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An improved PSO-based approach for the photovoltaic cell parameters identification in a single diode model

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ABSTRACT

The future power of photovoltaic systems (PVS) is gaining significant attention due to its rising potential. This has resulted in a substantial amount of research emphasizing the importance of optimizing the PVS efficiency. However, the identification of PV cell model parameters remains a challenging task, mainly due to the characteristics of PV cells and their dependence on varying meteorological conditions. In this work, we present a novel methodology based on an improved new multi objective particle swarm optimization (NMOPSO) algorithm for the PV cell parameters identification. The main goal is to minimize the root mean square error (RMSE) and to calculate the series resistance (Rs) by means of its non-linear equation form. The applied algorithm uses an evolving and adaptive search strategy to enhance both speed of convergence for the parameter identification process precision. Through extensive simulations, we demonstrate that proposed approach outperforms current methods in terms of accuracy, precision, and PV parameters extraction.

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1. INTRODUCTION

Over several decades, the extensive use of fossil fuels has resulted in considerable environmental pollution [1]. To reduce environmental pollution, the integration of renewable energy sources is poised to play a pivotal role in the future. Among these sources, solar energy is anticipated to gain widely popular due to its ease of installation, zero emissions, sustainability, and economic viability [2].

Solar power stands out as one of the most abundant and accessible forms of clean energy [3], as it can be connected in diverse locations such as rooftops, streets, mountains, prairies, and other areas with visible sunlight [4]-[6]. It is an integral component of renewable energy sources for electricity generation, alongside green energies like hydropower, geothermal, and wind power. Furthermore, solar energy owns a notable advantage as it is non-exploitative and environmentally friendly, contributing to a more sustainable and eco-conscious future [3], [6], [7].

While previous studies have extensively explored the advantages and potential of solar energy as a renewable energy source, there still exist notable gaps in our understanding and application of this technology. The efficiency and performance of photovoltaic (PV) systems are significantly dependent on the precise estimation of PV cell parameters [8]. In the field of PV modules, the parameters estimation of PV cells is a challenge task due to its difficult behavior and the numerous of involved variables. This task requires precise measurements to consider different factors such as non-linearity and variability among parameters. Furthermore, optimizing energy conversion efficiency within PV systems is based on accurate parameter estimation. Thus, accurate parameter estimation is pivotal for ensuring the optimal performance and sustainability of photovoltaic systems (PVS) in harnessing solar power.

Researchers are continually striving to enhance the accuracy of their models. This involves improving the mathematical frameworks used to describe PV modules. A crucial aspect of this search is the evaluation of PV parameters. Some studies apply mathematical techniques, while others use numerical analyses to solve complex and non-linear equations. Notably, the integration of metaheuristic methods offers efficient solutions compared to traditional approaches, further enhancing the modeling accuracy of PV systems.

Hussein [9], suggested an iterative technique based on the Newton–Raphson method to extract the single-diode parameters. The fundamental idea of this method is to establish four equations based on the remarkable points as functions of the five parameters. A closed-form expression is then derived to calculate the value of (R_s) while incrementing the ideality factor's value. The approach used in [9] stands out for its improved computational results, representing a significant improvement in precision compared to existing literature. Ndegwa *et al.* [10], a precise and efficient analytical method was introduced for parameter prediction. This method, based on data provided by the manufacturer, aims to simplify the calculation technique for evaluating the ideality factor. The use of particle swarm optimization (PSO) in [11] led to the achievement of remarkably low root mean square error (RMSE) values in parameter extraction with minimum computation time. This performance significantly surpassed competing methodologies and computational algorithms. The findings shows the substantial potential of PSO in determining solar cell parameters.

Saadaoui *et al.* [12], an innovative method based on the multiple learning JAYA algorithm is presented for extracting the parameters from PV models. This approach integrates adaptive weighting to accelerate the exploration of potential search spaces and improving the efficiency of parameter extraction techniques. Wang [13], suggested the use of the EPSO algorithm to minimize the mean squared error between measured and estimated data. Lidaighbi *et al.* [14] applied a hybrid analytical/iterative method, with the goal of minimizing disparities between calculated and experimental data, resulting in remarkable accuracy that outperformed other techniques. The improved firefly algorithm (IFA) was applied in [15] to proficiently extract the unidentified parameters of PV solar cells, precisely adjusting the global maximum power point (GMPP) in PV panels. This methodology introduced a novel approach to optimize energy production within PVS. Choulli *et al.* [16], a novel hybrid analytical/iterative methodology was applied to extract parameters of the single diode model (SDM). This technique is based on the Lambert function to resolve the nonlinear equation for (R_s). It leads to a significantly improved RMSE compared to other methods. The primary aim is to minimize the average error between simulated and experimental currents.

