Hindawi
International Journal of Photoenergy
Volume 2021, Article ID 3608138, 17 pages
https://doi.org/10.1155/2021/3608138

Review Article

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

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Received 29 May 2021; Revised 11 August 2021; Accepted 24 August 2021; Published 18 September 2021

Academic Editor: Ahmad Umar

The parameters of the photovoltaic cells and panels are very important to forecast the power generated. There are a lot of methods to extract the parameters using analytical, metaheuristic, and hybrid algorithms. The comparison between the widely used analytical method and some of the best metaheuristic algorithms from the algorithm families is made for datasets from the specialized literature, using the following statistical tests: absolute error, root mean square error, and the coefficient of determination. The equivalent circuit and mathematical model considered is the single diode model. The result comparison shows that the metaheuristic algorithms have the best performance in almost all cases, and only for the genetic algorithm, there are poorer results for one chosen photovoltaic cell. The parameters of the photovoltaic cells and panels and also the current-voltage characteristic for real outdoor weather conditions are forecasted using the parameters calculated with the best method: one for analytical—the five-parameter analytical method—and one for the metaheuristic algorithms—hybrid successive discretization algorithm. Additionally, the genetic algorithm is used. The forecast current-voltage characteristic is compared with the one measured in real sunlight conditions, and the best results are obtained in the case of a hybrid successive discretization algorithm. The maximum power forecast using the calculated parameters with the five-parameter method is the best, and the error in comparison with the measured ones is 0.48%.

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/m^2, 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:

$$I = I_{\mathrm{ph}} - I_{\mathrm{o}}\left(e^{(V+IR_{\mathrm{s}})/nV_{\mathrm{T}}} - 1\right) - \frac{V + IR_{\mathrm{s}}}{R_{\mathrm{sh}}}, \tag{1}$$

where I_{ph} is the photogenerated current, I_{o} 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, $V_{\mathrm{T}} = kT/q$. k is the Boltzmann constant, T is the temperature, and q is the elementary electrical charge.

The double diode model is described by

$$I = I_{\mathrm{ph}} - I_{\mathrm{o1}}\left(e^{(V+IR_{\mathrm{s}})/n_1V_{\mathrm{T}}} - 1\right) - I_{\mathrm{o2}}\left(e^{(V+IR_{\mathrm{s}})/n_2V_{\mathrm{T}}} - 1\right) - \frac{V + IR_{\mathrm{s}}}{R_{\mathrm{sh}}}, \tag{2}$$

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

$$I = N_{\mathrm{p}}I_{\mathrm{ph}} - N_{\mathrm{p}}I_{\mathrm{o}}\left(e^{(N_{\mathrm{p}}V+N_{\mathrm{s}}IR_{\mathrm{s}})/nN_{\mathrm{p}}N_{\mathrm{s}}V_{\mathrm{T}}} - 1\right) - \frac{N_{\mathrm{p}}V + N_{\mathrm{s}}IR_{\mathrm{s}}}{N_{\mathrm{s}}R_{\mathrm{sh}}}, \tag{3}$$

where N_{s} represents the number of the photovoltaic cells connected in series and N_{p} 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).

$$\mathrm{AE} = \sum_{i=1}^{n} \left| I_{ic} - I_{im} \right|, \tag{4}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} \left(I_{ic} - I_{im}\right)^2}{n}}, \tag{5}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} \left(I_{ic} - I_{im}\right)^2}{\sum_{i=1}^{n} \left(I_{im} - \bar{I}_{im}\right)^2}, \tag{6}$$

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]:

$$I_{\mathrm{ph}} = \frac{G}{G_{\mathrm{ref}}}\left[I_{\mathrm{ph,ref}} + \alpha_{\mathrm{sc}}(T, T_{\mathrm{ref}})\right], \tag{7}$$

where G is irradiance, T represent the temperature, and α_{sc} is the temperature coefficient of the current. The index ref

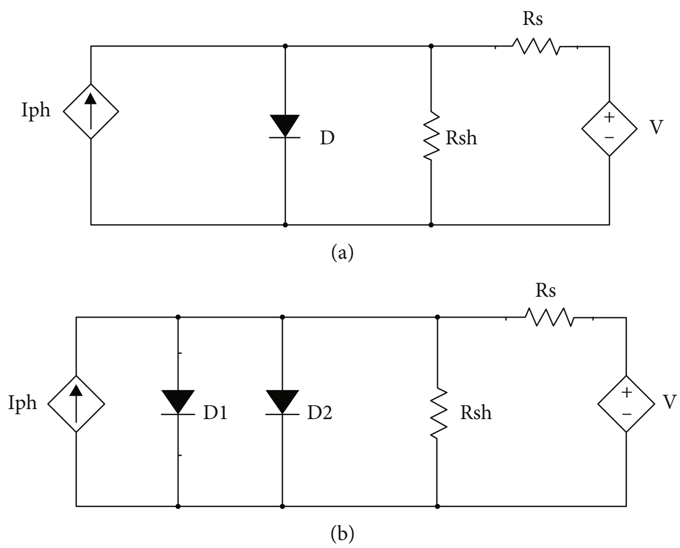


Figure 1: The equivalent circuit of photovoltaic cell: (a) one diode model; (b) two diode model.

is for the parameters at STC. The reverse saturation current can be calculated with Equation (8) [9, 10]:

$$I_o = I_{o,\mathrm{ref}} \left(\frac{T}{T_{\mathrm{ref}}} \right)^3 e^{q/Kn\left(\left(E_{g,\mathrm{ref}}/T_{\mathrm{ref}}\right)-\left(E_g/T_r\right)\right)}, \quad (8)$$

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

$$E_g = E_{g,\mathrm{ref}} \lfloor 1 - 0.0002677(T - T_{\mathrm{ref}}) \rfloor. \quad (9)$$

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

$$n = n_{\mathrm{ref}} \frac{T}{T_{\mathrm{ref}}}. \quad (10)$$

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

$$R_{\mathrm{sh}} = R_{\mathrm{sh,ref}} \frac{G_{\mathrm{ref}}}{G}. \quad (11)$$

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; β is constant and is considered equal to 0.217 [11, 14].

$$R_{\mathrm{sh}} = R_{\mathrm{sh,ref}} \frac{T}{T_{\mathrm{ref}}} \left(1 - \beta \ln \frac{G}{G_{\mathrm{ref}}} \right). \quad (12)$$

