Review Article

Analytical versus Metaheuristic Methods to Extract the Photovoltaic Cells and Panel Parameters

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1. Introduction

Nowadays, the power forecasting for the photovoltaic panels and systems plays a very important role for the investors to increase the investments having a realistic scenario. One of the steps to achieve this goal is to accurately and quickly determine the parameters of the photovoltaic cells and panels.

The extraction of the photovoltaic cell parameters is a widely studied issue [1, 2], but it remains current due to its importance and the new possibilities created by the metaheuristic algorithms and artificial intelligence [3].

The parameter extraction is possible if there is a dataset which consists of voltage-current pairs \((V, I)\) for the photovoltaic panel, or if the current-voltage characteristic \((I-V)\) is measured. The parameters and dataset can be obtained using the photovoltaic panel datasheet given by the producer [4].

The most commonly used mathematical model to characterize the photovoltaic cells and panels is the single diode model \((SD)\) [1], followed by the double diode model \((DD)\) [5] and rarely three diode model \((TD)\) [6]. The number of the parameters which have to be extracted varies, being five for SD, seven for DD, and nine for TD. There are a lot of methods to extract these parameters, their complexity growing with the increasing number of parameters.

The methods used to extract the parameters of the photovoltaic cells or panels can be classified into analytical, metaheuristic, and hybrid methods [7]. Each of these methods has both advantages and disadvantages.

The contributions and novelty of this paper are as follows:

(i) The main analytical methods and metaheuristic algorithms grouped on families are briefly presented...
(ii) The performance of the methods is analyzed in function of the accuracy with which the parameters are extracted analyzing the absolute error, the root mean square error, and the coefficient of determination.

(iii) Choosing the best analytical method considering the following: simplicity of application, the execution time, and the accuracy.

(iv) Choosing the metaheuristic algorithm with the smallest root mean square error (RMSE) for different photovoltaic cells and panels from all algorithms considered.

(v) Comparing for the first time the analytical method (modified five parameters) and metaheuristic algorithm (hybrid successive discretization algorithm) to forecast the I-V characteristic and the maximum power generated by the commercial monocrystalline photovoltaic panel, giving the manufacturers a tool to choose the best option to characterize the PV for their applications. Additionally, the genetic algorithm is considered in the comparison.

The rest of the paper is organized as follows: the equivalent circuits and diode models, statistical tests used for comparison, and the mathematical formulas for calculating the photovoltaic cells and panel parameters at different temperatures and irradiances in the function of their values at the standard test conditions (STC-irradiance 1000 W/m², temperature 25°C, and air mass 1.5) are described in Section 2. A brief presentation of the used methods is made in Section 3. The results and discussions are presented in Section 4, and the last section is dedicated to conclusions and future works.

2. Methods

2.1. Photovoltaic Cells and Panel Diode Models. The mathematical model which describes the dependence between the current and the voltage generated by the photovoltaic cells and panels depends on the mechanisms which are taken into account and consequently on the equivalent circuits, Figure 1. The simplest model is the ideal one. The most commonly used model is single diode, Figure 1(a), due to its simplicity but also because it manages to describe the behaviour of most types of photovoltaic cells and panels very well. Equation (1) is the mathematical relation for one diode model:

\[ I = I_{ph} - I_0 \left( e^{(V_r + R_s/I_0)V_T} - 1 \right) - \frac{V + IR_s}{R_{sh}}, \]

where \( I_{ph} \) is the photogenerated current, \( I_0 \) is the reverse saturation current, \( R_s \) is the series resistance, \( R_{sh} \) is the shunt resistance, \( n \) is the ideality factor of diode, and \( V_T \) is the thermal voltage, \( V_T = kT/q \). \( k \) is the Boltzmann constant, \( T \) is the temperature, and \( q \) is the elementary electrical charge.

The double diode model is described by

\[ I = I_{ph} - I_0 \left( e^{(V_r + R_s/I_0)V_T} - 1 \right) - I_{oa} \left( e^{(V_r + R_s/I_0)V_T} - 1 \right) - \frac{V + IR_s}{R_{sh}}, \]  

where index 1 relates to the diffusion mechanism and 2 the generation-recombination mechanism. The accuracy to determine the parameters of the photovoltaic cell increases especially at low solar radiation when the two diode model is used [8].

The mathematical model for the photovoltaic panel is described by

\[ I = N_p I_{ph} - N_p I_0 \left( e^{(N_r V_r + N_s R_s)/N_r N_s V_T} - 1 \right) - \frac{N_p V + N_s IR_s}{N_s R_{sh}}, \]

where \( N_p \) represents the number of the photovoltaic cells connected in series and \( N_s \) represents the number of the photovoltaic cells connected in parallel.

