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Study of a New Hybrid Optimization-Based Method for Obtaining Parameter Values of Solar Cells

Selma Tchoketch Kebir

Abstract

This chapter presents a comprehensive study of a new hybrid method developed for obtaining the electrical unknown parameters of solar cells. The combination of a traditional method and a recent smart swarm-based optimization method is done, with a big focus on the application of the topic of artificial intelligence algorithms into solar photovoltaic production. The combined approach was done between the traditional method, which is the noniterative Levenberg-Marquardt technic and between the recent meta-heuristic optimization technic, called Grey Wolf optimizer algorithm. For comparison purposes, some other classical solar cell parameter determination optimization-based methods are carried out, such as the numerical (iterative, noniterative) methods, the meta-heuristics (evolution, human, physic, and swarm) methods, and other hybrid methods. The final obtained results show that the used hybrid method outperforms the above-mentioned classical methods, under this study.

Keywords: solar cell, identification, optimization, meta-heuristics, swarm-based intelligence

1. Introduction

Solar photovoltaic energy is becoming the most popular renewable energy used in the world, at many caring of installations. Modeling and characterization are important topics that necessitate the determination of the exact solar photovoltaic (PV) cell's unknown parameters values and thus optimizing the PV power generated. Solar PV generator's performances are affected by many factors, where some of them are external, related to the environmental conditions like the weather's variations (irradiation and temperature), shading phenomenon, hotspot [1], dust, cell damage, wind velocity, and soiling [2]. Others are internal, related to the electrical, physical, and mathematical modeling. After the modeling step of any PV generator, their identified parameters values are used in the established model. Therefore, it is necessary to find the accurate values of the unknown electrical PV parameters by an appropriate approach. Besides, accurate parameter values of PV cells are essential for the development of good controlling techniques for Maximum Power Point Tracking (MPPT) based power electronic converters [3]. As shown in the **Figure 1** the importance of PV parameters' obtaining accurate values for a whole PV system.

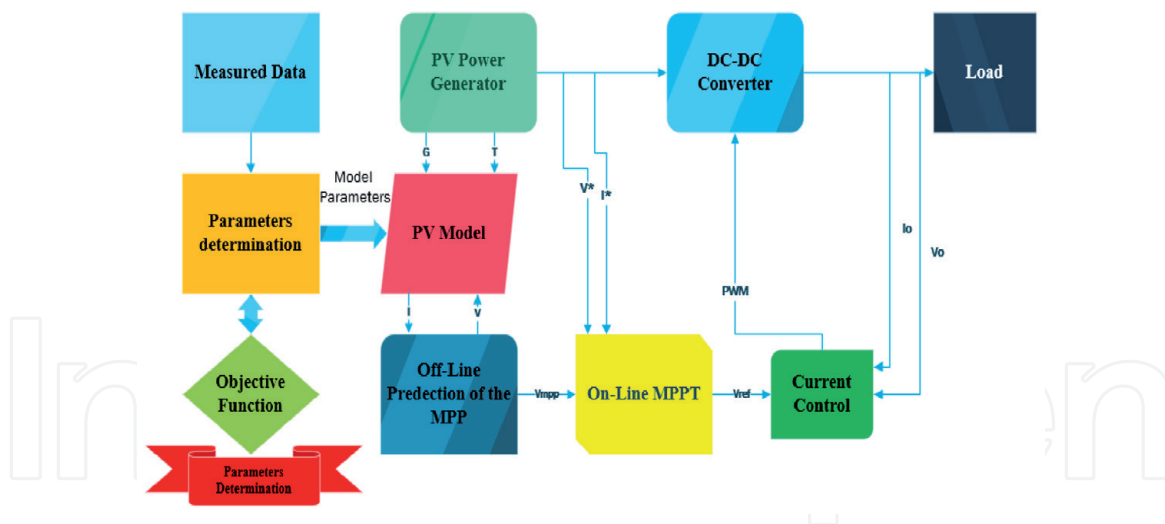


Figure 1.
Importance of determination of accurate PV parameter values in PV systems [3].