Long *et al.* [17], used a hybrid algorithm, namely the grey wolf optimizer and cuckoo search (GWOCS), to address various optimization challenges associated with parameter extraction in four distinct PV solar cell models. This hybrid method not only aimed to elevate the overall optimization standards but also specifically developed the GWOCS to tackle global optimization problems and extract parameters from several solar PV cell models under different operating conditions, while attempting to solve the (R_s) equation. Sharma and Tripathi [18], compared to traditional methods, metaheuristic techniques have demonstrated superior performance. Due to their ease of implementation and efficiency, these methods are suitable for solving non-linear optimization problems as (R_s) equation.

Our proposed method, based on new multi objective particle swarm optimization (NMOPSO) algorithm, introduced in 2022 [19], represents a novel approach that has demonstrated remarkable results in the domain of electric motors parameters optimization. This algorithm stands out for its ability to efficiently solve non-linear equations within minimal computation time. Notably, its application has surpassed the performance of conventional PSO and various enhanced PSO variants. The present study investigated the identification of the PV cell parameters by means of the NMOPSO algorithm. To achieve this goal, an optimization process, involving two objective functions, is applied. The first objective function aims to minimize the RMSE, while the second calculates the series resistance (R_s) by using its non-linear equation form. This technique is based on an adaptive and scalable search strategy. To evaluate the effectiveness of the proposed method, deep simulations, and comparisons with state of art techniques have been conducted. The remainder of this paper is structured as follows: the PV cell modelling based on SDM is described in section 2. In section 3, we define the optimization problem and introduce the used algorithm. The optimization results and the discussion are presented in section 4. Finally, we finish by a conclusion.

2. PV CELL MODELLING: SINGLE DIODE MODEL

The use of the SDM shows a good accuracy in modelling electrical features of different PV cell/modules variants under various environmental conditions. As shown in Figure 1, this model consists of a parallel arrangement of a diode and a constant current source of energy. When exposed to sunlight, the PV cell produces a light current. This current is determined by applying the Kirchhoff's law.

$$I = I_{ph} - I_D - I_{sh} \quad (1)$$

Where:

$$I_D = I_0 \left[exp(\frac{V+IR_s}{nV_t}) - 1\right] \quad (2)$$

$$I_{sh} = \frac{V+IR_s}{R_{sh}} \quad (3)$$

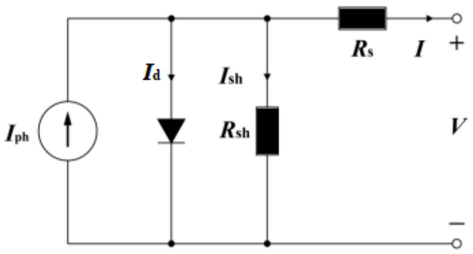

Figure 1. Equivalent circuit of SDM

Consequently, we can modify (1) as:

$$I = I_{ph} - I_0 \left[exp(\frac{V+IR_s}{nV_t}) - 1\right] - \frac{V+IR_s}{R_{sh}} \quad (4)$$

where (I_0), (I_{ph}), (n), (R_{sh}) and (R_s) represent: the saturation current of the diode, the photo-generated current, the diode ideality factor, the shunt, and R_s. The output voltage, (V_t), is expressed as (5):

$$\mathrm{V_t} = \frac{KT}{\mathrm{q}} \quad (5)$$

(T) is the PV module temperature in Kelvin, with $q = 1.602 * 10^{-19}C$ and $K = 1.3806 * 10^{-23}J/k$

2.1. PV cell parameters identification methods

2.1.1. Photocurrent (Iph)

Based on manufacturer's specifications regarding the short circuit condition at standard test conditions (STC), the calculation of the light-generated current (I_{ph}) is performed. The obtained expression is calculated by using the short circuit conditions (V = 0; I = I_{sc}) in (4).

$$I_{sc} = I_{ph} - I_0 \left[exp(\frac{\frac{R_s I_{sc}}{nV_t}}{}) - 1\right] - \frac{R_s I_{sc}}{R_{sh}} \quad (6)$$