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 the 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 the R_s and R_{sh} and $I_{ph} \sim I_{sc}$	Medium	Medium	[17]
Ortiz-Conde	$I_{ph}, I_o, n, R_s, \mathrm{R}_{sh}$	SD	Using the CC function to calculate the equation coefficients C_{V1}, C_{I1}, C_{V2} and C_{I2}	Low	Medium	[18]
Garrido-Alzar	$I_{ph}, I_{od}, I_{or}, n_r, R_s, R_{sh}$	DD	n_r 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	$I_{od}, I_{or}, n_r, R_s, R_{sh}$	DD	The parameters are determined in dark conditions	Low	Low	[22]
R_s model	$I_{od}, I_{or}, n_r, R_{s,}$	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	$I_{ph}, I_o, n, R_s, R_{sh}$	SD	Using two points for I_{sc} zone and V_{oc} zone to calculate the slopes	Medium	Medium	[9]
Cotfas	R_s and s	SD	Using I-V characteristic measured and the ideal one	Medium	Medium	[1]
Modified five parameters	$I_{ph}, I_o, n, R_s, R_{sh}$	SD	Using two empirically equations to calculate R_s and R_{sh}	Low	High	[25]
Elkholy	$I_{ph}, I_o, n, R_s, R_{sh}$	SD	Using a method based on the nonlinear least-squares algorithm; the parameters are calculated at different environmental conditions	Medium	Medium	[7]
Ndegwa	$I_{ph}, I_o, n, R_s, R_{sh}$	SD	n and I_o are calculated firstly using I_{sc}, I_m, V_m, V_{oc}, and $R_s = 0$, $R_{sh} \approx \infty$; R_s and R_{sh} are then evaluated for different values of n_s in the neighborhood of n_o $(1 \le n \le n_o)$	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]

slope around the open-circuit voltage to calculate R_{so}, Equation (12), and the short circuit current to calculate R_{sho}, Equation (13). The slope calculation requires having many points on the I-V characteristic in the two regions. In case this is not possible and to reduce the complexity of the method, R_{so} and R_{sho} can be calculated using Equations (15) and (16), empirically obtained in modified five parameters 5Pm [25].

$$R_{so} = -\left(\frac{dV}{dI}\right)_{V=V_{oc}}, \tag{13}$$

$$R_{sh} = R_{sho} = -\left(\frac{dV}{dI}\right)_{I=I_{sc}}, \tag{14}$$

$$R_{so} = 0.002102 + 0.318070 R_{sm}, R_{sm} = \frac{V_{oc} - V_m}{I_m}, \tag{15}$$

$$R_{sho} = -0.051914 + 2.505219 R_{sm}, R_{shm} = \frac{V_m}{I_{sc} - I_m}, \tag{16}$$

where I_m and V_m represent the maximum power point coordinates.

$$\begin{gathered} n = \frac{V_m + R_{so} I_m - V_{oc}}{V_t\left(\ln\left(I_{sc} - (V_m/R_{sh}) - I_m\right) - \ln\left(I_{sc} - (V_{oc}/R_{sh})\right) + I_m/\left(I_{sc} - (V_{oc}/R_{sh})\right)\right)}, \\ I_o = \left(I_{sc} - \frac{V_{oc}}{R_{sh}}\right) \exp\left(-\frac{V_{oc}}{nV_T}\right), \\ R_s = R_{so} - \frac{nV_t}{I_o} \exp\left(-\frac{V_{oc}}{nV_T}\right), \\ I_{ph} = I_{sc}\left(1 + \frac{R_s}{R_{sh}}\right) + I_o\left(\exp\left(\frac{I_{sc} R_s}{nV_T}\right) - 1\right). \end{gathered} \tag{17}$$

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_{cr}-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	[35]
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, 3 × 3 cm monocrystalline silicon photovoltaic cell, PWP201 photovoltaic panel	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, DD	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	—	-/5000 and 10000	[49]
Simulated annealing SA	Simple	SD, DD	57 mm R.T.C France solar cell, Photowatt-PWP201	—	-/-	[64]

Table 2: Continued.

Family algorithms	Type	Models	PV	Range set	Computational time/iterations	Reference
Simulated annealing LM-SA	Hybrid	SD	57 mm RTC France solar cell	—	-/2050	[50]
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	—	-/5000	[53]
Innovative global harmony search IGHS	Simple	SD, DD	57 mm RTC France solar cell	—	-/5000	[53]
Pattern search PS	Simple	SD, DD	57 mm RTC France solar cell, PWP201 photovoltaic panel	—	-/-	[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 R.T.C France solar cell, Photowatt-PWP201 KC200GT, SM55, thin-film Shell ST40	Yes	-/50000	[56]
Comprehensive learning JAYA algorithm CJAYA	Simple	SD, DD	57 mm RTC France solar cell, PWP201 photovoltaic panel	—	-/20000 and 48000	[57]
Teaching–learning-based optimization TLBO	Simple	SD, DD	57 mm RTC France solar cell, PWP201 photovoltaic panel	—	-/20000	[58]
Improved TLBO ITLBO	Simple	SD, DD	57 mm R.T.C France solar cell, PWP201 photovoltaic panel, STP6-120/36, STM6-40/36	—	5.95 s (30) and 6.60s (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]

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.

4. Results and Discussion

4.1. Analytical vs. Metaheuristic. The representative analytical method—modified five parameters—which has low difficulty to use and high accuracy, for SD model, it is compared with the best metaheuristic algorithms for each family, for several photovoltaic cells and panels when the results for the parameters are available. The parameter values for the SD model given in the references are used to calculate the statistical tests AE, RMSE, and R^2 used for comparison.

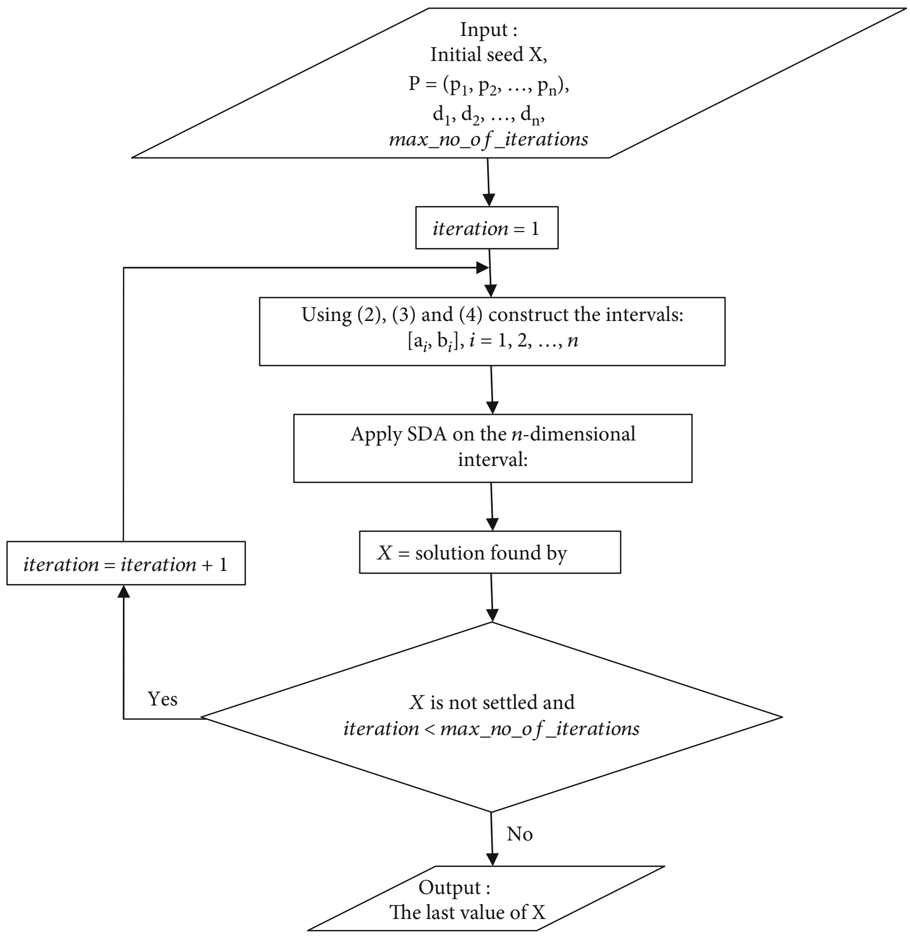


Figure 2: HSDA algorithm flow chart [44].