2.2. Statistical Test. The comparison between analytical and metaheuristic algorithms is achieved using different statistical error tests, such as absolute error (AE) Equation (4), the root mean square error Equation (5), and the coefficient of determination \( R^2 \) Equation (6).

\[ AE = \sum_{i=1}^{n} |I_{ic} - I_{im}|, \]

\[ \text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (I_{ic} - I_{im})^2}{n}}, \]

\[ R^2 = 1 - \frac{\sum_{i=1}^{n} (I_{ic} - I_{im})^2}{\sum_{i=1}^{n} (I_{im} - \bar{I}_{im})^2}, \]

where \( I_{ic} \) and \( I_{im} \) represent the calculated and the measured current, respectively, and \( n \) is the total number of measurements.

2.3. Irradiance and Temperature Dependence of the PV Parameters. The irradiance and temperature influence more or less the parameters of the photovoltaic cells and panels. The power generated is also dependent on these two factors. So, the relation for photogenerated current, function of the irradiance, and temperature is the following [9]:

\[ I_{ph} = \frac{G}{G_{ref}} \left[ I_{ph,ref} + \alpha_{sc}(T, T_{ref}) \right], \]

where \( G \) is irradiance, \( T \) represent the temperature, and \( \alpha_{sc} \) is the temperature coefficient of the current. The index ref
is for the parameters at STC. The reverse saturation current can be calculated with Equation (8) [9, 10]:

\[ I_o = I_{o,ref} \left( \frac{T}{T_{ref}} \right)^3 e^{\frac{E_g}{kT_{ref}}} \left( \frac{E_g}{T_{ref}} \right) \] (8)

where \( E_g \) is the energy bandgap. This value depends slightly on temperature [11, 12]:

\[ E_g = E_{g,ref} \left( 1 - 0.0002677(T - T_{ref}) \right) \] (9)

The ideality factor of diode depends slightly on the irradiance [13]. The temperature dependence can be written as Equation (10) [9]:

\[ n = n_{ref} \frac{T}{T_{ref}} \] (10)

The behaviour of the shunt resistance is inversely proportional to that of irradiance, the irradiance increasing as the shunt resistance decreases:

\[ R_{sh} = R_{sh,ref} \frac{G_{ref}}{G} \] (11)

The dependence of the series resistance on temperature and irradiance is described by Equation (12). It decreases linearly with the increase in temperature and increases with the increase of irradiance; \( \beta \) is constant and is considered equal to 0.217 [11, 14].

\[ R_{sh} = R_{sh,ref} \frac{T}{T_{ref}} \left( 1 - \beta \ln \frac{G}{G_{ref}} \right) \] (12)

3. Analytical and Metaheuristic Methods

Pillai and Rajasekar classified the methods to extract the parameters of the photovoltaic cells and panels in analytical, metaheuristic, and hybrid (consisting of those mentioned before) methods [8]. The analytical methods are based on formulas obtained using approximation and/or particular points on the I-V characteristic and some parts of the I-V characteristics. Multiobjective optimization problems were tough issues, but the development and use of metaheuristic algorithms in the last years led to solutions with a very good accuracy [15]. These metaheuristic algorithms were quickly adapted and used to solve the multimodal problem of the current-voltage dependence of the photovoltaic devices.

3.1. Analytical Methods. These methods were used to calculate the parameters of the photovoltaic cells since the 60s [13]. A lot of methods have been developed, especially for the SD model, but in the last years, they were developed for DD and even TD models. They can calculate one, more than one, or all parameters of the photovoltaic cells and panels. The several analytical methods are presented in Table 1.

The complexity of usage and the accuracy of the method to extract the parameters of the photovoltaic cells or panels are two key indicators. Three-level ratings are used for each of them: low, medium, and high. For the complexity of usage, they mean as follows: low: simple formulas are used; medium: complex formulas, fitting and iterative procedure are necessary; high: the analytical method needs dedicated computational software [29]. For the accuracy, the level rating is the function of the statistical test [29, 30]. The rating for each method is shown in Table 1. Their results can be used by the manufacturers to choose the optimum method to characterize the photovoltaic cells.

