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Estimation of Single-Diode and Two-Diode Solar Cell Parameters by Using a Chaotic Optimization Approach

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Abstract: Estimation of single-diode and two-diode solar cell parameters by using chaotic optimization approach (COA) is addressed. The proposed approach is based on the use of experimentally determined current-voltage (*I-V*) characteristics. It outperforms a large number of other techniques in terms of average error between the measured and the estimated *I-V* values, as well as of time complexity. Implementation of the proposed approach on the *I-V* curves measured in laboratory environment for different values of solar irradiation and temperature prove its applicability in terms of accuracy, effectiveness and the ease of implementation for a wide range of practical environment conditions. The COA-based parameter estimation is, therefore, useful for PV power converter designers who require fast and accurate model for PV cell/module.

Keywords: Solar cell parameters; single-diode model; two-diode model; COA

1. Introduction

The contribution of solar energy in total electric energy production is growing constantly. As the price of solar inverters and solar panels constantly decreases, most countries are basing their energy policy on higher use of solar energy. Studies on energy networks, and especially testing of the integration of solar energy sources into power networks, requires accurate calculation of the solar output power, as well as accurate modeling of solar cells. For that reason, modeling of solar cells (corresponding equivalent circuit and accurate parameters value) represents a very popular research field.

In the literature, two basic models of the equivalent circuits of solar cell can be found, namely the single-diode model (SDM) [1] and the double-diode model (DDM) [2]. DDM considers the composite effect of the neutral region of the junction, and, therefore, models the solar cells more accurately [3]. However, it is characterized by seven unknown parameters. Because of the complexity of DDM, some authors reduce the number of unknown parameters [3,4], which can greatly affect the model accuracy [5]. In this work, we focus on both SDM and DDM, without neglecting any of the model parameters of the solar cell.

For the estimation of solar cell parameters, two main sets of “input data” and corresponding estimations can be found, namely

(a) estimation based on datasheet information [6,7] and
(b) estimation based on experimental data [8].

The former uses the datasheet information (open circuit voltage, short circuit current, voltage and current value at maximum power point characteristics) provided by photovoltaic (PV) manufacturers under standard test conditions. However, recent research [7] on the usage of datasheet values for solar cell parameter estimation shows that current-voltage characteristic is not unique when designers focus on three datasheet points (open circuit, short circuit and maximum power). It is shown that by observing only three points, we can have multiple *I-V* characteristics, although in reality a solar cell has a single defined *I-V* characteristic corresponding to a specific set of cell parameters. To obtain unique and accurate *I-V* characteristic of PV cell, experimental data on more than three major points are necessary [7]. Research [7] has also implied that only approaches based on experimental data generate accurate models.

Evaluating the performance of solar cells (or PV panels) requires as accurate an estimation of the equivalent circuit solar cell parameters as possible. The approaches used for this purpose can be categorized as follows:

(a) analytical techniques [9–13],
(b) numerical extraction [13] and
(c) meta-heuristic techniques [14–59].

Analytical techniques provide mathematical expressions for solving equivalent circuit parameters based on some input data (manufacturer data or/and data obtained from measurements). A review and comparative assessment of non-iterative methods for the extraction of the single-diode model parameters of photovoltaic modules is given in [11]. In general, analytical techniques provide rapid solution. On the other hand, these techniques give erroneous results when the estimated and measure solar cell output characteristics are compared [12].

Numerical techniques are based on curve fitting, usually via iterative methods. However, the application of curve fitting to nonlinear diode equations is quite complex, making numerical determination of solar cell parameters unpopular [14].

Recently, meta-heuristic algorithms for solar cell parameter estimation have been proposed [14–58]. They impose no restrictions on the problem formulation, they are excellent in dealing with nonlinear equations, and they can be applied for different numbers of unknown parameters.

Of all the proposed techniques, none excels in terms of accuracy and efficiency with respect to others. This was our main incentive for doing research in this field. We propose both accurate and efficient parameter optimization of solar cell SDM and DDM through chaotic optimization approach (COA).

Recently, COA has been used in solving various optimization problems: parameter identification of Jiles-Atherton hysteresis model [59], single-phase transformer parameter estimation [60], design of PID parameters for automatic voltage regulation of synchronous machine [61], antenna array radiation pattern synthesis [62,63]. The main advantages of COA over other optimization techniques are easy implementation and short execution time [64]. It should be noted that different versions of chaotic algorithm have also been used in solar cell parameters estimation, namely chaotic heterogeneous comprehensive learning particle swarm optimizer variants [16], chaotic asexual reproduction optimization [33], mutative-scale parallel chaos optimization algorithm [41], chaos-embedded gravitational search algorithm [65], chaotic improved artificial bee colony algorithm [66], improved chaotic whale optimization algorithm [67], etc. Unlike methods proposed in [16,33,41,65–67], this paper will use COA based on Logistic map for solar cell parameter estimation. Logistic map has a simple form with one variable and one control parameter, and it can produce chaotic behavior similar to more complex chaotic systems. [68]. The power of this optimization approach is demonstrated in [60], where it was used for the estimations of the transformer's parameters.

The effectiveness of the proposed approach will be evaluated on different solar cells (different with respect to solar cell voltage and current level) found in the literature and the laboratory environment. Furthermore, COA-based parameter estimation will be compared with 50 various literature techniques for SDM, and with 12 various techniques for DDM. Also, we will compare parameters obtained by using the proposed method on the measured data with analytically and numerically obtained parameters. Finally, we will apply COA on the measured *I-V* characteristics using the laboratory environment.