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	53.714520885	$9.8602E-04$	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]	0.76079	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
ESCE-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	0.9999892
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	0.999086
GA [33]	0.7619	0.8087	1.5751	0.0299	42.3729	0.01908	0.277673	0.995997

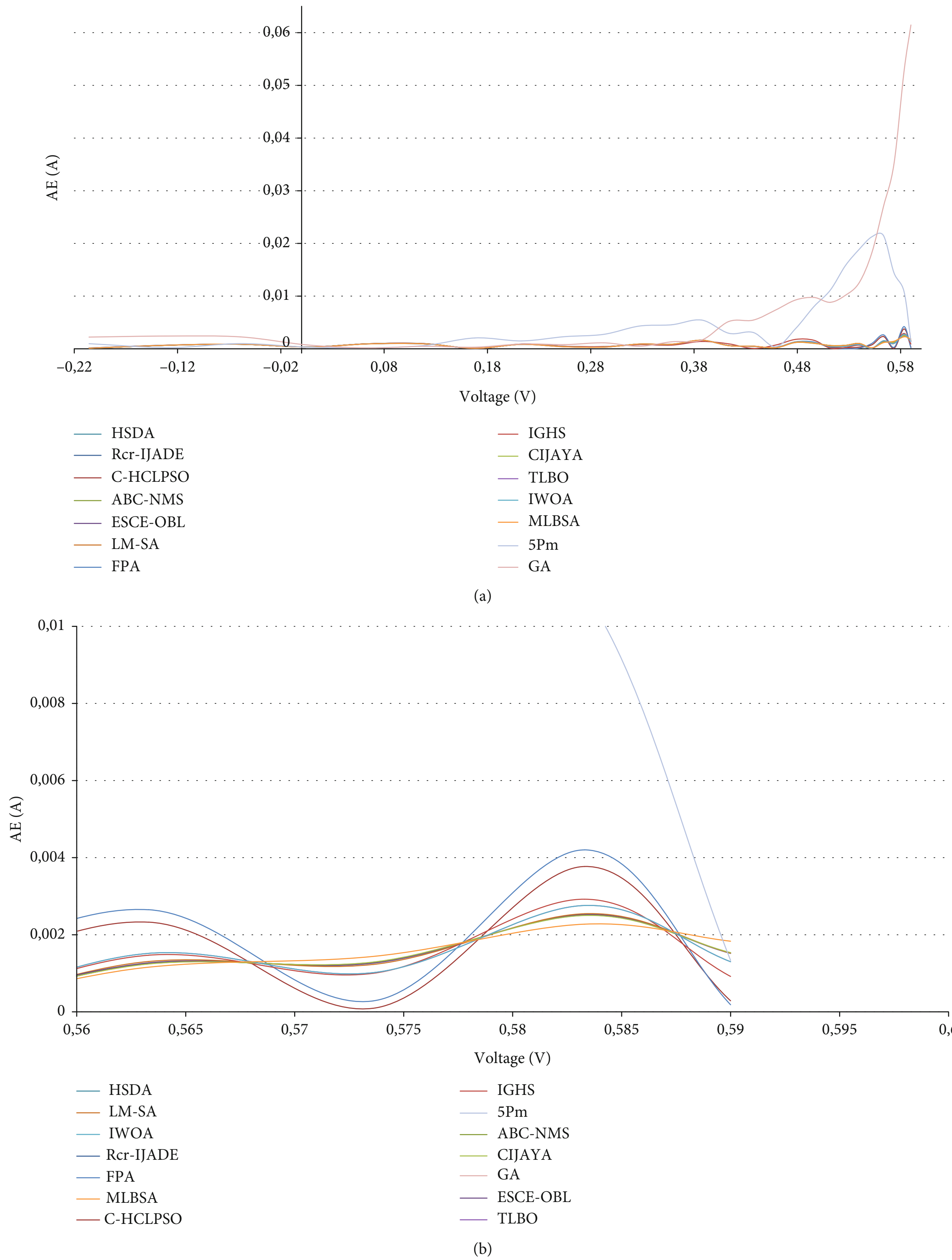


Figure 3: (a) The absolute current error (AE) for RTC France solar cell; (b) AE in open-circuit voltage region.

Table 4: The parameters and statistical tests for mSi commercial photovoltaic cell.

Algorithm	I_{ph} (A)	I_o (μA)	n	$R_s(\Omega)$	$R_{sh}(\Omega)$	RMSE	AE	R^2
HSDA [44]	0.42575316	0.516241613	1.67933406	0.09132898	99.075980176	$5.63098E-04$	0.0142648	0.9999853
5Pm [3]	0.4255	0.30645567	1.618311	0.10352224	145.222	$2.25639E-03$	0.047492	0.99976
GA [33]	0.4256882	0.8383311	1.73926	0.0859435	123.3659	$6.9741E-04$	0.0163354	0.99997

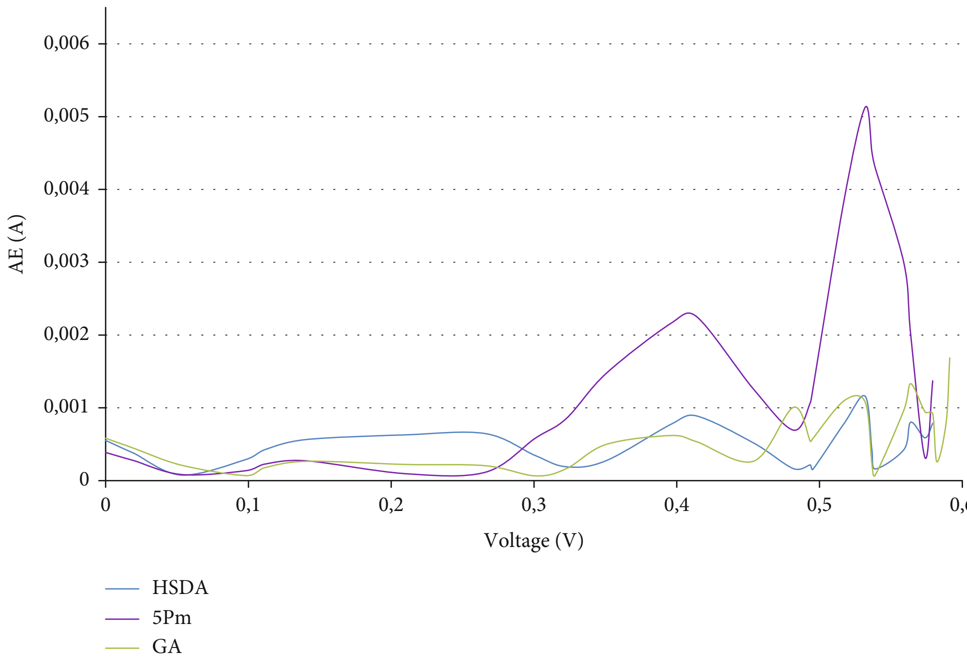


Figure 4: The absolute current error for mSi commercial photovoltaic cell.