With the complexity of the nonlinearity founded from the current-voltage relationship through the model used to represent the physical behavior of PV cells (Single Diode, Double Diode, Three Diode, and so on) [4]. The parameters to be found become more numerous, as the complexity of models increases. The PV parameters of a Single Diode Model (SDM), which are the most determined in literature, and which are the light and the diode saturation currents, the diode ideality factor, the series, and the shunt resistances. A challenge is to obtain the values of all the PV model's parameters value while keeping a reasonable compromise of some criteria, such as the fast speed of convergence, low implementation complexity, and so on.

Artificial intelligent (AI) algorithms have attracted attention lately, by the scientific community to be used for resolving many topic's problems. Among them solar photovoltaics' problems, such as modeling, identification, prediction, optimization, sizing, control, and many others [5]. The hybrid optimization-based methods have attracted more attention to achieve more efficiency and precision. For this reason, this paper presents a combination of the traditional Levenberg-Marquardt (LM) with the recent meta-heuristic Grey Wolf optimizer (GWO) method. This hybrid LMGWO method has seemed to be the most performing, which we finally have chosen to be used in this work.

The remaining of this chapter is structured as follow. After the introduction given in this Section 1. Section 2 presents a classification of the optimization-based methods used in the literature to estimate the PV parameters values. In the Section 3, models are presented of the PV cell (single diode), and the problem of PV parameters obtaining values is presented. Section 4 gives some details about the hybrid used method to estimate the SDM parameters values. Moreover, this section provides the basic concept of the LM and the GWO. Finally, Section 5 shows some results comparing one method of each type proposed in the classification and the LMGWO. Some conclusions are given in Section 6.

2. Classification and literature review

Earliest, numerous research workings have been developed only for obtaining parasitic resistances (series and shunt) values [6] by the cause of their high influences on the PV's performances. Then, it has been observed some influences of all PV's electrical parameters on the PV's performances [7], which leads the researchers, for doing a large number of studies for obtaining their accurate values.

In literature, different approaches, that allow the evaluation of the PV cell’s electrical parameters values, exist [8–11]. There are some analytical approaches [12–15], and those based on the optimization process. By the cause of limits of the analytical method to achieve with high precision the PV parameters values, our interest is gone for the optimization-based methods. This latter can be classified as in **Figure 2**.

The optimization algorithms are classified into traditional, heuristic/meta-heuristic, and hybrid groups. More details about each group of optimization-based are given at the following subsections.

2.1 Numeric traditional

The numeric traditional optimization-based methods are used to find the optimum of a function using gradient or hessian. These numeric-traditional methods applied for PV parameters obtaining values, are based on the reduction of the number of parameters to be evaluated, such as Kashif’s one [16]. In this subsection’s methods, the traditional iterative Newton-Raphson (NR) approach [17], iterative curve-fitting [18], can also be used. It necessitates an iterative process with good initialization guess of PV parameters values, to converge to the best solutions. Others build a set of nonlinear transcendental equations (based on short-circuit, open-circuit, MPP, derivatives of the I-V curve) and execute an optimization problem instead of solving by numerical methods [17]. For the noniterative method, the Levenberg-Marquardt [19] can be cited.

Even though with their effectiveness to get a good local search, they still have other limitations, such as the need of a convex, continuous, and differentiability of the objective function. Besides, good guessing of initial parameters values is necessary for a good converging process. Also, as the complexity of the modeling process increase, as the optimizer loses the ability for obtaining better results.