The paper is organized as follows. SDM and DDM for solar cells are described in Section 2. In Section 3, COA and its implementation for solar cell parameters estimation are described. The comparison of solar cell parameters estimation accuracy obtained by using the COA-based and other methods, for one solar cell and one solar module, is presented in Section 4. The experimental setup for measuring *I-V* curves is presented in Section 5, along with the COA-based parameter estimation results. The concluding remarks are given in Section 6.

2. Mathematical Modeling of Single and Double Solar Cells

SDM is commonly used model for solar cell representation [1], and the equivalent circuit is shown in Figure 1a. The *I-V* relationship for this model can be described by the following equation:

$$I = I_{pv} - I_o\left(e^{\frac{V+IR_s}{n \cdot V_{th}}} - 1\right) - \frac{V + IR_s}{R_p} \tag{1}$$

where I_{pv} is the photo-generated current, R_s the series parasitic resistance, R_p the parallel parasitic resistance, I_0 the saturation current, n is ideality factor and $V_{th} = k_B T/q$ is the thermal voltage (k_B is Boltzmann constant equal to 1.38×10^{-23} J/K, T the temperature and q the electron charge equal to 1.602×10^{-19} C).

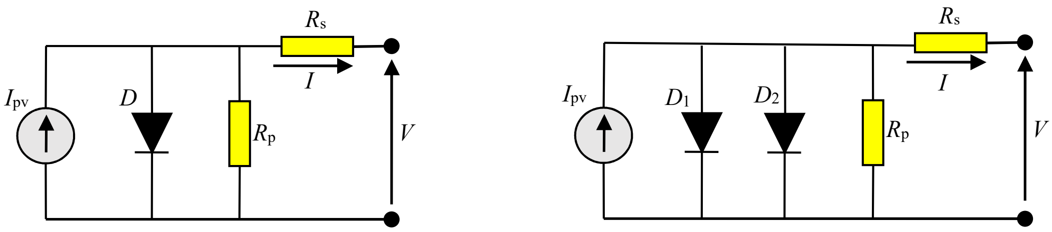

Figure 1. (**a**) SDM, and (**b**) DDM of a solar cell.

The equivalent circuit with DDM for the solar cell is shown in Figure 1b. Therefore, unlike the SDM model, the DDM model of the solar cell, in addition to the rectifying diode, includes one more diode to consider the space charge recombination current [48]. The *I-V* characteristic of DDM is given as

$$I = I_{pv} - I_{o1}\left(e^{\frac{V+IR_s}{n_1 \cdot V_{th}}} - 1\right) - I_{o2}\left(e^{\frac{V+IR_s}{n_2 \cdot V_{th}}} - 1\right) - \frac{V + IR_s}{R_p} \tag{2}$$

where I_{o1} and I_{o2} are the diffusion and saturation currents, whereas n_1 and n_2 are the diffusion and recombination diode ideality factors [48]. The ideality factor is discussed in [69,70], whereas [71] presents a method for ideality factor calculation.

3. COA and Objective Function

COA is a very powerful optimization technique that has found numerous scientific applications [59–63]. This approach is based on the theory of chaos, which is, in a mathematical sense, described by ordinary differential equations or by an iterative map [64].

Different chaotic systems, including the logistic map, lozi map, tent map and Lorenz system, can be found in the literature. In this paper, we will base COA on the logistic map [59–64].

The task of COA is to estimate a set of unknown parameters X which minimizes the objective function (*OF*). In our case, for SDM, X = [R_s, R_p, I_{pv}, I_o, n], and for DDM, X = [R_s, R_p, I_{pv}, I_{o1}, I_{o2}, n_1, n_2].

Therefore, in general, vector $X = [x_1, x_2, \ldots x_n]$ contains variables limited to the lower (*LV*) and upper (*UV*) permitted value, i.e, $x_i \in [L_i, U_i]$. On the other side, the *OF* for SDM is

$$OF = \sum_{t=1}^{P}\left(I_{pv} - I_o\left(e^{\frac{V_t + I_t R_s}{n \cdot V_{th}}} - 1\right) - \frac{V_t + I_t R_s}{R_p} - I_t\right) \tag{3}$$

whereas for DDM it reads

$$OF = \sum_{t=1}^{P}\left(I_{pv} - I_{o1}\left(e^{\frac{V_t + I_t R_s}{n_1 \cdot V_{th}}} - 1\right) - I_{o2}\left(e^{\frac{V_t + I_t R_s}{n_2 \cdot V_{th}}} - 1\right) - \frac{V_t + I_t R_s}{R_p} - I_t\right) \tag{4}$$

where P is the number of measured *I-V* pairs from the *I-V* characteristics, and V_t and I_t represent the voltage and current value of pair t.

Figure 2 presents the search procedure, i.e., the COA flowchart. The detailed description of COA flowchart can be found in [59].