Table 5: The parameters and statistical tests for PWP201 photovoltaic panel.

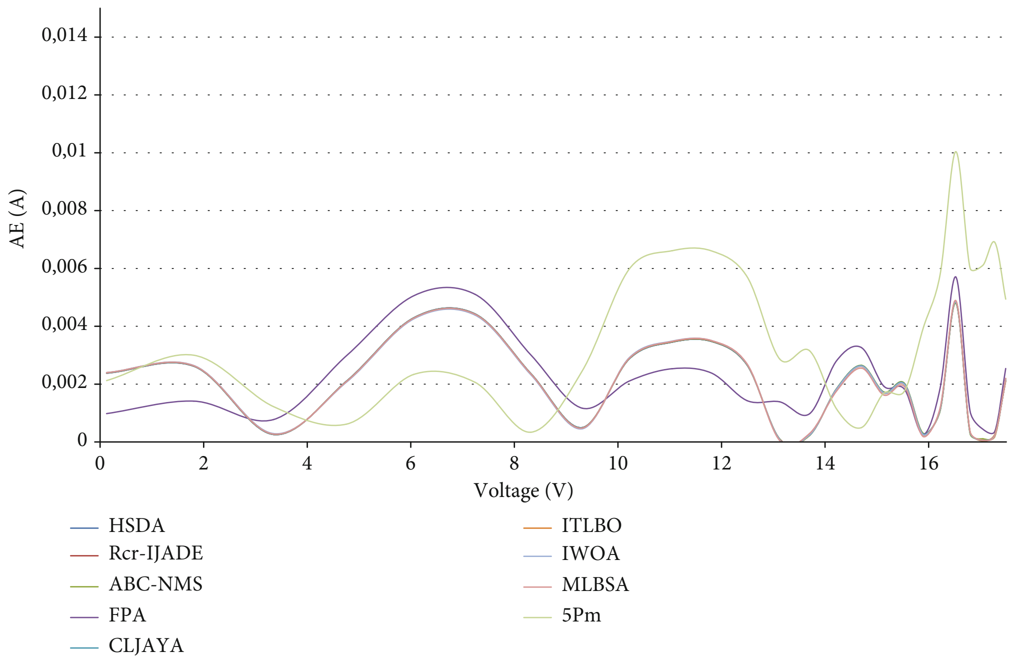
Algorithm	I_{ph} (A)	I_o (μA)	n	$R_s(\Omega)$	$R_{sh}(\Omega)$	RMSE	AE	R^2
HSDA [44]	1.0305143	0.348226304	48.642835	1.201271	981.201271	$2.42507E-03$	0.0489237	0.99997
R_{cr}-IJADE [36]	1.0305143	3.4822629	48.642835	1.201271	981.98216	$2.42507E-03$	0.0489237	0.99997
ABC–NMS [47]	1.03051	3.48226	48.643	1.20127	981.982	$2.42518E-03$	0.0489454	0.99997
FPA [51]	1.032091	3.047538	48.13128	1.217583	811.3721	$2.57361E-03$	0.0533746	0.99996
CLJAYA [57]	1.030514	3.4822628	48.64283	1.201271	981.982279	$2.42507E-03$	0.0489227	0.99997
ITLBO [59]	1.0305	3.4823	48.6428	1.2013	981.9823	$2.42519E-03$	0.0488878	0.99997
IWOA [61]	1.0305	3.4717	48.6313	1.2016	978.6771	$2.42523E-03$	0.0488933	0.99997
MLBSA [62]	1.0305	3.4823	48.6428	1.20163	981.9823	$2.42561E-03$	0.04878	0.99997
5Pm [3]	1.034	3.571	48.71	1.206	1123.00	$4.019E-03$	0.0833522	0.99991

Additionally, the GA which will be used for forecast is considered.

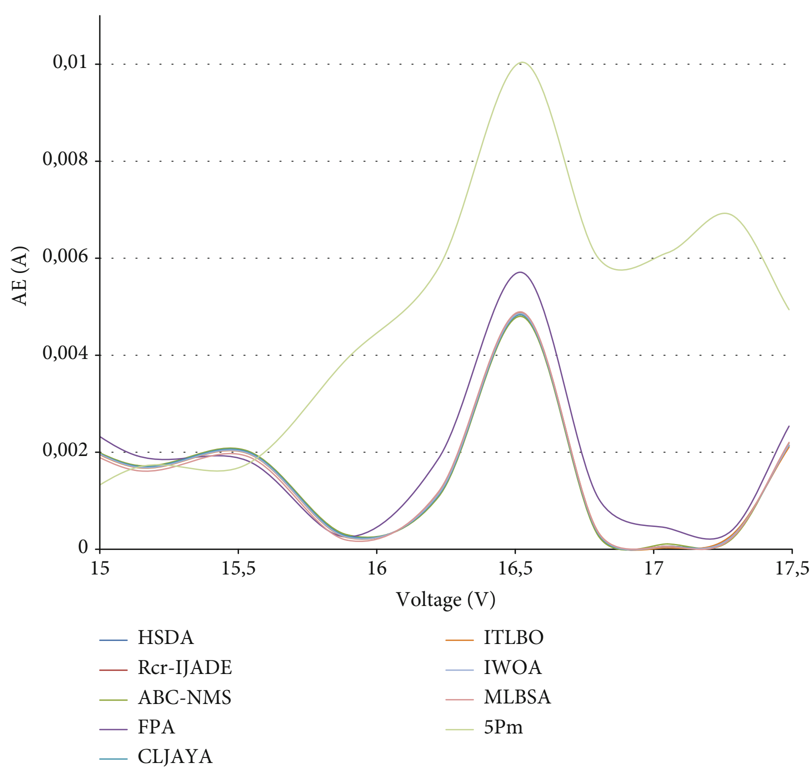
4.1.1. RTC France Solar Cell. The first comparison is made for the RTC France solar cell, one of the widely used by researchers to prove the performance of the developed algorithms to extract the parameters of the photovoltaic cells and panels. The result of the parameters and the statistical tests, 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



(a)



(b)

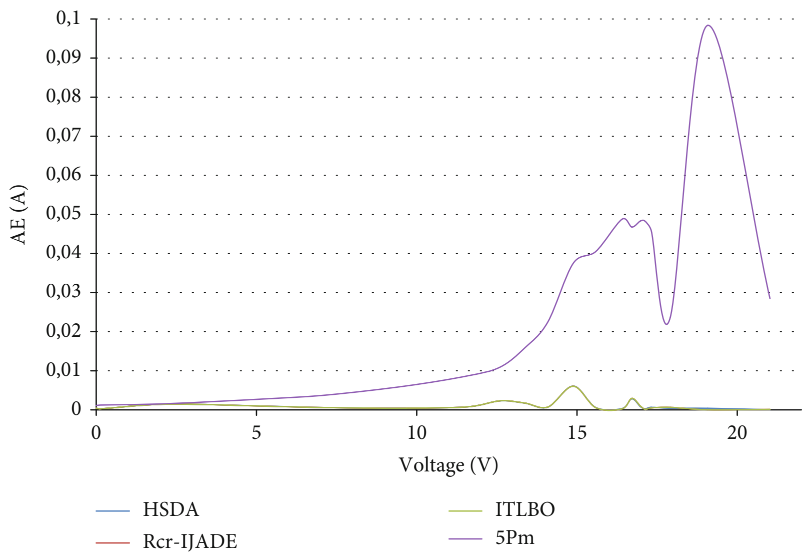
Figure 5: (a) The absolute current error (AE) for PWP201 photovoltaic panel; (b) AE in open-circuit voltage region.