Since the value of (R_s)is exceptionally low [14], the following expression is derived:

$$I_{ph} = \frac{R_s+R_{sh}}{R_{sh}} I_{sc} \quad (7)$$

2.1.2. Diode saturation current (I_0)

The expression is derived by substituting the open circuit conditions (I=0; V=V_{oc}) in (4).

$$I_0 = \frac{I_{ph} - \frac{v_{oc}}{R_{sh}}}{exp\left(\frac{v_{oc}}{n\,V_t}\right) - 1} \quad (8)$$

2.1.3. Parallel resistance (R_{sh})

In this study, we apply the (R_{sh}) in (9), originally given by [12]:

$$R_{sh} = \frac{V_{OC}\left(\exp\left(\frac{V_{mp}+I_{mp}R_s}{nV_t}\right)-\exp\left(\frac{I_{sc}R_s}{nV_t}\right)\right)-V_{mp}\left(\exp\left(\frac{V_{oc}}{nV_t}\right)\right)-\exp\left(\frac{I_{sc}R_s}{nV_t}\right)}{I_{mp}(\exp\left(\frac{V_{oc}}{nV_t}\right))-\exp\left(\frac{I_{sc}R_s}{nV_t}\right))-I_{sc}\left(\exp\left(\frac{V_{oc}}{nV_t}\right)\right)-\exp\left(\frac{V_{mp}+I_{mp}R_s}{nV_t}\right)} - R_s \quad (9)$$

2.1.4. The series resistance (R_s)

To calculate the R_s in the SDM of a solar panel, the (10) can be used [14]:

$$\exp\left(\frac{(V_{mp}+I_{mp}R_s)-V_{oc}}{nV_t}\right) = \frac{nV_tV_{mp}(2I_{mp}-I_{sc})}{V_{mp}I_{sc}+(I_{mp}-I_{sc})(V_{mp}-R_sI_{mp})-nV_t(V_{mp}I_{sc}-V_{oc}I_{mp})} \quad (10)$$

2.1.5. Diode ideality factor (n)

In practice, the ideality factor (n) can be expressed as a function of the cell voltage, and it depends on temperature, cell's PV module number, and voltage variations. In this study, a novel iterative method is introduced to calculate the ideality factor (n), based on the results shown in [14]. This approach enhances the reliability of calculating this parameter. It is expressed by (11).

$$n = n_0 + 0.01\, V_t \quad (11)$$

Chegaar *et al.* [20], it was demonstrated that the ideality factor is contingent on the intensity of the irradiation, increasing linearly with radiation levels above 350 W/m^2.Therefore, we can modify the (11) by:

$$n = n_0 + 0.01\, V_t \;\; + k/G \quad (12)$$

where (n_0) is the ideality factor initial value, (k) is a coefficient representing the influence of solar irradiance on (n), (G) is the solar irradiance. This relationship suggests that the ideality factor (n)can slightly change with variations in solar irradiance and temperature. Although these influences are relatively small, they contribute to achieving more accurate results.

3. MULTI-OBJECTIVE OPTIMIZATION PROCESS

Stochastic optimization algorithms play a key role in solving complex PV cell problems. In this section, the optimization problem is defined by introducing decision variables and specifying the two objective functions. The decision variables are derived from the parameters of the SDM circuit. Subsequently, two objective functions are identified: the first aimed to solve the nonlinear equation for the R_s, while the second aimed to minimize the (RMSE).

To conduct simulations, we implemented the NMOPSO algorithm using "Eclipse" software and JAVA programming language. We extracted the parameters obtained from the NMOPSO algorithm and applied them to the circuit of the SDM using MATLAB/Simulink. This step was crucial in validating the results obtained from the optimization process.

3.1. Decision variables

The decision variables of this optimization problem are the five parameters (R_s), (R_{sh}), (I_0), (I_{ph}), and (n). Table 1 provides the variation ranges for each parameter of each cell.