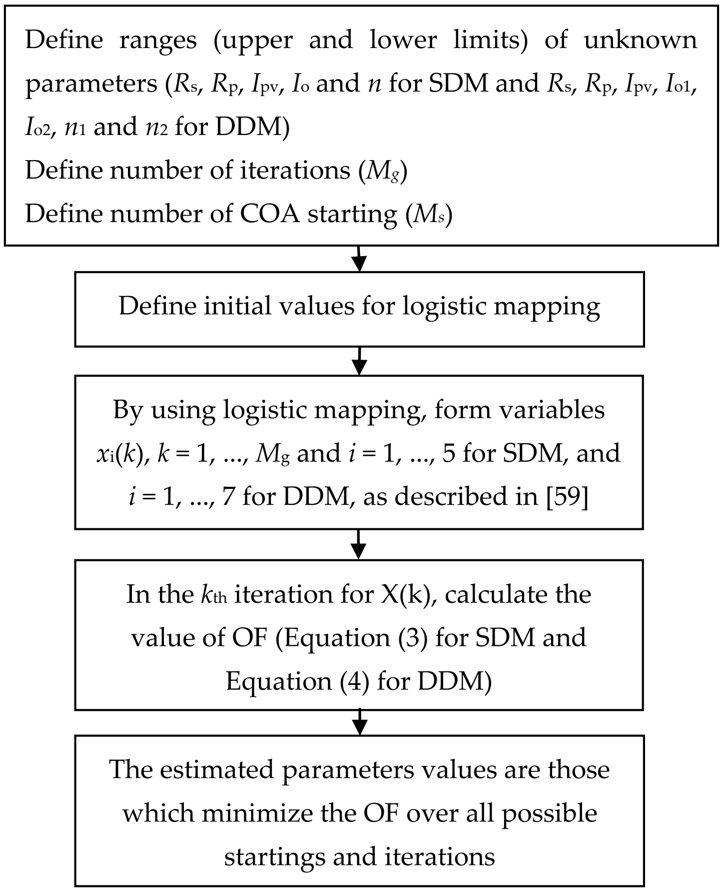

Figure 2. COA flowchart.

In this paper, the following COA parameters were used: $M = 1000$, $N = 50{,}000$. The COA-based estimation is compared with other approaches through the root mean square error (*RMSE*), defined as follows:

$$RMSE = \sqrt{\frac{\sum_{k=1}^{P}\left(I_{est,k} - I_{meas,k}\right)}{P}} \tag{5}$$

where $I_{est,k}$ and $I_{meas,k}$ represent the estimated and the measured values of solar output current in point k, respectively.

4. Simulation Results

To evaluate COA for solar cell parameters estimation, we first applied the proposed method to an experimental current-voltage characteristic extracted from the manufacturer's datasheets of a well-known R.T.C. France solar cell operating under standard test conditions.

The values of parameters obtained by using COA for the R.T.C. France solar cell are summarized, by year of publication, in Table 1, for SDM and Table 2 for DDM. These values are compared with the values of parameters published in recent papers (column Reference) for the same experimental data. During the estimation process, the parameter ranges for SDM estimation were $R_s(\Omega) \in [0.02,\ 0.05]$, $I_{pv}(A) \in [0.74,\ 0.78]$, $I_o(\mu A) \in [0.2,\ 0.4]$, $R_p(\Omega) \in [50,\ 55]$ and $n \in [1.35,\ 1.6]$, whereas for DDM, they were $R_s(\Omega) \in [0.02,\ 0.04]$, $R_p(\Omega) \in [54,\ 58]$, $n_1 \in [1.4,\ 1.5]$, $n_2 \in [1.95,\ 2]$, $I_{pv}(A) \in [0.75,\ 0.77]$ $I_{o1}(\mu A) \in [0.2,\ 0.25]$ and $I_{o2}(\mu A) \in [0.7,\ 0.8]$.

Table 1. Calculated SDM parameters for the R.T.C France solar cell.