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.

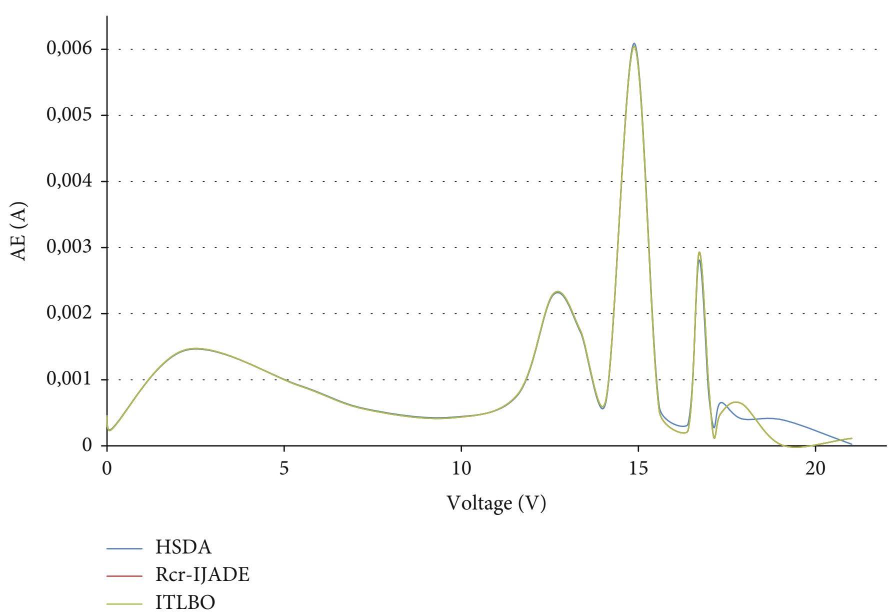
4.1.2. Commercial Monocrystalline Silicon Photovoltaic Cell. There are three methods to extract parameters of mSi commercial photovoltaic cell. The 5Pm analytical method gives

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
R_{cr}-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



(a)



(b)

Figure 6: (a) The absolute current error (AE) for STM6-40 photovoltaic panel; (b) AE in open-circuit voltage region.

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 mSi photovoltaic cell, the RMSE is 4.5 times higher, but the GA algorithm significantly improves its performance.

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

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

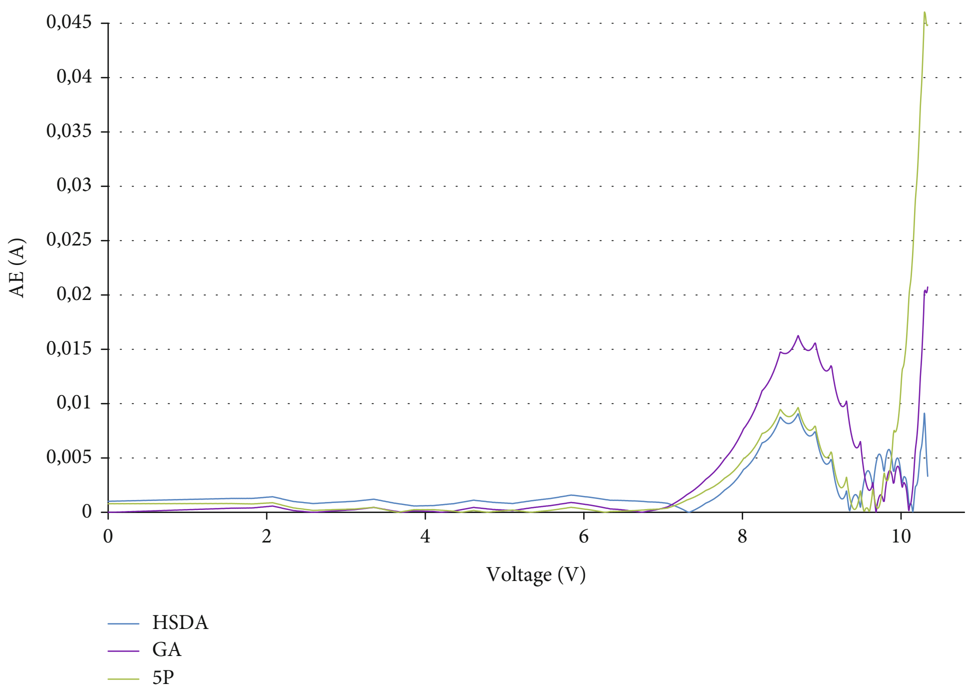


Figure 7: The absolute current error for mSi photovoltaic panel.

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, R_{cr}-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.

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

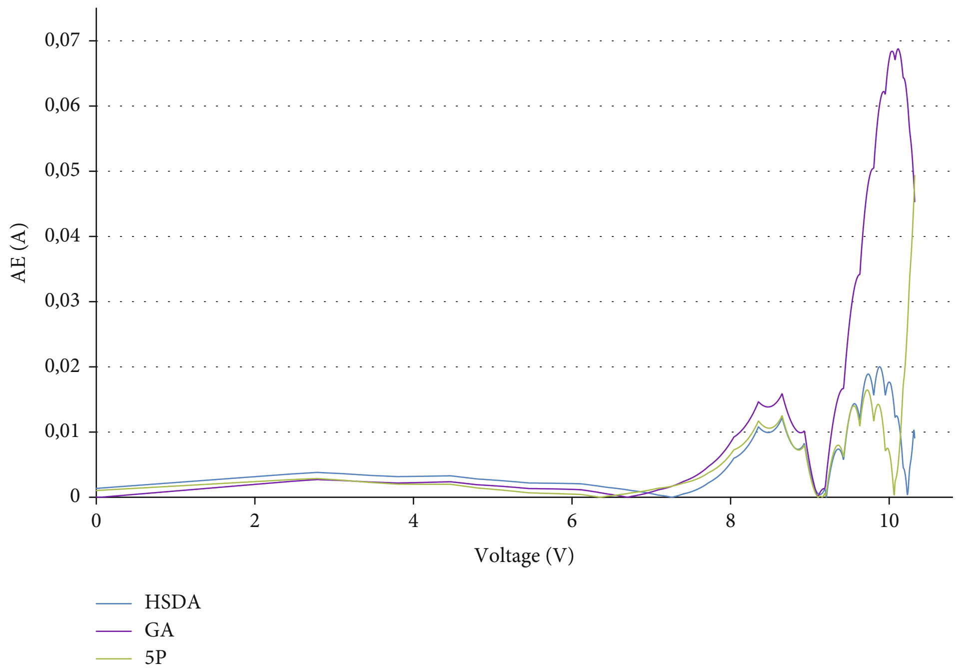
Algorithm	RMSE f	RMSE m
HSDA [44]	$5.30433E-03$	$3.234E-03$
GA [33]	$1.63618E-02$	$6.707E-03$
5Pm [3]	$6.23956E-03$	$2.86E-02$

The 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.