Table 1. Decision variables

	BP 5170 S	STM640/36	Photowatt-PWP201	RTC Fr	PVM752GaAs	STM6 120/36
$R_s(\Omega)$	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]
$R_{sh}(\Omega)$	[100,400]	[100,600]	[300,800]	[0,100]	[300,800]	[100,400]
I_0(A)	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]
I_{ph}(A)	[0,10]	[0,10]	[0,10]	[0,5]	[0,1]	[0,10]
N	[1,2]	[1,2]	[1,2]	[1,2]	[1,2]	[1,2]

3.2. Objective functions

As previously mentioned, our study focuses on two objective functions: the first aims to minimize the RMSE for each PV cell, while the second aims to calculate the R_s. The equation determining the R_s is nonlinear. Various methods have been explored in the literature to approximate (R_s), including the utilization of the Lambert function as referenced in [16]. In our work, we apply the NMOPSO algorithm. The expression for the first objective function is as follows:

$$f_1 = Minimize\ (RMSE) \tag{13}$$

the RMSE is given by:

$$RMSE = \frac{1}{N}\sqrt{\sum_{i=1}^{N}(I_{measured} - I_{cal})^2} \tag{14}$$

($I_{measured}$) and (I_{cal}) are the measured and estimated currents.

The equation representing the R_s has a non-linear form. Therefore, to find R_s, it is necessary to simplify its expression at first. Based on (10), we can derive the following expression:

$$R_s = \frac{(nV_t \ln\left(\frac{nV_tV_{mp}(2I_{mp}-I_{sc})}{V_{mp}I_{sc}+(I_{mp}-I_{sc})(V_{mp}-R_sI_{mp})-nV_t(V_{mp}I_{sc}-V_{oc}I_{mp})}\right)-I_{mp}(V_{mp}-V_{oc}))}{I_{mp}} \tag{15}$$

either:

$$\frac{(nV_t \ln\left(\frac{nV_tV_{mp}(2I_{mp}-I_{sc})}{V_{mp}I_{sc}+(I_{mp}-I_{sc})(V_{mp}-R_sI_{mp})-nV_t(V_{mp}I_{sc}-V_{oc}I_{mp})}\right)-I_{mp}(V_{mp}-V_{oc}))}{I_{mp}R_s} = 1 \tag{16}$$

for simplifying calculation, we assume two auxiliary variables (A) and (B) that respectively represent the numerator and the denominator of (16). The optimization algorithm aims to identify optimal values of R_s, ensuring that the ratio (A/B) approximates a value close to 1. Therefore, the second objective function can be expressed as (17).

$$f_2 = Minimize\ (1 - \mathrm{A/B}) \tag{17}$$

3.3. Used optimization algorithm

The investigated method uses a recently developed algorithm known as NMOPSO [19]. This stochastic algorithm encompasses a randomized process for generating points within the search space, coupled with a heuristic facilitating convergence. In this approach, particles are represented as vectors navigating through a D-dimensional search space with the objective of aligning themselves with an optimal solution. Each particle is described by both a position (x_{id}) and a velocity (v_{id}). All particles in the swarm can communicate, establishing a global neighborhood of informants. Additionally, each particle maintains a memory that stores the best-visited position (p_{id}) known as the "individual leader", and the optimal position achieved within its neighborhood based on Pareto dominance (p_g) known as the "global leader". Indeed, the incorporation of the global neighborhood technique not only improves exploration of the search space but also facilitates more intelligent movement of particles, aiding in the discovery of optimal solutions. Certainly, the collaborative team behavior demonstrates greater insight compared to that of an individual particle, enabling a more sophisticated approach to the optimization process. To avoid getting trapped in local optima, the NMPSO algorithm monitors the position of an extra particle known as the "contemporary leader" (n_{id}). This position is constantly updated by estimating two random particles in the swarm according to their crowding distance. The solution that is simultaneously non-dominated and less crowded between these particles is designated as the new contemporaneous particle.

During its movement, the particle has multiple choices: it can continue along its current path (with its current velocity v_{id}), return to its previously identified best position (p_{id}), trail the best position identified by its neighborhood (p_g), or advance towards the position of the contemporaneous particle (n_{id}). The computation of the movement and the velocity of particles is determined by means of these four tendencies and considering a specific probability. The movement of particles is calculated using (18).

$$v_{id}(t+1) = \begin{cases} \omega_d(t)v_{id}(t) + c_1r_1(p_{id} - x_{id}) + c_2r_2(p_g - x_{id}) if rand(\ \ ) \geq \eta \\ \omega_d(t)v_{id}(t) + c_1r_1(p_{id} - x_{id}) + c_2r_2(p_g - x_{id}) if rand(\ \ ) < \eta \\ \qquad +c_3r_3(n_{id} - x_{id}) \end{cases} \tag{18}$$

(ω_d) is the inertia factor ($\omega_d \in [\omega_{min}, \omega_{max}]$), ($c_1$), ($c_2$), and ($c_3$) are the learning factors, and (r_1), (r_2), and (r_3) are a random numbers belonging to [0.1], determined following a probabilistic distribution.