No.	Algorithm	Reference	First Author, Year	I_{pv} (A)	I_0 (μA)	n	R_s (Ω)	R_p (Ω)	*RMSE*
	Proposed Method—COA			**0.7607745**	**0.3230018**	**1.4811774**	**0.0363775**	**53.73**	$\mathbf{9.860221 \times 10^{-4}}$
1.	HISA *	[15]	Dhruv, 2019	0.7607078	0.3106845918	1.47726778	0.03654694	52.88979426	9.8911×10^{-4}
2.	HCLPSO *	[16]	Dalia, 2019	0.76079	0.31062	1.4771	0.036548	52.885	1.12009×10^{-3}
3.	OBWOA *	[17]	Abd, 2018	0.76077	0.3232	1.5208	0.0363	53.6836	1.1417×10^{-3}
4.	MPSO *	[18]	Manel, 2018	0.760787	0.310683	1.475262	0.036546	52.88971	7.33007×10^{-3}
5.	ER-WCA	[19]	Kler D, 2017	0.760776	0.322699	1.481080	0.036381	53.69100	9.8609×10^{-4}
6	MSSO	[20]	Lin P, 2017	0.760777	0.323564	1.481244	0.036370	53.742465	1.0599×10^{-3}
7	BPFPA *	[21]	Ram JP, 2017	0.7600	0.3106	1.4774	0.0366	57.7151	1.2536×10^{-3}
8	ICA	[22]	Fathy A, 2017	0.7603	0.14650	1.4421	0.0389	41.1577	1.1582×10^{-1}
9	GOTLBO	[23]	Chen X, 2016	0.760780	0.331552	1.483820	0.036265	54.115426	9.8744×10^{-4}
10	CSO	[24]	Guo L, 2016	0.76078	0.3230	1.48118	0.03638	53.7185	9.8612×10^{-4}
11.	NM-MPSO	[25]	Hamid N, 2016	0.76078	0.32306	1.48120	0.03638	53.7222	9.8620×10^{-4}
12.	PCE	[26]	Zhang Y, 2016	0.760776	0.323021	1.481074	0.036377	53.718525	1.0606×10^{-3}
13.	TONG	[27]	Tong NT, 2016	0.7610	0.3635	1.4935	0.03660	62.574	2.3859×10^{-3}
14.	MABC	[28]	Jamadi M, 2016	0.760779	0.321323	1.481385	0.036389	53.39999	2.7610×10^{-3}
15.	MVO	[29]	Ali EE, 2016	0.7616	0.32094	1.5252	0.0365	59.5884	1.2680×10^{-1}
16.	DET	[30]	Chellaswamy C, 2016	0.751	0.315	1.487	0.036	54.532	2.4481×10^{-2}
17.	WCA			0.760908	0.4135540	1.504381	0.035363	57.669488	7.6069×10^{-3}
18.	TLBO	[31]	Jordehi AR, 2016	0.760809	0.312244	1.47578	0.036551	52.8405	7.2723×10^{-3}
19.	GWO			0.760996	0.2430388	1.451219	0.037732	45.116309	7.2845×10^{-3}
20.	TVACPSO			0.760788	0.3106827	1.475258	0.036547	52.889644	7.3438×10^{-3}
21.	PPSO	[32]	Ma J, 2016	0.7608	0.3230	1.4812	0.0364	53.7185	9.9161×10^{-4}
22.	CARO	[33]	Yuan X, 2015	0.76079	0.31724	1.48168	0.03644	53.0893	8.1969×10^{-3}
23.	LI	[34]	Lim LHI, 2015	0.7609438	0.3456572	1.48799169	0.03614233	49.482205	1.3462×10^{-3}
24.	MBA	[35]	El-Fergany A. 2015	0.7604	0.2348	1.4890	0.0388	44.61	1.1672×10^{-1}
25.	FPA *	[36]	Alam DF, 2015	0.76079	0.310677	1.47707	0.0365466	52.8771	1.2121×10^{-3}
26.	LMSA	[37]	Dkhichi F, 2014	0.76078	0.31849	1.47976	0.03643	53.32644	9.8649×10^{-4}
27.	DE			0.76068	0.35515	1.49080	0.03598	56.5533	1.0035×10^{-3}
28.	BBO	[38]	Niu Q, 2014	0.76098	0.86100	1.58742	0.03214	78.8555	2.3929×10^{-3}
29.	BBO-M			0.76078	0.31874	1.47984	0.03642	53.36227	9.8656×10^{-4}
30.	STLBO	[39]	Niu Q, 2014	0.76078	0.32302	1.48114	0.03638	53.7187	9.9763×10^{-4}
31.	TLBO			0.76074	0.32378	1.48136	0.03641	54.4029	1.0016×10^{-3}
32.	ABC	[40]	Oliva D, 2014	0.7608	0.3251	1.4817	0.0364	53.6433	1.0967×10^{-3}
33.	HPEPD	[8]	Laudani A, 2014	0.7607884	0.3102482	1.4769641	0.03655304	52.859056	1.1487×10^{-3}
34.	MPCOA	[41]	Yuan X, 2014	0.76073	0.32655	1.48168	0.03635	54.6328	2.3131×10^{-3}
35.	TLBO	[42]	Patel SJ, 2014	0.7608	0.3223	1.4837	0.0364	53.76027	9.6960×10^{-3}
36.	BMO	[43]	Askarzadeh A, 2013	0.76077	0.32479	1.48173	0.03636	53.8716	9.8622×10^{-4}
37.	ABSO	[44]		0.76080	0.30623	1.47583	0.03659	52.2903	9.9125×10^{-4}
38.	IADE	[45]	Jiang LL, 2013	0.7607	0.33613	1.4852	0.03621	54.7643	9.9076×10^{-4}
39.	CS	[46]	Ma J, 2013	0.7608	0.323	1.4812	0.0364	53.7185	9.9161×10^{-4}
40.	ABSO			0.76080	0.30623	1.47986	0.03659	52.2903	1.4169×10^{-2}
41.	ABCDE	[47]	Hachana O, 2013	0.76077	0.32302	1.47986	0.03637	53.7185	4.8548×10^{-3}
42.	DE			0.76077	0.32302	1.48059	0.03637	53.7185	2.3423×10^{-3}
43.	MPSO			0.76077	0.32302	1.47086	0.03637	53.7185	3.9022×10^{-2}
44.	GGHS			0.76092	0.32620	1.48217	0.03631	53.0647	9.9089×10^{-4}
45.	HS	[48]	Askarzadeh A, 2012	0.76070	0.30495	1.47538	0.03663	53.5946	9.9515×10^{-4}
46.	IGHS			0.76077	0.34351	1.48740	0.03613	53.2845	1.0335×10^{-3}
47.	PS	[49]	AlHajri MF, 2012	0.7617	0.9980	1.6000	0.0313	64.10256	1.4936×10^{-2}
48.	SA	[50]	El-Naggar KM, 2012	0.7620	0.4798	1.5172	0.0345	43.10345	1.8998×10^{-2}
49.	GA	[51]	AlRashidi MR, 2011	0.7619	0.8087	1.5751	0.0299	42.37288	1.9078×10^{-2}
50.	PSO	[52]	Ye M, 2009	0.760798	0.322721	1.48382	0.0363940	53.7965	9.6545×10^{-3}

* for this method, a real RMSE are given [56].

Table 2. Calculated DDM parameters for the R.T.C France solar cell.