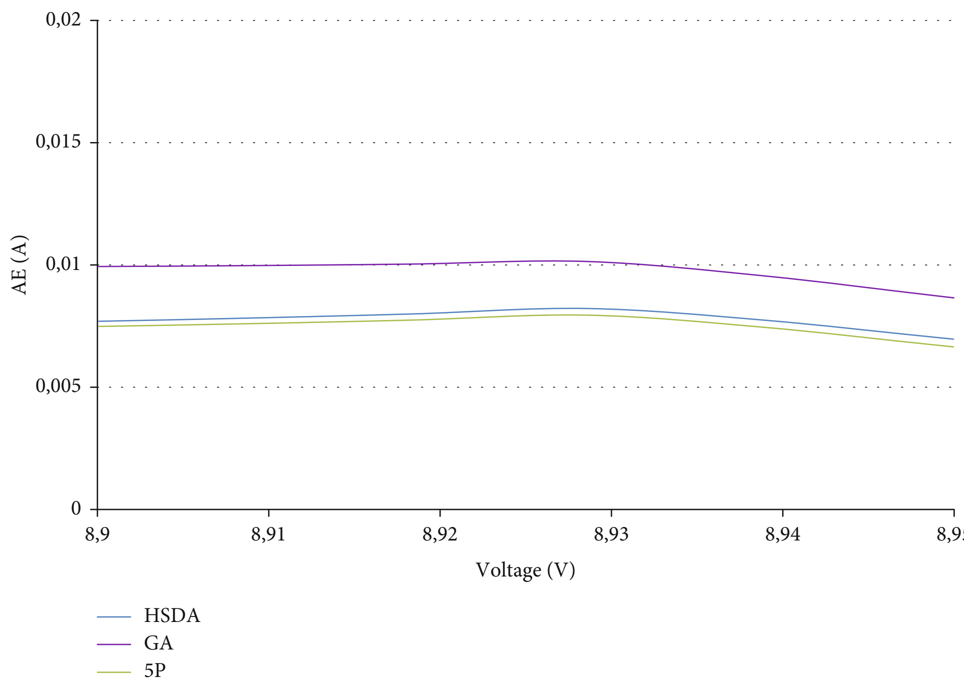
The behaviour of the AE around the open-circuit voltage is similar for the ITLBO and the R_{cr}-IJADE algorithms, Figure 6(b). The AE for the HSDA algorithm has some small variations.

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



(a)



(b)

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.

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.

TABLE 9: The P_{max} forecasted and measured.

Algorithm	HSDA [44]	GA [33]	5Pm [3]	Measured
P_{max} (W)	13.807	13.795	13.809	13.875
$P_{max,f}/P_{max,m}$ (%)	99.509	98.45	99.52	

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

Table 10: Advantages and disadvantages.

Method	Advantages	Disadvantages
Analytical	(i) Using the 5Pm method is very easy, the R_{so} and R_{sh} are calculated with the empirical equations [25] (ii) Very easy to implement on the computer for all software which allows calculation (iii) The necessary time to extract the parameters is very short for the 5Pm method (duration is under ms) (iv) Does not require a powerful or dedicated PC, which leads to the small cost of the PC, and the used software can be a common one	(i) The accuracy of the parameters extracted decreases due to approximations used [8] (ii) If some points of the I-V characteristic are used, the equation system obtained is nonlinear and it is necessary to use software that allows solving this (this can be costly) (iii) The complexity increases when the two diode model is used (seven equations are needed)
Metaheuristic	(i) The accuracy is higher than that of the analytical methods (ii) The number of iterations can be reduced (for example, for the ISCE algorithm, the iteration number is 5000) (iii) The algorithms can be easily adapted for the two diode model, but the computational time will increase (iv) Using algorithms as grey wolf, prey predator, and fire fly optimization, the performance of the parameters extraction can be improved [8] (v) GA algorithm family can easy be part of the hybrid algorithm [65] (vi) DE algorithm family has a high convergence (vii) PSO can be improved if it is used together with Nelder-Mead methods, this hybridisation can reduce the computational resources [65] (viii) SDA family has very good performance, and it can be easily used with other algorithms in hybrid structure (ix) Improved version of SCE has performance comparable with HSDA	(i) The computational time can be high, it depends on the PC power and the metaheuristic algorithm (the number of the iterations and the complexity), there are algorithms with over 100000 iterations or even 350000-NM-MPSO algorithm [41] (ii) The cost of the PC can be high and the dedicated software must be used (iii) The performance of the most metaheuristic algorithms depend by the initial parameter range (iv) Requires very good knowledge for implementation (v) GA, SCE, TLBO, WOA, and BSA algorithms have a slow convergence (vi) DE and PSO algorithms can converge prematurely (vii) The computational time is high in case of the PSO algorithms (viii) The computational time is relatively high, but using parallelization, it can be reduced; in the case presented, the time was reduced 6 times

panel for the irradiance of 700 W/m^2 and 983 W/m^2. The measurements were made on the roof of the university building [3].

The I-V characteristic measured at 700 W/m^2 was used to extract the parameters of the mSi photovoltaic panel with three methods HSDA algorithm, GA algorithm, and 5Pm analytical method. These parameters are considered as $I_{ph,ref}$, $I_{o,ref}$, n_{ref}, $R_{s,ref}$, and $R_{sh,ref}$. The parameters of the mSi photovoltaic panel are calculated for 983 W/m^2 irradiance, using Equations (7)–(11). These values are used to compare the measured I-V characteristic for 983 W/m^2 in real conditions with the ones forecasted with the five parameters calculated with Equations (7)–(11). The temperature coefficient of the current was determined, and it is 15.76 mA/°C.

The root mean square error for the forecasted I-V characteristic of the mSi photovoltaic panel is presented in Table 8 in comparison with one for the I-V characteristic measured. The RMSE f obtained when the parameters are calculated with Equations (7)–(11) is worse in the case of the HSDA and GA algorithms than the RMSE m obtained using the extracted parameters with those algorithms for the measured characteristic. In case of the 5Pm methods, the results are improved.

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, $P_{max,m}$, 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 ones 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 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.

Acknowledgments

This work was supported by a grant of the Romanian Ministry of Education and Research, CCCDI-UEFISCDI, project number PN-III-P2-2.1-PED-2019-2028, within PNCDI III.

References

[1] D. T. Cotfas, P. A. Cotfas, and S. Kaplanis, "Methods to determine the dc parameters of solar cells: a critical review," *Renewable and Sustainable Energy Reviews*, vol. 28, pp. 588–596, 2013.

[2] A. M. Humada, M. Hojabri, S. Mekhilef, and H. M. Hamada, "Solar cell parameters extraction based on single and double-diode models: a review," *Renewable and Sustainable Energy Reviews*, vol. 56, pp. 494–509, 2016.

[3] D. T. Cotfas, A. M. Deaconu, and P. A. Cotfas, "Application of successive discretization algorithm for determining photovoltaic cells parameters," *Energy Conversion and Management*, vol. 196, pp. 545–556, 2019.