The analytical five-parameter method, 5P, is the most widely used of the analytical ones to extract the parameters of the photovoltaic cells. The first step is to calculate the...
Table 1: The analytical methods.

| Methods                  | Parameters                  | Models | Remarks                                                                 | Complexity of usage | Accuracy | Ref. |
|---------------------------|-----------------------------|--------|--------------------------------------------------------------------------|----------------------|----------|------|
| Analytical five-parameter method | $I_{ph}, I_o, n, R_s, R_{sh}$ | SD     | Using part of $I$-$V$ characteristic to determine $R_s$ and $R_{sh}$     | Medium               | High     | [16] |
| Tivanov                   | $I_{ph}, I_o, n, R_s, R_{sh}$ | SD     | Using part of $I$-$V$ characteristic to determine $R_s$ and $R_{sh}$ and $I_{ph} \sim I_{sc}$ | Medium               | Medium   | [17] |
| Ortiz-Conde               | $I_{ph}, I_o, n, R_s, R_{sh}$ | SD     | Using the CC function to calculate the equation coefficients $C_{V1}, C_{V2}$ and $C_{12}$ | Low                  | Medium   | [18] |
| Garrido-Alzar             | $I_{ph}, I_{od}, I_{ao}, n, R_s, R_{sh}$ | DD    | $n_s$ is considered 1, and four points $(V, I)$ are using               | Medium               | Low      | [19] |
| Generalized area          | $n, R_s, R_{sh}$            | SD     | Using $I_{ph} \sim I_{sc}$ and the subgraphic area for three $I$-$V$ characteristics | High                 | Low      | [20] |
| Area                      | $R_s$                       | SD     | Using subgraphic area for $I$-$V$ characteristic and $n = 1$           | Low                  | Low      | [21] |
| Kaminski                  | $I_{od}, I_{ao}, n, R_s, R_{sh}$ | DD    | The parameters are determined in dark conditions                        | Low                  | Low      | [22] |
| $R_s$ model               | $I_{od}, I_{ao}, n, R_s, R_{sh}$ | SD     | $R_{sh}$ is considered∞                                                  | Medium               | Low      | [23] |
| L. function               | $R_s, R_{sh}$               | SD     | Using Lambert W function                                                | High                 | Medium   | [24] |

Explicit method for the five parameters

Cotfas

| Parameters                  | Models | Remarks                                                                 | Complexity of usage | Accuracy | Ref. |
|-----------------------------|--------|--------------------------------------------------------------------------|----------------------|----------|------|
| Elkholy                     | $I_{ph}, I_o, n, R_s, R_{sh}$ | SD     | Using two empirically equations to calculate $R_s$ and $R_{sh}$          | Medium               | Medium   | [7]  |
| Ndegwa                      | $I_{ph}, I_o, n, R_s, R_{sh}$ | SD     | Using a method based on the nonlinear least-squares algorithm; the parameters are calculated at different environmental conditions $n$ and $I_o$ are calculated firstly using $I_{sc}, m, V_m, V_{oc}$, and $R_s = 0, R_{sh} = \infty$; $R_s$ and $R_{sh}$ are then evaluated for different values of $n_s$ in the neighborhood of $n_o$ $(1 \leq n \leq n_o)$ | Medium               | Medium   | [26] |
| TRDLA                       | $I_{ph}, I_o, n, R_s, R_{sh}$ | SD     | $n$ is calculated firstly using the data provided by the manufacturer’s datasheet; the other four parameters are calculated using the trust-region-dogleg algorithm | Medium               | Medium   | [27] |
| Brano                       | $I_{ph}, I_o, n, R_s, R_{sh}$ | SD     | Using five equations derived from Equation (1)                           | Medium               | Medium   | [28] |

\[
R_{so} = -\left(\frac{dV}{dT}\right)_{V=V_{oc}}, \quad (13)
\]

\[
R_{sh} = R_{sho} = -\left(\frac{dV}{dT}\right)_{I=I_{sc}}, \quad (14)
\]

\[
R_{so} = 0.002102 + 0.318070 R_{sm}, R_{sm} = \frac{V_{oc} - V_m}{I_m}, \quad (15)
\]

\[
R_{sho} = -0.051914 + 2.505219 R_{sm}, R_{shm} = \frac{V_m}{I_{sc} - I_m}, \quad (16)
\]

\[
n = \frac{V_m + R_s I_m - V_{oc}}{V_m + R_s I_m - V_{oc}} \ln \frac{I_m (V_m - (V_m/R_{sho}) - I_m) - \ln (I_m - (V_m/(V_m/R_{sho}))) + I_m (I_m - (V_m/(V_m/R_{sho})))}{I_m}.
\]

3.2. Metaheuristic Methods. The metaheuristic algorithms have been used to extract the parameters of the PV since the 2000s, when Jervase et al. used the genetic algorithms.
Table 2: The metaheuristic algorithms.