The inertia factor and the learning factors are employed to govern the particle's motion, striking a balance between exploitation and exploration within the search space. In this algorithm, an evolutionary strategy used to adjust the values of these factors. Indeed, this approach integrates the adaptive inertia factor technique and gives heightened importance to the intelligence of individual particles from the initial stages. As the process unfolds, NMOPSO then highlights the collective intelligence of the entire swarm in later stages. These factors are expressed as follows:

$$\omega_d(t) = \begin{cases} \omega_{max} & if x_{id}(t) > x_{mean} \\ \omega_{min} - \frac{(\omega_{max}-\omega_{min})\times(x_{id}(t)-x_{min})}{(x_{mean}-x_{min})} & if x_{id}(t) \leq x_{mean} \end{cases} \tag{19}$$

$$c_1 = 0.5 + 2 \times \cos\left(\frac{\pi\times(t-1)}{2\times(T-1)}\right) \tag{20}$$

$$c_2 = 0.5 + 2 \times \sin\left(\frac{\pi\times(t-1)}{2\times(T-1)}\right) \tag{21}$$

$$c_3 = c_1 \tag{22}$$

where (x_{min}) is the minimum value of (x_{id}), (x_{mean}) is the mean value of (x_{id}), and T is the maximum number of generations.

Finally, this algorithm uses the mutation mechanism on two thirds of the particles and incorporates the crowding distance to enhance the diversity of solutions. Additionally, it utilizes an external archive to store the optimal solutions. The pseudocode for the NMOPSO algorithm is provided in algorithm 1.

Algorithm 1. Pseudocode of NMOPSO
```
Initialize the positions of the particles in the swarm
Evaluate the particles
Initialize the individual and the global leaders
Compute the crowding distance for the global leaders
Initialize the contemporary leaders
Repeat
    For each particle do
        Choose the global leader.
        Update the velocity and position
        Mutate particle based on a specified probability
        Evaluate the particle
        Update the individual leader.
    End for
    Update the global and contemporary leaders of particles.
    Send global leaders to the external archive.
    Compute the crowding distance for global leaders
Until (maximum number of generations is reached)
Return the external archive
```

4. RESULTS AND DISCUSSION

To evaluate the accuracy of our proposed method and quantify the variance between the obtained results and measurements, we apply the RMSE criterion. This criterion is determined for various solar cell configurations, including:

– The BP 5170 S PV module uses 72 monocrystalline silicon cells connected in series, operating at a temperature of 25 °C with an irradiation of 1,000 W/m^2.
– The Photowatt-PWP 201 Polycrystalline solar modules consist of 36 cells connected in series, operating at a temperature of 45°C under an irradiation of 1,000 W/m^2.
– The STM6 40/36 and STM6 120/36, both working at STC at a temperature of 25 °C with an irradiation of 1,000 W/m^2.
– The PVM 752 GaAs thin film cell, which operates at STC conditions, 25 °C temperature, and 1,000 W/m^2 irradiation.
– The RTC France silicon solar cell, featuring a 57 mm diameter, operates at 33 °C temperature with an irradiation of 1,000 W/m^2.

The diverse configurations used for evaluating the accuracy of our method across a broad spectrum of solar cell types and environmental conditions. Moreover, accurately predicting the I-V curves of commercial PV modules is crucial to validate the accuracy of the algorithm used as a tool for characterizing the performance of these modules. The analyzed PV cells are defined with electrical characteristics which are: the number of cells in series (N_s), the maximum power current (I_{mp}), the maximum power voltage (V_{mp}), the short-circuit current (I_{sc}), and the open-circuit voltage (V_{oc}). These electrical characteristics are summarized in Table 2. Table 3 presents the results of the five parameters from the applied NMOPSO based technique for the tested six PV cells/modules. Based on these results, we can notice a good agreement between the experimental and the calculated data, proving the capability of our approach in determining the parameters of the SDM.