[4] D. Sera, R. Teodorescu, and P. Rodriguez, "PV panel model based on datasheet values," in *2007 IEEE International Symposium on Industrial Electronics*, pp. 2392–2396, Vigo, Spain, 2007.

[5] J. P. Ram, H. Manghani, D. S. Pillai, T. S. Babu, M. Miyatake, and N. Rajasekar, "Analysis on solar PV emulators: a review," *Renewable and Sustainable Energy Reviews*, vol. 81, pp. 149–160, 2018.

[6] G. Huang, Y. Liang, X. Sun, C. Xu, and F. Yu, "Analyzing S-Shaped _I_ - _V_ characteristics of solar cells by solving three-diode lumped-parameter equivalent circuit model explicitly," *Energy*, vol. 212, p. 118702, 2020.

[7] A. Elkholy and A. A. Abou El-Ela, "Optimal parameters estimation and modelling of photovoltaic modules using analytical method," *Heliyon*, vol. 5, no. 7, article e02137, 2019.

[8] D. S. Pillai and N. Rajasekar, "Metaheuristic algorithms for PV parameter identification: a comprehensive review with an application to threshold setting for fault detection in PV systems," *Renewable and Sustainable Energy Reviews*, vol. 82, no. 3, pp. 3503–3525, 2018.

[9] J. Bai, S. Liu, Y. Hao, Z. Zhang, M. Jiang, and Y. Zhang, "Development of a new compound method to extract the five parameters of PV modules," *Energy Conversion and Management*, vol. 79, pp. 294–79303, 2014.

[10] M. Kumar and A. Kumar, "An efficient parameters extraction technique of photovoltaic models for performance assessment," *Solar Energy*, vol. 158, pp. 192–206, 2017.

[11] D. T. Cotfas, P. A. Cotfas, and O. M. Machidon, "Study of temperature coefficients for parameters of photovoltaic cells," vol. 2018, 2018International Journal of Photoenergy, 2018.

[12] B. Van Zeghbroeck, *Principles of Semiconductor Devices and Heterojunctions*, Prentice Hall, Englewood Cliffs, New Jersey, 1st edition, 2008.

[13] M. Wolf and H. Rauschenbach, "Series resistance effects on solar cell measurements," *Advanced Energy Conversion*, vol. 3, no. 2, pp. 455–479, 1963.

[14] A. Virtuani, E. Lotter, and M. Powalla, "Performance of $Cu(In,Ga)Se_2$ solar cells under low irradiance," *Thin Solid Films*, vol. 431-432, pp. 443–447, 2003.

[15] S. Nesmachnow, "An overview of metaheuristics: accurate and efficient methods for optimisation," *International J. Metaheuristics*, vol. 3, no. 4, pp. 320–347, 2014.

[16] D. S. H. Chan, J. R. Phillips, and J. C. H. Phang, "A comparative study of extraction methods for solar cell model parameters," *Solid-State Electronics*, vol. 29, no. 3, pp. 329–337, 1986.

[17] M. Tivanov, A. Patryn, N. Drozdov, A. Fedotov, and A. Mazanik, "Determination of solar cell parameters from its current-voltage and spectral characteristics," *Solar Energy Materials and Solar Cells*, vol. 87, no. 1-4, pp. 457–465, 2005.

[18] A. Ortiz-Conde, F. J. G. Sánchez, and J. Muci, "New method to extract the model parameters of solar cells from the explicit analytic solutions of their illuminated _I -V_ characteristics," *Solar Energy Materials and Solar Cells*, vol. 90, no. 3, pp. 352–361, 2006.

[19] C. L. Garrido-Alzar, "Algorithm for extraction of solar cell parameters from I-V curve using double exponential model," *Renewable Energy*, vol. 10, no. 2-3, pp. 125–128, 1997.

[20] B. Arcipiani, "Generalization of the area method for the determination of the parameters of a non-ideal solar cell," *Revue de Physique Appliquée*, vol. 20, no. 5, pp. 269–272, 1985.

[21] G. L. Araujo and E. Sanchez, "A new method for experimental determination of the series resistance of a solar cell," *IEEE Transactions on Electron Devices*, vol. 29, no. 10, pp. 1511–1513, 1982.

[22] A. Kaminski, J. J. Marchand, A. Fave, and A. Laugier, "New method of parameters extraction from dark I–V curve," in *Conference Record of the Twenty Sixth IEEE Photovoltaic Specialists Conference - 1997*, pp. 203–206, Anaheim, CA, USA, 1997.

[23] N. N. Ulapane, C. H. Dhanapala, S. M. Wickramasinghe, S. G. Abeyratne, N. Rathnayake, and P. J. Binduhewa, "Extraction of parameters for simulating photovoltaic panels," in *2011 6th International Conference on Industrial and Information Systems*, pp. 539–544, Kandy, Sri Lanka, 2011, IEEE.

[24] F. Ghani and M. Duke, "Numerical determination of parasitic resistances of a solar cell using the Lambert W-function," *Solar Energy*, vol. 85, no. 9, pp. 2386–2394, 2011.

[25] O. Mares, M. Paulescu, and V. Badescu, "A simple but accurate procedure for solving the five-parameter model," *Energy Conversion and Management*, vol. 105, pp. 139–148, 2015.

[26] R. Ndegwa, J. Simiyu, E. Ayieta, and N. Odero, "A Fast and accurate analytical method for parameter determination of a photovoltaic system based on manufacturer's data," *Journal of Renewable Energy*, vol. 2020, 7580218 pages, 2020.

[27] A. Hali and Y. Khlifi, "Photovoltaic panel parameters determination using two numerical methods," *Materials Today: Proceedings*, vol. 45, pp. 7377–7382, 2021.

[28] V. Lo Brano and G. Ciulla, "An efficient analytical approach for obtaining a five parameters model of photovoltaic modules using only reference data," *Applied Energy*, vol. 111, pp. 894–903, 2013.

[29] A. Orioli and A. Di Gangi, "A criterion for rating the usability and accuracy of the one-diode models for photovoltaic modules," *Energies*, vol. 9, no. 6, p. 427, 2016.

[30] A. M. Humada, S. Y. Darweesh, K. G. Mohammed et al., "Modeling of PV system and parameter extraction based on experimental data: review and investigation," *Solar Energy*, vol. 199, pp. 742–760, 2020.

[31] J. A. Jervase, H. Bourdoucen, and A. Al-Lawati, "Solar cell parameter extraction using genetic algorithms," *Measurement Science and Technology*, vol. 12, no. 11, pp. 1922–1925, 2001.

[32] M. Zagrouba, A. Sellami, M. Bouaicha, and M. Ksouri, "Identification of PV solar cells and modules parameters using the genetic algorithms: application to maximum power extraction," *Solar Energy*, vol. 84, no. 5, pp. 860–866, 2010.

[33] D. T. Cotfas, P. A. Cotfas, and A. Cataron, "Using the genetic algorithm to determine the parameters of photovoltaic cells and panels," in *2018 International Symposium on Electronics and Telecommunications (ISETC)*, pp. 1–4, Timisoara, Romania, November 2018.