| Family algorithms                  | Type  | Models                        | PV                             | Range set               | Computational time/iterations | Reference |
|-----------------------------------|-------|-------------------------------|--------------------------------|-------------------------|------------------------------|-----------|
| Genetic                           | Simple| SD                            | 50 W panel                     | Partially              | -/50                         | [31]      |
| Genetic                           | Simple| SD                            | 57 mm RTC France solar cell    | Yes                     | -/-                          | [32]      |
| GA-R                              | Simple| SD                            | 57 mm RTC France solar cell, mSi commercial photovoltaic cell | Partially              | 56 s/5000                   | [33]      |
| Genetic GA-LS                     | Hybrid| SD                            | 57 mm RTC France solar cell    | Yes                     | -/-                          | [34]      |
| Differential evolution DE         | Simple| SD, DD                        | 57 mm RTC France solar cell, PWP201 photovoltaic panel | Yes                    | 12 s and 16 s/10000 and 20000 | [35]      |
| Differential evolution R_{r} IJADE| Simple| SD, DD                        | 57 mm RTC France solar cell    | Yes                     | 33 s and 58 s/10000 and 20000 | [36]      |
| Penalty differential evolution P-DE| Simple| DD                            | pSi-S75 and S115 mSi-SM55 and SQ150PC tin film-ST36 and ST40 | Partially              | 42 s/500                     | [37]      |
| Differential evolution with an individual-dependent mechanism IDE | Simple| SD, DD                        | 57 mm RTC France solar cell, PWP201 photovoltaic panel | Yes                    | -/10000 and 20000            |           |
| Linear population success-history-based adaptive DE L-SHADE | Simple| SD, DD                        | 57 mm RTC France solar cell, PWP201 photovoltaic panel | Yes                    | 35.4 and 62.66 s/10000 and 20000 | [35]      |
| Differential evolution DEIM       | Hybrid| SD, DD                        | KC120 PV module                | Yes                     | 32 s/10000 and 20000         | [38]      |
| Particle swarm optimization CPSO  | Simple| SD                            | 57 mm RTC France solar cell    | Yes                     | -/4500                       | [39]      |
| Particle swarm optimization VCPSO | Simple| DD                            | —                              | No                      | -/-                          | [40]      |
| Particle swarm optimization NM-MPSO| Hybrid| SD, DD                        | 57 mm RTC France solar cell    | Yes                     | -/350000                     | [41]      |
| Fractional chaotic ensemble particle swarm optimizer FC-EPSO | Hybrid| SD, DD                        | 57 mm RTC France solar cell    | Yes                    | 11.5 s and 12 s/200          | [42]      |
| Chaotic heterogeneous comprehensive learning PSO C-HCLPSO | Hybrid| SD, DD                        | 57 mm RTC France solar cell    | Yes                    | 204 s and 225 s/2000         | [43]      |
| Hybrid successive discretization algorithm HSDA | Hybrid| SD, DD                        | 57 mm RTC France solar cell, 3 × 3 cm monocrystalline silicon photovoltaic cell, PWP201 photovoltaic panel, STP6-120/36, STM6-40/36, etc. | Yes                    | 28 s and 46 s/4               | [44]      |
| Discretization SDA                | Simple| SD                            | 57 mm RTC France solar cell    | Yes                     | 142 s and 266 s/4            | [3]       |
| Discretization PSDA               | Simple| SD, DD                        | 57 mm RTC France solar cell, PWP201 photovoltaic panel, Kyocera KC200GT photovoltaic panel | Yes                    | 28 s and 46 s/4               | [45]      |
| Artificial bee colony optimization ABCO | Simple| SD, DD                        | 57 mm RTC France solar cell, PWP201 photovoltaic panel, STM6-40/36 | Yes                    | -/10000                      | [46]      |
| Artificial bee colony optimization ABC-NMS | Hybrid| SD                            | 57 mm RTC France solar cell, PWP201 photovoltaic panel | Yes                    | -5000                        | [47]      |
| Shuffled complex evolution ISCE    | Simple| SD                            | 57 mm RTC France solar cell, PWP201 photovoltaic panel | Yes                    | -5000 and 10000              | [48]      |
| Shuffled complex evolution-opposition-based learning ESCE-OBL | Hybrid| SD, DD                        | 57 mm RTC France solar cell, PWP201 photovoltaic panel | Yes                    | -/5000 and 10000             | [49]      |
| Simulated annealing SA            | Simple| SD, DD                        | 57 mm R.T.C France solar cell, Photowatt-PWP201 | Yes                    | -/5000 and 10000             | [64]      |
and the DD model to extract the seven parameters of the photovoltaic cell [31]. By using metaheuristic algorithms, all parameters of the photovoltaic cells and panels can be calculated. There are a lot of metaheuristic algorithms applied to extract the parameters of the photovoltaic cells and panels. The lower and upper values for the photovoltaic cells or panel parameters are necessary to be considered for the limitation of the global optimum search. Table 2 presents some of them, classified on family and on whether they are simple or hybrid [8]. The families of the algorithms presented are genetic algorithms (GA) [31–34], differential evolution (DE) [35–38], particle swarm optimization (PSO) [39–43], discretization [3, 44, 45], artificial bee colony (ABC) [46, 47], shuffled complex evolution [48, 49], simulated annealing (SA) [50, 51], flower pollination algorithm (FPA) [52, 53], harmony search (HS) [54], JAYA algorithm [55–57], teaching–learning-based optimization algorithm [58, 59], whale optimization algorithm [60, 61], and backtracking search algorithm [62, 63]. Additionally, the diode model is shown, computational time and the iteration number when these are given.

