, D., Cuevas, E., & Pajares, G. (2014). Parameter identification of solar cells using artificial bee colony optimization. *Energy*, 72, 93-102.

Pourmousa, N., Ebrahimi, S. M., Malekzadeh, M., & Alizadeh, M. (2019). Parameter estimation of photovoltaic cells using improved Lozi map based chaotic optimization Algorithm. *Solar Energy*, 180, 180-191.

Ramadan, A. E., Kamel, S., Khurshaid, T., Oh, S. R., & Rhee, S. B. (2021). Parameter extraction of three diode solar photovoltaic model using improved grey wolf optimizer. *Sustainability*, 13(12), 6963.

Rizk-Allah, R. M., El-Sehiemy, R. A., & Abdelwanis, M. I. (2024). Improved Tasmanian devil optimization algorithm for parameter identification of electric transformers. *Neural Computing and Applications*, 36(6), 3141-3166.

Sahu, B. K. (2015). A study on global solar PV energy developments and policies with special focus on the top ten solar PV power producing countries. *Renewable and Sustainable Energy Reviews*, 43, 621-634.

Solarin, S. A. (2020). An environmental impact assessment of fossil fuel subsidies in emerging and developing economies. *Environmental Impact Assessment Review*, 85, 106443.

Wang, W., & Lyu, L. (2024). Adaptive Tasmanian Devil Optimizer for Global Optimization and Application in Wireless Sensor Network Deployment. *IEEE Access*.

Wu, L., Zheng, Y., Ezzahrae, E. H. F., Chen, C., Zhang, Z., Hong, Z., & Zhao, S. (2025). Improved Particle Swarm Optimization Algorithm Based Robust Parameter Estimation of Photovoltaic Array Model under Partial Shading Conditions. *IEEJ Transactions on Electrical and Electronic Engineering*, 20, 899-909.