No.	Algorithm	Ref.	First Author, Year	I_{pv}(A)	I_{o1}(μA)	I_{o2}(μA)	R_s(Ω)	R_p(Ω)	n_1	n_2	*RMSE*
	Proposed Method—COA			**0.76078105**	**0.2259742**	**0.749346**	**0.03674043**	**55.4854236**	**1.45101673**	**2**	**$9.82484852 \times 10^{-4}$**
1.	GOFPANM	[53]	X Shuhui, 2017	0.7607811	0.7493476	0.2259743	0.0367404	55.485449	2	1.4510168	9.82485×10^{-4}
2.	SATLBO	[54]	Y Kunjie, 2017	0.76078	0.25093	0.545418	0.03663	55.117	1.45982	1.99941	9.82941×10^{-4}
3.	MSSO	[20]	P Lin, 2017	0.760748	0.234925	0.671593	0.036688	55.714662	1.454255	1.995305	1.059101×10^{-3}
4.	WDO	[55]	M Derick, 2017	0.7606	0.2531	0.0482	0.037433	52.6608	151.162	1.38434	1.095213×10^{-3}
5.	CSO	[24]	L Guo, 2016	0.76078	0.22732	0.72785	0.036737	55.3813	1.45151	1.99769	9.82532×10^{-4}
6.	GOTLBO	[23]	X Chen, 2016	0.760752	0.800195	0.220462	0.036783	56.0753	1.999973	1.448974	9.83152×10^{-4}
7.	PCE	[26]	Y Zhang, 2016	0.760781	0.226015	0.749340	0.03674	55.483160	1.450.923	2	9.8248×10^{-4}
8.	MABC	[28]	M Jamadi, 2016	0.7607821	0.24102992	0.6306922	0.03671215	54.7550094	1.4568573	2.0000.538	9.8276×10^{-4}
9.	FPA	[36]	DF Alam, 2015	0.760795	0.300088	0.166159	0.0363342	52.3475	1.47477	2	1.24239×10^{-3}
10.	BMO	[43]	A. Askarzadeh, 2013	0.76078	0.2111	0.87688	0.03682	558.081	1.44533	1.99.997	9.82661×10^{-4}
11.	ABSO	[44]	A. Askarzadeh, 2013	0.73078	0.26713	0.38191	0.03657	54.6219	1.46512	1.98152	9.8359×10^{-04}
12.	IGHS	[48]	A. Askarzadeh, 2012	0.76079	0.97310	0.16791	0.03690	56.8368	1.92126	1.42814	9.86572×10^{-4}

Tables 1 and 2 report parameters as they appear in the cited papers with no modification. However, in some papers in the Energy Conversion and Management journal (in Table 1 marked by *), inaccuracies occurred in parameter estimation of the PV cell using metaheuristic techniques. Namely, the results proposed in [15–18,21] do not correspond to the objective function [56].

The presented results, especially the value of RMSE, show that COA offers solar characteristics closer to the measured characteristics than the other existing methods, i.e., it outperforms other methods in terms of accuracy. In addition, by observing Tables 1 and 2, it is also evident that DDM characterizes solar cells more accurately than SDM, which supports the conclusion regarding DDM accuracy noted in [3].

It can be seen that COA outperforms several other techniques, such as evaporation rate-based water cycle algorithm (ER-WPA) [19] and cat swarm optimization (CSO) [24] for SDM, and with the generalized opposition-flower pollination algorithm-nelder-mead simplex method (GOFPANM) [53], by a small margin. However, the implementation of COA is simpler than implementation of ER-WPA, CSO and GOFPANM. Furthermore, COA is computationally less demanding than CSO since CSO requires changing the operation mode during the estimation process [24]. On the other side, GOFPANM is a hybrid algorithm which combines local and global search as well as different algorithms during estimation [53]. In general, most evolutionary algorithms have the complexity of $O((np + C_{of}\, p)N_i)$, where O is the big O notation, n is the dimension of the parameter space, p is the population size, N_i is the number of iterations and C_{of} is the complexity of the *OF*. The complexity of COA is $O(QC_{of})$, where Q is the number of points in the parameter space in which the OF is calculated. Therefore, the proposed COA-based estimation has significantly lower computational complexity than evolutionary algorithms.

To show the additional advantage of COA over other techniques, we conducted a comparison in terms of required time for one iteration. In that sense, in MATLAB 2015 (MathWorks, Natick, MA, USA) we have implemented the following algorithms for solar cell parameter estimation: evaporation rate-based water cycle algorithm (ER-WCA) [19], cuckoo search (CS) [46] and harmony search (HS) [48]. ER-WCA algorithm has a very good accuracy, very close to that obtained by the proposed method (see Table 1). On the other hand, HS and CS also have a good accuracy (~10^{-4}). All computer simulations were carried out on a PC with Intel(R) Core (TM) i3-7020U CPU @ 2.30 GHz and 4 GB RAM. The obtained results, i.e., the mean, maximal and minimal required time per one iteration, obtained over 20 runs, are presented in Table 3. Clearly, the COA-based algorithm is the most efficient method, as it is characterized by the lowest value of required time per iteration. Note, in order to draw a fair comparison between the considered algorithms, MATLAB implementation follows the same rules for each algorithm (e.g., avoiding loops and using array operations such as dot product and matrix product whenever possible).

Table 3. Time per iteration comparison.