One of the new and the best algorithms, HSDA [44], is used against the modified analytical method to forecast the I–V characteristic and maximum power generated. The HSDA algorithm is an improved version of the SDA algorithm [3]. It is a hybrid one. The first algorithm used is one of the existent algorithms and gives a solution for SDA. A vicinity is considered around it, and the parameters can be extracted with very good accuracy using SDA for this vicinity. The flow chart of the HSDA algorithm is presented in Figure 2.

### Table 2: Continued.

| Family algorithms                  | Type       | Models                  | PV                        | Range set | Computational time/iterations | Reference |
|------------------------------------|------------|-------------------------|---------------------------|-----------|------------------------------|-----------|
| Simulated annealing LM-SA          | Hybrid     | SD, DD                  | 57 mm RTC France solar cell, Photowatt-PWP201 | Partially | -20000                      | [52]      |
| Flower pollination FPA             | Simple     | SD, DD                  | 57 mm RTC France solar cell, Photowatt-PWP201 | Yes       | -25000                      | [51]      |
| Flower pollination BPFPA           | Hybrid     | SD, DD                  | 57 mm RTC France solar cell | Partially | -20000                      | [52]      |
| Harmony search HS                  | Simple     | SD, DD                  | 57 mm RTC France solar cell | Partially | -5000                       | [53]      |
| Innovative global harmony search IGHS | Simple   | SD, DD                  | 57 mm RTC France solar cell | Partially | -5000                       | [53]      |
| Pattern search PS                  | Simple     | SD, DD                  | 57 mm RTC France solar cell, PWP201 photovoltaic panel | Yes | -50000                      | [54]      |
| JAYA algorithm IJAYA               | Simple     | SD, DD                  | 57 mm RTC France solar cell, PWP201 photovoltaic panel | Yes | -50000                      | [55]      |
| Performance-guided JAYA algorithm PGJAYA | Simple | SD, DD                  | 57 mm RTC France solar cell, Photowatt-PWP201 | Yes | -50000                      | [56]      |
| Comprehensive learning JAYA algorithm CJAYA | Simple | SD, DD                  | 57 mm RTC France solar cell, PWP201 photovoltaic panel | -20000 and 48000 | 50000                     | [57]      |
| Teaching–learning-based optimization TLBO | Simple | SD, DD                  | 57 mm RTC France solar cell, PWP201 photovoltaic panel | Yes | -20000                      | [58]      |
| Improved TLBO ITLBO               | Simple     | SD, DD                  | 57 mm RTC France solar cell, PWP201 photovoltaic panel, STP6-120/36, STM6-40/36 | 5.95 s (30) and 6.60 s (30) | 50000         | [59]      |
| Whale optimization algorithm WOA   | Simple     | SD, DD                  | KC200GT                   | Yes       | -45000                      | [60]      |
| Improved version of WOA IWOA      | Simple     | SD, DD                  | 57 mm RTC France solar cell, PWP201 photovoltaic panel, JAM6-60-295W-4BB, CS6U-320P | Yes | -100000                     | [61]      |
| Multiple learning backtracking search algorithm MLBSA | Simple | SD, DD                  | 57 mm RTC France solar cell, PWP201 photovoltaic panel | Yes | 39 and 44 s/ 50000         | [62]      |
| BSA-Lévy flight (LFBSA)            | Simple     | SD, DD                  | 57 mm RTC France solar cell, PWP201 photovoltaic panel | Yes | -50000                      | [63]      |
Input:
Initial seed $X$, $P = (p_1, p_2, \ldots, p_n)$,
$d_1, d_2, \ldots, d_n$,
$max\_no\_of\_iterations$

Using (2), (3) and (4) construct the intervals:
$[a_i, b_i], i = 1, 2, \ldots, n$

Apply SDA on the $n$-dimensional interval:

iteration $= 1$

Using (2), (3) and (4) construct the intervals:
$[a_i, b_i], i = 1, 2, \ldots, n$

Apply SDA on the $n$-dimensional interval:

iteration $= \text{iteration} + 1$

$X = \text{solution found by}$

Yes

$X$ is not settled and
iteration $< \text{max\_no\_of\_iterations}$

No

Output:
The last value of $X$

Figure 2: HSDA algorithm flow chart [44].