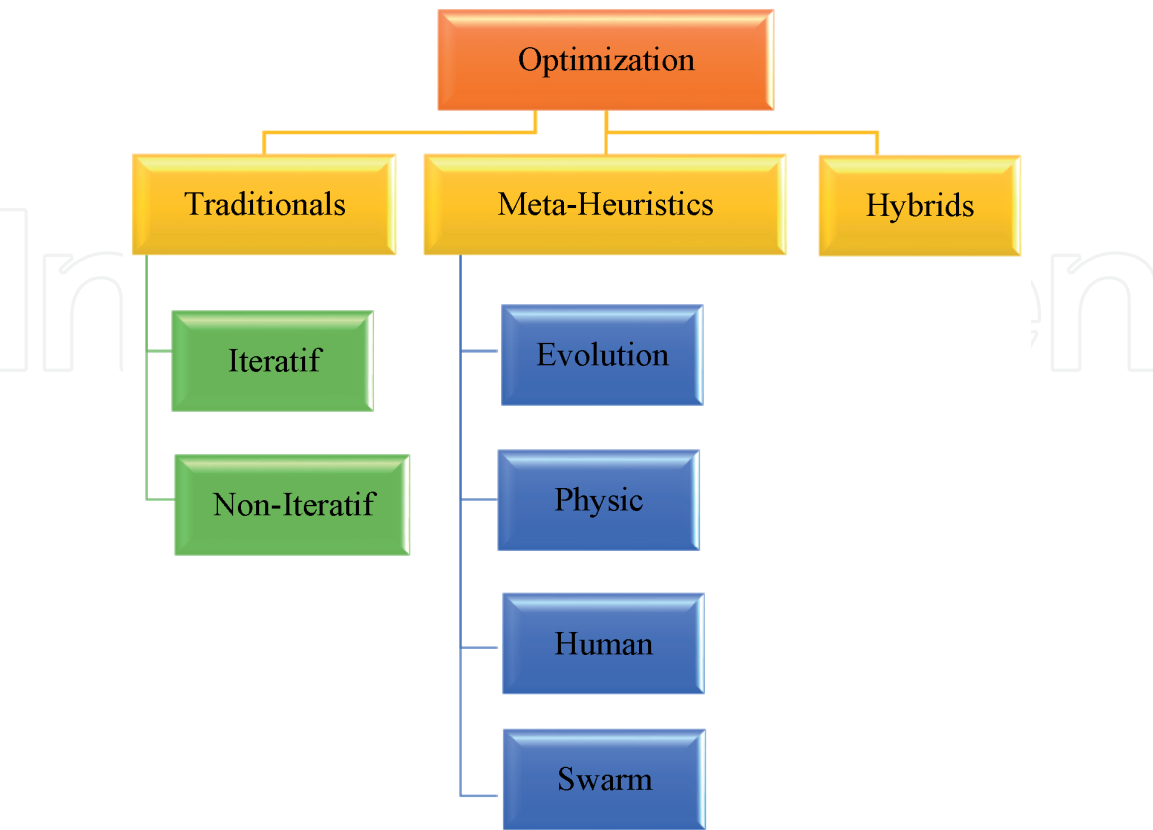


Figure 2.
Classification of PV cell’s electrical parameter determination optimization-based methods.

2.2 Meta-heuristics

In recent times, meta-heuristic optimization-based methods, using Artificial-Intelligence (AI) inspired algorithms, have attracted the care of researchers to obtain with good precision, the unknown PV parameters values.

The metaheuristic methods use bio-inspired algorithms in the search process to identify the PV parameters values at real-time, using the errors between the real experimental data and the simulated data. These approaches are based on an experimental process and are known as identification methods [20]. These approaches are graphically based on curve characteristics fitting.

Meta-heuristics are categorized into four main sets such as evolution-based [21], physic-based [22], immune-human-based [23] and swarm-based intelligence methods [24]. Some of each category is used for obtaining PV parameters values as presented on what follow.

2.2.1 Evolution-based

Evolutionary Algorithm (EA) [25], Differential Evolutionary (DE) [23], Genetic Algorithms (GAs) [25], Pattern Search (PS) [21], Simulated Annealing (SA) [26], Improved Shuffled Complex Evolution (ISCE) [27], Repaired Adaptive Differential Evolution (Rcr-IJADE) [28].

2.2.2 Physic-based

Electromagnetic Field Optimization (EFO), Gravitational Search Algorithm (GSA), Electromagnetism-Like Algorithm (EMA), Weighted Superposition Attraction (WSA) [29].

2.2.3 Human-based

Harmony Search (HS) [30], Bacterial Foraging Algorithm (BFA) [31], Simplified Teaching-Learning-Based Optimization (STLBO) [32], Discrete Symbiosis Organism Search (DSOS) [33], Artificial Immune system (AIS) [34].

2.2.4 Swarm-based

The swarm-based, Particle Swarm Optimization (PSO) [3, 35, 36], Bird Mating Optimization (BMO) [37], Artificial Bee Swarm Optimization (ABSO) [38], Grey Wolf Optimizer (GWO) [39], Chaotic Whale Optimization Algorithm (CWOA) [40], Cat Swarm Optimization (CSO) [41], and Cluster Analysis (CA) [3].