Table 2. Electrical characteristics of the analyzed PV cells

Electrical feature	BP 5170 S	STM6 40/36	Photowatt PWP201	R T C France	PVM 752 GaAs	STM6 120/36
V_{mp} (V)	36	16.98	12.649	0.4507	0.8053	14.93
I_{mp} (A)	4.72	1.5	0.9120	0.6894	0.0937	6.83
V_{oc} (V)	44.2	21.02	16.778	0 .5728	0.9926	19.21
I_{sc} (A)	5	1.663	1.030	0 .7603	0.0998	7.48
N_s	72	36	36	1	1	36

Table 3. Optimization results

	BP 5170 S	STM6 40/36	Photowatt-PWP 201	RTC France	PVM 752 GaAs	STM6 120/36
$R_s(\Omega)$	0.0703778	0.3311865	1.1911289623	0.417162634	0.811289641	0.1781934744
$R_{sh}(\Omega)$	310.87934	561.50323	746.4801465	47.1474685	714.8837096	332.9372046
I_0(A)	1.83508109E-9	3.7497114E-6	1.31882751E-9	1.06120171E-7	4.574814706E-6	3.3688578E-6
I_{ph}(A)	4.5840218286	6.01105736	5.770375599	0.90047277	0.0860941433	6.011057366
N	1.3255348	1.3151594	1.1911289623	1.63263594	1.20986271	1.268352761

According to the obtained results, we can also notice, that the error between the measured current and the calculated one is nearly negligible, which shows the accuracy of the proposed method. The optimization outcomes achieved by the NMOPSO algorithm for minimizing RMSE are contrasted with alternative methods, each referenced accordingly. The results for the four solar cells are presented in Tables 4 to 6.

For the PVM 752 GaAs listed in Table 4, the NMOPSO algorithm exhibits exceptional accuracy, gives a significantly lower RMSE (0.915 10^{-3}) compared to alternative models. Similar conclusions are noticed for the STM6-40/36 cell, where NMOPSO surpasses other models with a lower RMSE (1.019 10^{-3}) compared to other algorithms. Furthermore, for the Polycrystalline Photowatt-PWP 201 results illustrated in Table 5, NMOPSO maintains its remarkable accuracy with a minimal RMSE of (0.212 10^{-3}). This performance notably exceeds the RMSE obtained with other techniques, confirming the NMOPSO's effectiveness in estimating the characteristics of this polycrystalline solar module. For the solar cell -RTC France, NMOPSO demonstrates its superiority by achieving an impressively low RMSE of (0.14 10^{-3}). Notably, NMOPSO outperforms alternative methods such as enhanced leader particle swarm optimization (ELPSO), conventional particle swarm optimization (CPSO), backtracking search algorithm (BSA), and artificial bee colony (ABC). Table 7 present the values of the second objective function, all of which converge to nearly zero. This convergence validates the accuracy of the R_s obtained, validating the efficacy of NMOPSO in solving the non-linear equation.

Table 4. Calculated RMSE for PVM 752 GaAs and STM6-40/36 cells

Model	RMSE PVM 752 GaAs	RMSE STM6-40/36
NMOPSO	0.915 .10^{-3}	1.019 .10^{-3}
Lidaighbi *et al.* [14]	1.865 .10^{-3}	1.903 .10^{-3}
ELPSO	25.40 .10^{-3}	2.18 .10^{-3}
CPSO	25.40 .10^{-3}	2.18 .10^{-3}
BSA	2.14 .10^{-3}	3.62 .10^{-3}
ABC	2.04 .10^{-3}	2.39 .10^{-3}

Table 5. Calculated RMSE for polycrystalline photowatt-PWP 201

Model	RMSE Photowatt-PWP 201
NMOPSO	0.212 .10^{-3}
Kareem and Saravanan [21]	6.54 .10^{-3}
Cubas *et al.* [22]	2.94 .10^{-3}
Phang *et al.* [23]	3.549 .10^{-3}
Lidaighbi *et al.* [14]	2.164 .10^{-3}

Table 6. Calculated RMSE for solar cell -RTC France

Model	RMSE solar cell-RTC France
NMOPSO	$0.14 .10^{-3}$
Lidaighbi *et al.* [14]	$0.886.10^{-3}$
Peng *et al.* [24]	$3.54 .10^{-3}$
Louzazni *et al.* [25]	$5.80 .10^{-3}$
Toledo *et al.* [26]	$0.777 .10^{-3}$
Ishibashi *et al.* [27]	8.08010^{-3}
Akbaba and Alattawi [28]	$23.60 .10^{-3}$
Das [29]	$31.74 .10^{-3}$
Lun *et al.* [30]	$14.01 .10^{-3}$
Pindado and Cubas [31]	$7.63 .10^{-3}$
Oulcaid *et al.* [32]	$31.99 .10^{-3}$
BSA [33]	$1.44 .10^{-3}$
ABC [33]	$0.88 .10^{-3}$
GWOCS [17]	$0.98 .10^{-3}$
MPSO [34]	$7.330 .10^{-3}$
HCLPSO [35]	$1.12 .10^{-3}$