Table 3: The parameters and statistical tests for RTC cell.

| Algorithm     | $I_{ph}$ (A) | $I_o$ (μA) | $n$ | $R_s(\Omega)$ | $R_{sh}(\Omega)$ | RMSE | AE      | $R^2$   |
|---------------|--------------|------------|-----|----------------|-----------------|------|---------|---------|
| HSDA [44]     | 0.7607758    | 0.323016532| 1.48118232 | 0.03637708    | 53.715420885    | 9.8602E-04 | 0.0215277 | 0.9999893 |
| $R_{cr}$-IJADE [36] | 0.76077553 | 0.3230208 | 1.4811836 | 0.03637709 | 53.718525 | 9.86021E-4 | 0.0215271 | 0.9999893 |
| C-HCLPSO [43] | 0.760797  | 0.31062   | 1.4771 | 0.036548 | 52.885 | 1.1201E-03 | 0.0209115 | 0.999986   |
| ABC-NMS [47]  | 0.760776   | 0.323021  | 1.481184 | 0.036377 | 53.718521 | 9.86023E-04 | 0.021533 | 0.9999893 |
| ECE-OBL [49]  | 0.76078   | 0.32302  | 1.48118 | 0.03638 | 53.7185 | 9.8602E-04 | 0.0215269 | 0.9999893 |
| LM-SA [50]    | 0.76078    | 0.31849   | 1.47976 | 0.03643 | 53.32644 | 9.8646E-04 | 0.0215104 | 0.9999892 |
| FPA [51]      | 0.76079    | 0.31062   | 1.47707 | 0.03655 | 52.8771 | 1.214E-03 | 0.0216788 | 0.9999837 |
| IGHS [53]     | 0.76077 | 0.34351 | 1.48740 | 0.03613 | 53.2845 | 1.033E-03 | 0.0212025 | 0.9999882 |
| CLJAYA [57]   | 0.76078 | 0.3230208 | 1.481184 | 0.0363771 | 53.718521 | 9.8603E-04 | 0.0215415 | 0.999992   |
| ITLBO [59]    | 0.7608    | 0.3230   | 1.4812 | 0.0364 | 53.7185 | 9.9161E-04 | 0.021809 | 0.9999891 |
| IWOA [61]     | 0.7608    | 0.3232  | 1.4812 | 0.0364 | 53.7317 | 9.9486E-04 | 0.021131 | 0.9999891 |
| MLBSA [62]    | 0.7608    | 0.32302 | 1.4812 | 0.0364 | 53.7185 | 9.8969E-04 | 0.0217216 | 0.9999892 |
| 5Pm [3]       | 0.7612    | 0.1966 | 1.43 | 0.042 | 95.28 | 8.674E-03 | 0.159698 | 0.999986   |
| GA [33]       | 0.7619    | 0.8087 | 1.5751 | 0.0299 | 42.3729 | 0.01908 | 0.277673 | 0.995997   |
Figure 3: (a) The absolute current error (AE) for RTC France solar cell; (b) AE in open-circuit voltage region.
Additionally, the GA which will be used for forecast is considered.

4.1.1. RTC France Solar Cell. The first comparison is made for the RTC France solar cell, one of the widely used by researchers to prove the performance of the developed algorithms to extract the parameters of the photovoltaic cells and panels. The result of the parameters and the statistical tests, RMSE, AE, and $R^2$, are presented in Table 3.

In the case of the RTC France solar cell, the 5Pm method has the RMSE, which is widely used to measure the performance of the methods, higher than the ones obtained for the metaheuristic algorithms with the exception of the GA. Also, for the AE and $R^2$, the values are higher.

To have a complete image of the results obtained using different methods, Figure 3(a) presents the absolute current error. The 5Pm method and GA algorithm overestimate or underestimate the current around the open-circuit voltage.
point, where the other algorithms calculate the current better. The reverse saturation current extracted with the GA algorithm is more than two times higher than that calculated with HSDA. The parasitic resistances, the series resistance, and the shunt resistance present also a high variation. Figure 3(b) shows the behaviour of the AE around the open-circuit voltage region. The AE values for the C-HCLPSO and FPA algorithms alternate around the AE average of the other algorithms considered, having high values for some regions and very small for other regions.