[34] X. Lingyun, S. Lefei, H. Wei, and J. Cong, "Solar cells parameter extraction using a hybrid genetic algorithm," in *2011 Third International Conference on Measuring Technology and Mechatronics Automation*, pp. 306–309, Shanghai, China, 2011.

[35] X. Yang, W. Gong, and L. Wang, "Comparative study on parameter extraction of photovoltaic models via differential evolution," *Energy Conversion and Management*, vol. 201, p. 112113, 2019.

[36] W. Gong and Z. Cai, "Parameter extraction of solar cell models using repaired adaptive differential evolution," *Solar Energy*, vol. 94, pp. 209–220, 2013.

[37] K. Ishaque, Z. Salam, S. Mekhilef, and A. Shamsudin, "Parameter extraction of solar photovoltaic modules using penalty-based differential evolution," *Applied Energy*, vol. 99, pp. 297–308, 2012.

[38] D. H. Muhsen, A. B. Ghazali, T. Khatib, and I. A. Abed, "Parameters extraction of double diode photovoltaic module's model based on hybrid evolutionary algorithm," *Energy Conversion and Management*, vol. 105, pp. 552–561, 2015.

[39] H. Wei, J. Cong, X. Lingyun, and S. Deyun, "Extracting solar cell model parameters based on chaos particle swarm algorithm," in *2011 International Conference on Electric Information and Control Engineering*, pp. 398–402, Wuhan, China, 2011.

[40] V. Khanna, B. K. Das, D. Bisht, Vandana, and P. K. Singh, "A three diode model for industrial solar cells and estimation of solar cell parameters using PSO algorithm," *Renewable Energy*, vol. 78, pp. 105–113, 2015.

[41] N. F. A. Hamid, N. A. Rahim, and J. Selvaraj, "Solar cell parameters identification using hybrid Nelder-Mead and modified particle swarm optimization," *Journal of Renewable and Sustainable Energy*, vol. 8, no. 1, 2016.

[42] D. Yousri, S. B. Thanikanti, D. Allam, V. K. Ramachandaramurthy, and M. Eteiba, "Fractional chaotic ensemble particle swarm optimizer for identifying the single, double, and three diode photovoltaic models' parameters," *Energy*, vol. 195, p. 116979, 2020.

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

[44] D. T. Cotfas, A. M. Deaconu, and P. A. Cotfas, "Hybrid successive discretisation algorithm used to calculate parameters of the photovoltaic cells and panels for existing datasets," *IET Renewable Power Generation*, pp. 1–27, 2021.

[45] A. M. Deaconu, D. T. Cotfas, and P. A. Cotfas, "Calculation of seven photovoltaic cells parameters using parallelized successive discretization algorithm," *International Journal of Photoenergy*, vol. 2020, Article ID 6669579, 13 pages, 2020.

[46] D. Oliva, E. Cuevas, and G. Pajares, "Parameter identification of solar cells using artificial bee colony optimization," *Energy*, vol. 72, pp. 93–102, 2014.

[47] Z. Chen, L. Wu, P. Lin, Y. Wu, and S. Cheng, "Parameters identification of photovoltaic models using hybrid adaptive Nelder- Mead simplex algorithm based on eagle strategy," *Applied Energy*, vol. 182, pp. 47–57, 2016.

[48] X. Gao, Y. Cui, J. Hu et al., "Parameter extraction of solar cell models using improved shuffled complex evolution algorithm," *Energy Conversion and Management*, vol. 157, pp. 460–479, 2018.

[49] Y. Chen, Z. Chen, L. Wu, C. Long, P. Lin, and S. Cheng, "Parameter extraction of PV models using an enhanced shuffled complex evolution algorithm improved by opposition-based learning," *Energy Procedia*, vol. 158, pp. 991–997, 2019.

[50] F. Dkhichi, B. Oukarfi, A. Fakkar, and N. Belbounaguia, "Parameter identification of solar cell model using Levenberg-Marquardt algorithm combined with simulated annealing," *Solar Energy*, vol. 110, pp. 781–788, 2014.

[51] D. F. Alam, D. A. Yousri, and M. B. Eteiba, "Flower pollination algorithm based solar PV parameter estimation," *Energy Conversion and Management*, vol. 101, pp. 410–422, 2015.

[52] J. P. Ram, T. S. Babu, T. Dragicevic, and N. Rajasekar, "A new hybrid bee pollinator flower pollination algorithm for solar PV parameter estimation," *Energy Conversion and Management*, vol. 135, pp. 463–476, 2017.

[53] A. Askarzadeh and A. Rezazadeh, "Parameter identification for solar cell models using harmony search-based algorithms," *Solar Energy*, vol. 86, no. 11, pp. 3241–3249, 2012.

[54] M. F. AlHajri, K. M. el-Naggar, M. R. AlRashidi, and A. K. al-Othman, "Optimal extraction of solar cell parameters using pattern search," *Renewable Energy*, vol. 44, pp. 238–245, 2012.

[55] K. Yu, J. Liang, B. Qu, X. Chen, and H. Wang, "Parameters identification of photovoltaic models using an improved JAYA optimization algorithm," *Energy Conversion and Management*, vol. 150, pp. 742–753, 2017.

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

[57] Y. Zhang, M. Ma, and Z. Jin, "Comprehensive learning Jaya algorithm for parameter extraction of photovoltaic models," *Energy*, vol. 211, p. 118644, 2020.

[58] S. J. Patel, A. K. Panchal, and V. Kheraj, "Extraction of solar cell parameters from a single current-voltage characteristic using teaching learning based optimization algorithm," *Applied Energy*, vol. 119, pp. 384–393, 2014.

[59] S. Li, W. Gong, X. Yan et al., "Parameter extraction of photovoltaic models using an improved teaching- learning-based optimization," *Energy Conversion and Management*, vol. 186, pp. 293–305, 2019.

[60] O. S. Elazab, H. M. Hasanien, M. A. Elgendy, and A. M. Abdeen, "Parameters estimation of single- and multiple-diode photovoltaic model using whale optimisation algorithm," *IET Renewable Power Generation*, vol. 12, no. 15, pp. 1755–1761, 2018.

[61] G. Xiong, J. Zhang, D. Shi, and Y. He, "Parameter extraction of solar photovoltaic models using an improved whale optimization algorithm," *Energy Conversion and Management*, vol. 174, pp. 388–405, 2018.

[62] K. Yu, J. Liang, B. Qu, Z. Cheng, and H. Wang, "Multiple learning backtracking search algorithm for estimating parameters of photovoltaic models," *Applied Energy*, vol. 226, pp. 408–422, 2018.

[63] Y. Zhang, Z. Jin, X. Zhao, and Q. Yang, "Backtracking search algorithm with Levy flight for estimating parameters of photovoltaic models," *Energy Conversion and Management*, vol. 208, p. 112615, 2020.

[64] K. M. el-Naggar, M. R. AlRashidi, M. F. AlHajri, and A. K. al-Othman, "Simulated annealing algorithm for photovoltaic parameters identification," *Solar Energy*, vol. 86, no. 1, pp. 266–274, 2012.

[65] S. Li, W. Gong, and Q. Gu, "A comprehensive survey on metaheuristic algorithms for parameter extraction of photovoltaic models," *Renewable and Sustainable Energy Reviews*, vol. 141, p. 110828, 2021.