Algorithm	Mean Value of Requested Time (s)	Maximal Value of Requested Time (s)	Minimal Value of Requested Time (s)
COA	0.016416	0.017023	0.015871
ER-WCA [19]	0.021063	0.024145	0.019492
CS [46]	0.029179	0.037177	0.027130
HS [48]	0.021103	0.023264	0.020393

The measured *I-V* and *P-V* characteristics and the corresponding simulated characteristics, for parameters obtained by using COA, are shown in Figure 3. Very good agreement can be seen between the measured and estimated curves. Also, the difference between the DDM and SDM simulated curves is small but consistent and always in favor of DDM. In addition, in Table 4, we presented the estimated value of the unknown DDM parameters of the BPSolar MSX-60 module. These parameters are obtained by using COA as well as by using analytical, numerical, iteration and Newton methods presented in the literature. In the COA-based estimation, the ranges of parameters were $R_s(\Omega) \in [0.2\ 0.4]$, $R_p(\Omega) \in [150,\ 300]$, $n_1 \in [0.5,\ 1.5]$, $I_{pv}(A) \in [3.5,\ 4]$, $I_{o1}(A) \in \left[10^{-10},\ 10^{-6}\right]$, $I_{o2}(A) \in \left[10^{-10},\ 10^{-6}\right]$, and $n_2 \in [1.5,\ 2]$. From the presented results, it is clear that COA outperforms the considered non-metaheuristic methods for solar cell parameters determination in terms of accuracy.

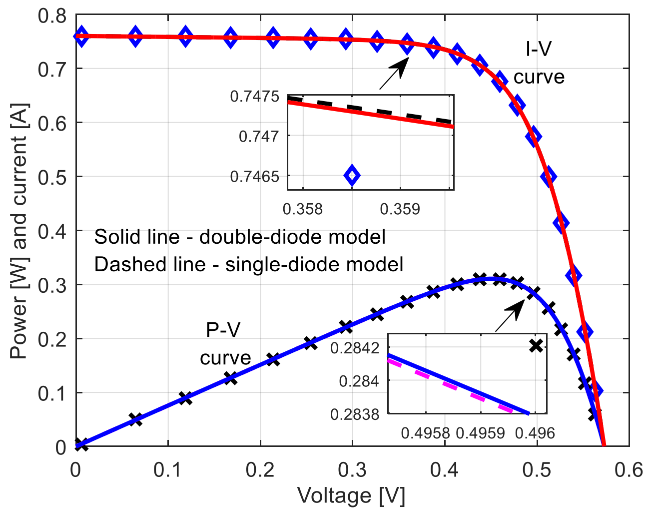

Figure 3. *I-V* and *P-V* characteristics of R.T.C. France solar cell.

Table 4. Calculated DDM parameters for the BPSolar MSX-60 module.

Parameter	Analytical Method [13]	Numerical Method [13]	Iteration Method [57]	Newton Method [58]	COA
I_{pv} (A)	3.8752	3.8046	3.8	3.8084	3.8418
I_{o1} (A)	3.6129×10^{-10}	3.9901×10^{-10}	4.704×10^{-10}	4.8723×10^{-10}	4.95821×10^{-8}
I_{o2} (A)	9.3773×10^{-6}	4.033×10^{-6}	4.704×10^{-10}	6.1528×10^{-10}	9.54961×10^{-9}
R_s (Ω)	0.3084	0.3397	0.35	0.3692	0.2495
R_p (Ω)	280.6449	280.2171	176.4	169.0471	267.57
n_1	1	0.99859	1	1.0003	1.2569
n_2	2	2.0014	1.2	1.9997	1.9345
RMSE	0.0358	0.0517	0.1211	0.1636	0.0194

The measured and corresponding simulated *I-V* and *P-V* characteristics, for parameters obtained by using COA and other methods, are shown in Figures 4 and 5, respectively. It is evident that COA outperforms the other methods in terms of approaching the measured characteristics.

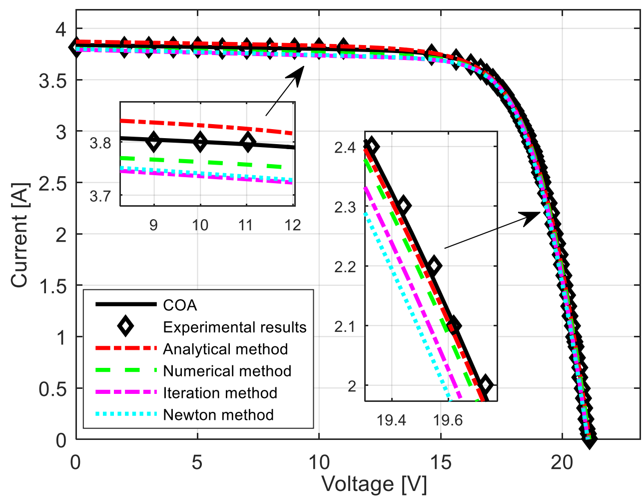

Figure 4. *I*-*V* characteristics of BPSolar MSX-60 module.

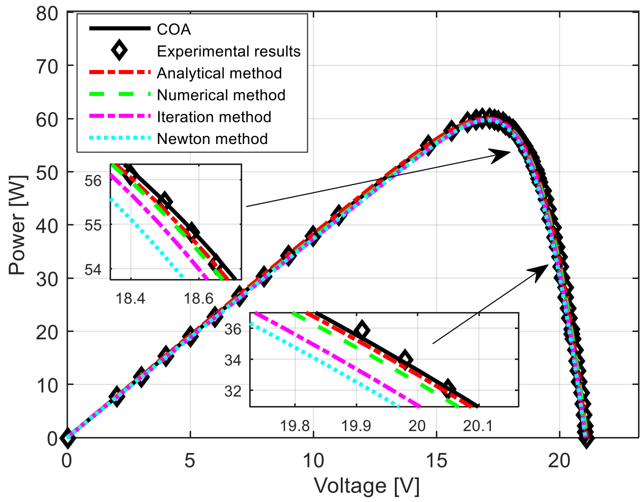

Figure 5. *P*-*V* characteristics of BPSolar MSX-60 module.