4.1.2. Commercial Monocrystalline Silicon Photovoltaic Cell.
There are three methods to extract parameters of mSi commercial photovoltaic cell. The 5Pm analytical method gives

![Figure 5: (a) The absolute current error (AE) for PWP201 photovoltaic panel; (b) AE in open-circuit voltage region.](image)
the weakest results for all statistical tests, Table 4. If in the
case of the RTC photovoltaic cell, the RMSE obtained using
the 5Pm method is almost ten times higher; for the nSi pho-
tovoltaic cell, the RMSE is 4.5 times higher, but the GA algo-
rithm significantly improves its performance.

These changes in the performance of the methods can be
easily observed in Figure 4. The performance of the GA algo-
rithm is substantially improved for the region around the
open circuit point, while the 5Pm method shows weakness
in this region.

### Table 6: The parameters and statistical tests for the STM6-40 photovoltaic panel.

| Algorithm | $I_{ph}$ (A) | $I_{o}$ (μA) | $n$ | $R_s$ (Ω) | $R_{sh}$ (Ω) | RMSE | AE | $R^2$ |
|-----------|--------------|--------------|-----|------------|--------------|-------|----|-------|
| HSDA [44] | 1.6639047799 | 1.7386543978 | 54.730899 | 0.153855932 | 543.41834985 | 1.72981E − 03 | 0.0219035 | 0.99997731 |
| Rcr-IJADE [36] | 1.6639 | 1.7387 | 54.7308 | 0.1548 | 573.4188 | 1.73428E − 03 | 0.0216148 | 0.99997719 |
| ITLBO [59] | 1.6639 | 1.7387 | 54.7308 | 0.1548 | 573.4188 | 1.73428E − 03 | 0.0216148 | 0.99997719 |
| 5Pm [3] | 1.6636 | 2.6541E − 4 | 33.3534 | 0.9121 | 898.16 | 3.53507E − 02 | 0.540948 | 0.98999793 |

**Figure 6:** (a) The absolute current error (AE) for STM6-40 photovoltaic panel; (b) AE in open-circuit voltage region.
4.1.3. PWP201 Photovoltaic Panel. Analyzing the results obtained for RMSE in the case of the PWP201 photovoltaic panel, RMSE and AE obtained with the 5Pm method are 1.65 times higher than the ones obtained with the HSDA algorithm. There are three algorithms with the best values for all three statistical tests, HSDA, Rcr-IJADE, and CLJAYA, Table 5.

The absolute current errors for PWP201 photovoltaic panel are under 0.01 (A), having a uniform distribution, but keeping the high values in the open-circuit voltage region, Figure 5(a). Although, in this case, the methods estimate the current without high difference for certain voltages in comparison with the ones measured, the RMSE and AE have high values. The AE for the PWP201 photovoltaic panel around the open-circuit voltage is higher for the FPA and 5Pm methods. The other algorithms considered have the same behaviour, Figure 5(b).

4.1.4. STM6-40 Photovoltaic Panel. The 5Pm method has the statistical test high values, Table 6. The (V, I) pairs of the STM6-40 photovoltaic panel are not uniformly distributed. There are very few points in the open-circuit voltage region [46], which leads to poorer results in this case. The value of the coefficient of determination confirms this issue.

4.1.5. Commercial Monocrystalline Silicon Photovoltaic Panel. The statistical tests for commercial mSi photovoltaic panel are presented in Table 7. The shape of the absolute current error curves is the same in the case of the mSi photovoltaic panel. The highest

Table 7: The parameters and statistical tests for mSi photovoltaic panel.

| Algorithm | $I_{ph}$ (A) | $I_o$ (μA) | $n$ | $R_s$ (Ω) | $R_{sh}$ (Ω) | RMSE | AE | $R^2$
|-----------|-------------|------------|-----|-----------|-----------|------|----|------|
| HSDA [44] | 1.224206    | $4.677E-4$ | 18.364994 | 0.14407   | 1544.361724 | 2.77734E-03 | 1.93926 | 0.99956777 |
| GA [33]   | 1.223082    | $4.988143E-3$ | 20.5289   | 0.02147292 | 1765.388    | 4.96271E-03 | 2.61456 | 0.9984 |
| 5Pm [3]   | 1.224       | $0.334E-3$  | 18.02     | 0.134     | 1242.91     | 6.21773E-03 | 2.42416 | 0.9978 |

The best results are obtained for the HSDA algorithm for RSME and $R^2$. The plot of the absolute current errors, Figure 6(a), shows the weakness of the 5Pm method in the region around the open-circuit voltage. For some points, the current calculated with the 5Pm method is twenty times higher than the ones calculated with the HSDA algorithm.