Table 7. Results of the second objective function

	BP 5170 S	STM6 40/36	Photowatt-PWP 201	RTC France	PVM 752 GaAs	STM6 120/36
f_2	0.000101	0.000098	0.00032	0.00011	0.00002	0.00001

Concerning the computational time of several swarm optimization algorithms, we calculated the average time of the NMOPSO algorithm. We executed the algorithm ten times for each cell, and we evaluate the average performance. The results are presented in Table 8. Among all the studied algorithms, NMOPSO exhibits the shortest execution time, highlighting its rapid convergence.

The comparison among diverse algorithms applied to specific cell types, including PVM 752 GaAs, STM6-40/36, Photowatt-PWP 201, and solar cell-RTC France, shows that the proposed method in this study tended the minimum RMSE values. To demonstrate the precision of the proposed algorithm, extensive simulations were carried out using MATLAB. Figure 2 serves as an example using the STM6 40/36 PV cell/module. After extracting the parameters values from the NMOPSO algorithm, we applied them within our Simulink model. The obtained simulation results are presented in Figures 3 to 6. These figures illustrate the I(V) curves extracted from the module datasheets under STC.

Table 8. Run time

	NMOPSO	EPSO [13]	IPSO [13]	PSO [13]	DE [13]	ABC [13]
Run time (second)	3.299	3.8990	4.768	4.484	9.318	11.12

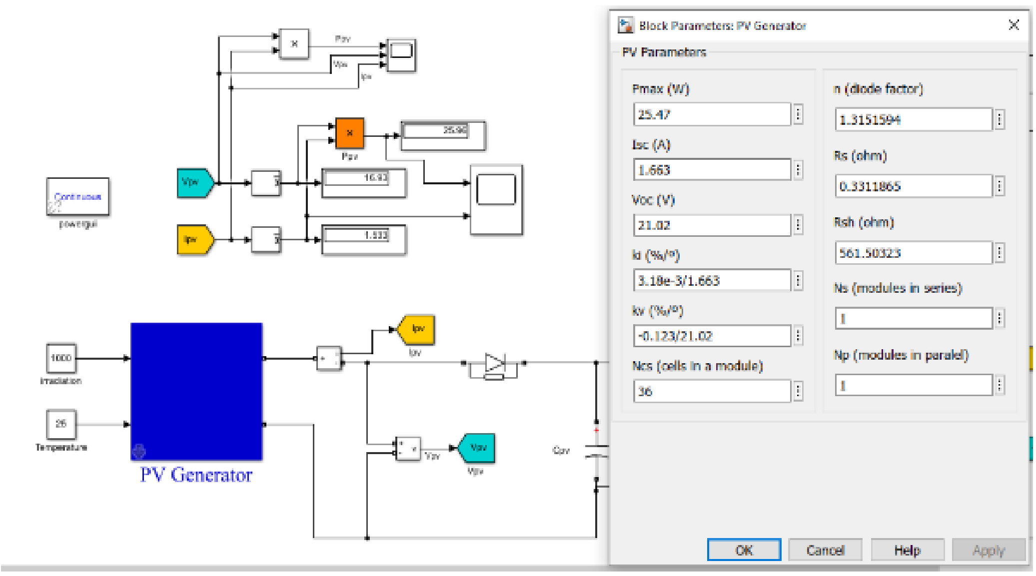

Figure 2. Simulation of STM6 40/36 PV cell/module

The red points on the graphs represent the experimental I(V) data collected directly from the datasheet. The continuous blue line, on the other hand, represents the simulated curves generated using the parameters extracted through the proposed method. From these figures, we can clearly notice that the simulated and experimental I(V) characteristics are practically identical. These figures also show a high degree of agreement between experimental and calculated data, validating the efficacy of the proposed method.

This analysis includes the evaluation of diverse algorithms for different cell models, including an extensive variety of methods, such as analytical, numerical, and metaheuristic techniques. Our study submit an evaluation, comparing the NMOPSO-based approach against a spectrum of analytical methods in [14], [24]-[26], explicit models [28]-[31], and significant metaheuristic strategies such as the GWO in [32]. By comparing the results of RMSE values for algorithms like ELPSO, CPSO, BSA, and ABC [33], the proposed algorithm turns to be the best.