Based on all of the presented results, it can be concluded that COA can precisely estimate the solar cell/module circuit parameters, outperforming the other metaheuristics as well as analytical or numerical methods in terms of estimation accuracy.

5. Experimental Results and Analysis

To check the applicability and efficiency of COA for solar cell parameter estimation, we also observed solar cells from the Clean Energy Trainer setup. The main motivation to use these solar modules is that this setup enables adjustable solar insolation, USB data monitoring for PC-supported data acquisition and analysis, as well as highly advanced didactic software for system control and real-time data plotting.

The observed system contains of:

1. two solar modules and one module: 4 solar cells, 400 mW, 2 V, 0.5 A,
2. TES 1333R data logging Solar power meter—instrument with range of 2000 W/m^2, high resolution (0.1 W/m^2), and wide spectral resolution (400–1100 nm), etc.
3. lamp—special double spotlight lamp that simulates sunlight. It provides the optimal light spectrum for the solar module.
4. USB Data Monitor—used for data acquisition. Also, it is connected to the computer and software through the USB port.

5. load—simulates electric consumer load.
6. software—designed to facilitate system control, parameter monitoring, data acquisition and graphical representation of the collected data.

The experimental setup, installed in Laboratory for Automatics, at the Faculty of Electrical engineering, University of Montenegro, is presented in Figure 6.

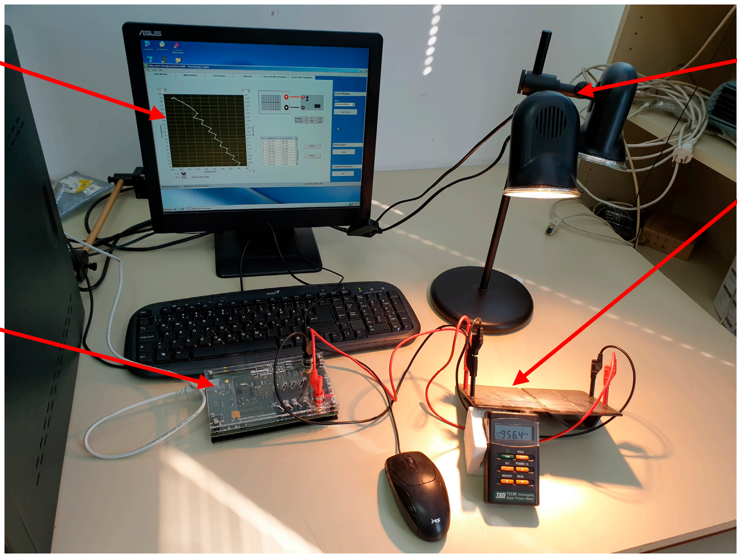

Figure 6. Experimental setup.

Firstly, we measured the *I-V* characteristics for insolation of 1285 W/m^2 and temperature of 42 °C. For the measured *I-V* pairs, we determined single and double diode solar cell parameters (see Table 5). The parameter ranges for SDM estimation were $R_s(\Omega) \in [0.1,\ 0.4]$, $I_{pv}(A) \in [0.2,\ 0.4]$, $I_o(A) \in \left[5 \times 10^{-8},\ 15{\times}10^{-8}\right]$, $R_p(\Omega) \in [200,\ 600]$ and $n \in [0.2,\ 1]$, whereas for DDM were $R_s(\Omega) \in [0.1,\ 0.4]$, $R_p(\Omega) \in [600,\ 900]$, $n_1 \in [0.2,\ 1]$, $n_2 \in [1.95,\ 2]$, $I_{pv}(A) \in [0.2,\ 0.4]$, $I_{o1}(A) \in \left[5 \times 10^{-8},\ 15{\times}10^{-8}\right]$, and $I_{o2}(A) \in \left[5 \times 10^{-8},\ 15{\times}10^{-8}\right]$. Then we measured the *I-V* and *P-V* characteristics for different values of insolation and temperature. The corresponding simulated characteristics were determined by taking into account the change of parameters with insolation and temperature (see [13]). The measured and estimated *I-V* and *P-V* characteristics for different values of insolation and temperature are presented in Figures 7–10. The agreement between the measured and estimated characteristics is evident (see zoomed parts in these figures). Finally, we repeated the estimation procedure on all measured *I-V* characteristics. The estimated values of parameters were in range of ±4% of the initially observed, which confirms that we can use any of the measured characteristics for parameter estimation. On the other hand, by observing the data provided in Table 5, even for this module, it is evident that DDM is more accurate than SDM.

Table 5. Estimated value of experimentally tested solar module parameters.