The behaviour of the AE around the open-circuit voltage is similar for the ITLBO and the Rcr-IJADE algorithms, Figure 6(b). The AE for the HSDA algorithm has some small variations.

Table 8: The statistical tests for the forecast I-V characteristic.

| Algorithm | RMSE $f$ | RMSE $m$ |
|-----------|----------|----------|
| HSDA [44] | $5.30433E-03$ | $3.234E-03$ |
| GA [33]   | $1.63618E-02$ | $6.707E-03$ |
| 5Pm [3]   | $6.23956E-03$ | $2.86E-02$ |

The shape of the absolute current error curves is the same in the case of the mSi photovoltaic panel. The highest
value for the AE is again in the region of the open-circuit voltage, Figure 7.

The coefficient of determination for all photovoltaic cells and panels is very good, less for the GA algorithm in case of RTC photovoltaic cell and STM6-40 photovoltaic panel.

4.2. Forecast Comparison. Two I-V characteristics are measured for the commercial monocrystalline photovoltaic

![Figure 8: (a) The absolute current error (AE) for the forecasted I-V characteristic for photovoltaic panel; (b) AE in the voltage which corresponds to maximum power region.](image)

| Algorithm | HSDA [44] | GA [33] | 5Pm [3] | Measured |
|-----------|-----------|---------|---------|----------|
| $P_{\text{max}}$ (W) | 13.807 | 13.795 | 13.809 | 13.875 |
| $P_{\text{max, f}}/P_{\text{max, m}}$ (%) | 99.509 | 98.45 | 99.52 |
The absolute current error calculated for the forecast $I_V$ characteristic in comparison with the ones measured is presented in Figure 8(a). The highest values for AE are in the region of the open-circuit voltage. The behaviour of the curves obtained with parameters calculated with Equations (7)–(11) for HSDA and 5Pm methods is very similar, while the ones obtained with GA algorithms have an accentuated increase in the open-circuit voltage region.

Figure 8(b) shows the behaviour of the absolute current error around the maximum voltage, $V_{m}$, which is the voltage coordinate for the maximum power point. The best results are obtained for the 5Pm method for all regions considered. The comparison between maximum power generated, $P_{max}$, the mSi panel calculated from real measurements and ones forecasted, $P_{max,f}$, using the extracted parameters with the three methods, Table 9, shows that the best estimation is for the maximum power estimated with parameters extracted with the 5Pm method.

By analyzing the results obtained through comparison between the analytic method and metaheuristic algorithms, it can be concluded that the 5Pm method can be used to extract the parameters of the photovoltaic cells and panels. Additionally, the analytical method can be used to estimate the $I-V$ characteristics and the power generated using the parameters given by the producers. It can be used due to the advantages which are presented in Table 10.

### 5. Conclusions

The paper briefly reviews the analytical methods and metaheuristic algorithms used to extract the five or seven parameters for the photovoltaic cells and panels. The 5Pm
analytical method and one of the best metaheuristic algorithms from different families are compared for five datasets, two for photovoltaic cells, and three for photovoltaic panels.

By analyzing the results obtained, the supremacy of the metaheuristic algorithms for accuracy is shown. In all cases studied, the algorithms have better results for all statistical tests used. The analytical method has a better performance than the GA algorithm for the RTC photovoltaic cell. The performance of the HSDA algorithm is one of the best for all photovoltaic cells and panels analyzed, and it was chosen to be compared in the forecast process.

Two I-V characteristics, measured for the commercial Si mSi photovoltaic panel, are used to compare the influence of the extract parameter methods on the forecast of the maximum power and I-V characteristic at different values of the irradiance and temperature. Using the parameters calculated with the HSDA algorithm, the forecast of the I-V characteristic was better than for GA and 5Pm methods. However, the 5Pm method forecasted better the maximum power, only 0.48% less than the real one. These are preliminary results, which will further be developed in future research by analysis for various cases. This analysis will be made on different panels, under various irradiance and illumination conditions.

The 5Pm methods are based on several relations which are easy to implement, for the measured I-V characteristic, datasets, or the datasheet parameters, the latter offered by the producer, and the parameters can be quickly calculated with very good accuracy. The necessary time to calculate the parameters is very small, and it does not require a powerful PC, as for the metaheuristic algorithms. These prove that the 5Pm method is a valuable candidate for photovoltaic cells and panel manufacturers. They can use the 5Pm method to characterize the photovoltaic devices and to obtain the optimum photovoltaic panels using cells with the same values of the parameters. The production time and the costs can be optimized.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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