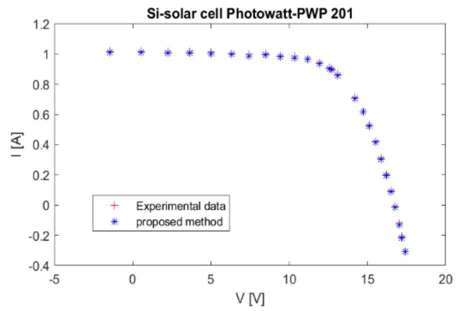

Figure 3. Curve I-V related PWP201 (T=45 °C, 1,000 W/m^2)

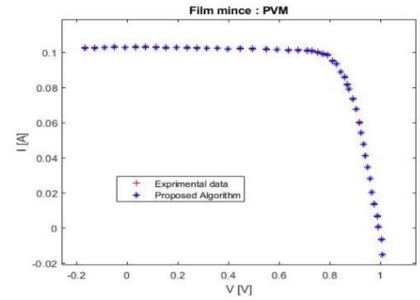

Figure 4. Curve I-V related to PVM 752 GaAs (T=25 °C, G=1,000 W/m^2)

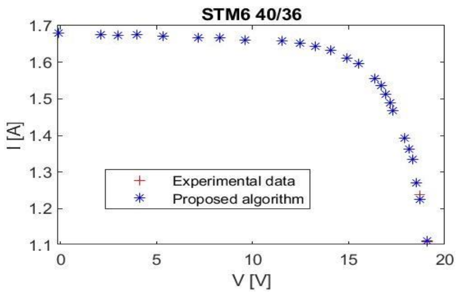

Figure 5. Curve STM6 40/36 T=25 °C, G=1,000 W/m^2

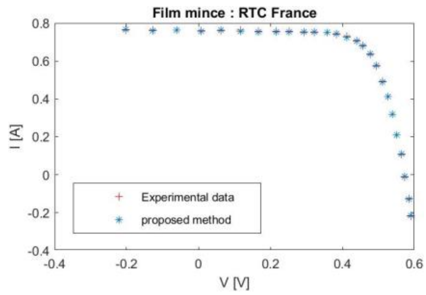

Figure 6. curve I-V curves related to RTC (T=33 °C, G=1,000 W/m^2)

Furthermore, NMOPSO-based algorithm outperformed other techniques not only in accuracy but also in execution time. Its ability to converge faster makes it an appealing and reliable tool for rapid and dependable parameter extraction in the PV domain.

Overall, the comprehensive analysis underscores the robustness and effectiveness of NMOPSO, presenting it as a highly accurate method for characterizing and evaluating these specific types of cells within the field of solar energy research. This proposed approach not only improves the accuracy and efficiency of parameters extraction but also establishes a novel enhance PSO in the optimization of PV cell parameters. While our study establishes the application of the NMOPSO as a superior optimization strategy, future research can delve into its applicability in dynamic environmental conditions, scalability to larger solar energy systems, and integration with emerging technologies in the solar energy sector.

5. CONCLUSION

In the present work, we apply an innovative method based on the improved NMOPSO to accurately extract essential parameters of PV cells. Our approach focuses on minimizing the RMSE while precisely computing R_s. The proposed algorithm integrates an evolutionary search strategy, enhancing both convergence and the precision of parameter identification processes.

Recent observations suggest that the precision in parameter extraction significantly impacts the performance of PV cells. Our findings provide conclusive evidence that the NMOPSO algorithm is associated with enhanced accuracy in parameter extraction and minimal RMSE values. Through extensive simulations, our method significantly outperformed existing approaches. NMOPSO-based optimization technique demonstrated superior accuracy by minimizing RMSE values, enabling closer alignment between simulated and experimental data. This heightened accuracy is crucial for precise modeling and prediction of PV cell behavior. Furthermore, our approach was also applied for the determination of the R_s which is a critical parameter impacting PV cell efficiency. Indeed, the results highlight the effectiveness and superiority of our technique compared to existing approaches. Its accuracy and satisfying results make it a valuable and reliable technique for characterizing and determining PV cell parameters. Our study demonstrates the efficiency of evolutionary techniques in determining PV cells parameters for SDMs. Moreover, futures studies may explore the extension of the obtained findings to other models.

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