SDM		DDM	
R_s (Ω)	0.2283	R_s (Ω)	0.2513
R_{sh} (Ω)	439.55	R_{sh} (Ω)	782.9911
I_o (A)	10.56×10^{-8}	I_{o1} (A)	6.8452×10^{-8}
I_{pv} (A)	0.2987	n_1	0.3342
n	0.3441	I_{pv} (A)	0.2972
		I_{o2} (A)	6.0643×10^{-8}
RMSE	4.3418×10^{-4}	n_2	1.9906
		RMSE	4.146×10^{-4}

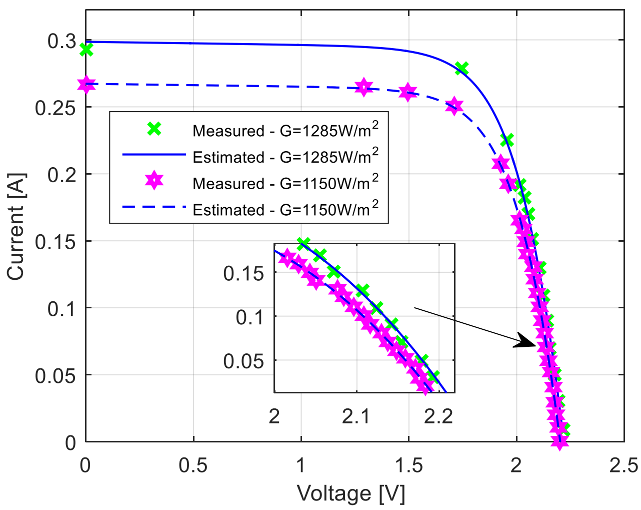

Figure 7. Current-voltage characteristics for two different insolation values and for temperature T = 42 °C.

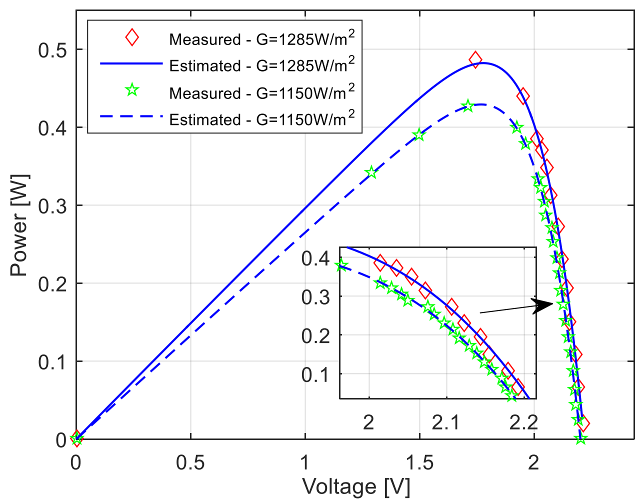

Figure 8. Power-voltage characteristics for two different insolation values and for temperature T = 42 °C.

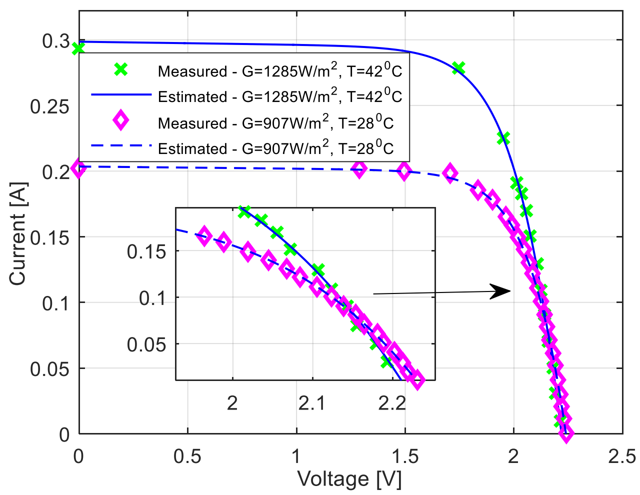

Figure 9. Current-voltage characteristics for two different temperatures and insolation values.

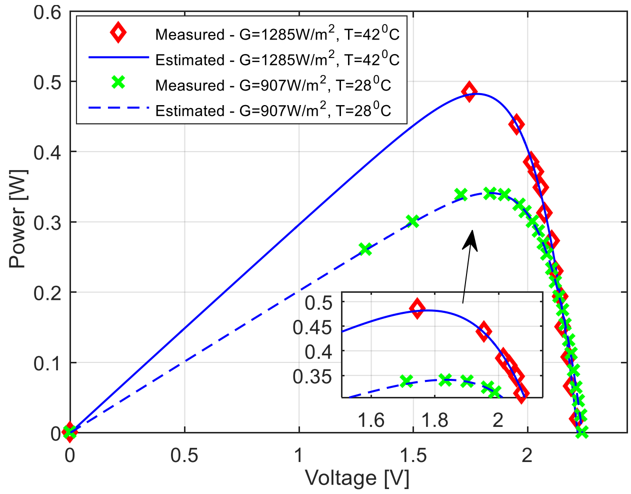

Figure 10. Power-voltage characteristics for two different temperatures and insolation values.

6. Conclusions

Modeling of solar cells is a very popular research direction, which is supported by numerous recent contributions in the literature. This paper proposes COA as a very successful approach for this purpose.

The proposed method is verified using practical data from various manufacturers. Its accuracy is confirmed by comparing its RMSE with numerous metaheuristics and non-metaheuristics methods for different solar cells. Experimental testing of COA applicability for parameter estimation is also implemented in laboratory environment. In all considered scenarios, a high level of accuracy is demonstrated. Apart from this, excellent matching of the simulated *I-V* and *P-V* curves with the measured characteristics additionally confirms the COA accuracy and its applicability for parameter estimation.

In future work, our attention will be focused on the usage of COA for estimation of solar cell parameters when solar cell output current is represented through the Lambert W function.

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