The metaheuristics are more attractive than the deterministic traditional methods in terms of accuracy and robustness, by the cause of their good global research achieving. Besides, they do not require a gradient or differentiable of the objective function. Besides, the initial guess of parameters values is not a necessity, but it necessitates the upper and lower limits of an interval of research.

2.3 Hybrids

The hybrid method combines different approaches. These methods make a mix of other methods, i.e. analytical and numeric-traditional methods [15]; analytical and meta-heuristics, numeric-traditional and meta-heuristics optimization; a combination of two different meta-heuristics, etc. [38]. We can site, hybrid adaptive Nelder-Mead simplex algorithm based on eagle strategy (EHA-NMS) [41], Nelder-Mead simplex algorithm based on eagle strategy (EHA-NMS) [41], Nelder-Mead and Modified

Particle Swarm Optimization (NM-MPSO) [42], Artificial Bee Colony-Differential Evolution (ABC-DE) [43], Trust-Region Reflective deterministic algorithm with the Artificial Bee Colony (ABC-TRR) [43], Teaching-learning-based Artificial Bee Colony (TLABC) [43]. Our proposed Levenberg-Marquardt with Grey Wolf optimizer (LM-GWO), and so on. Those methods, which are called hybrid, have excellent performances because they restrict the universe in the search process without losing precision (without losing the optimum). They achieve outstanding results with a smaller number of iterative steps when compared with pure optimization methods.

3. Modeling and problem formulation

There are several electrical models, used by researchers, to describe the physical behaviors of PV cells. The Single Diode Model, containing the five unknown parameters, used in this paper is represented in **Figure 3**. By the cause of compromise between accuracy and simplicity, the SDM is selected herein.

The mathematical expressions related to the current-voltage, (I-V) relationship of the PV cell is as follow.

$$I = I_L - I_D - I_{sh} \tag{1}$$

$$I = I_L - I_{ds} \left(e^{\left(\frac{V + R_s \cdot I}{n \cdot V_t} \right)} - 1 \right) - \frac{V + R_s \cdot I}{R_{sh}} \tag{2}$$

The overhead mathematical equation is in a nonlinear form and has a set of five unknown parameters (I_L , I_{ds} , n , R_s , R_{sh}). The main challenge is to get the accurate values of all the PV model's parameters values while keeping a reasonable computational effort.

Several approaches permit the formulation of the optimal nonlinear PV parameters determination problem, using the error (between real and simulated data) [10].

Our focus is to estimate the PV parameters values of the SDM model using RTC France data at the conditions of irradiance about 1000 W/m² and of temperature about 300°C. We do not review the identification process as detailed on our previous work [20]; our focus is restricted on the third part of identification process, which is the estimation of PV parameters values. The big focus is to optimize the damping factor of LM through GWO. The characteristics of RTC France Silicon-cell data from datasheet are presented on the following **Table 1**.

The real experimental data used of RTC France are presented on the following **Table 2**.

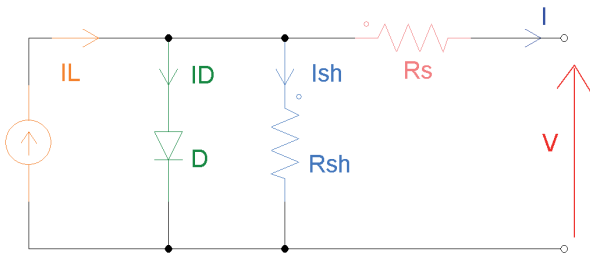


Figure 3.
PV cell's electrical equivalent circuit (SDM) [12].

Characteristic data	R.T.C France
I_{sc} (A)	0.7603
V_{oc} (V)	0.5728
V_{mpp} (V)	0.4507
I_{mpp} (A)	0.6894
P_{mpp} (W)	0.311
R_{sho} (Ω)	246.80*
R_{so} (Ω)	0.0907*
T (K)	306.15
N	1
K_v	71.44
K_i	0.035

Table 1.
Characteristic data from R.T.C. France (Si solar cell).

Measurement	V (Volts)	I (Ampere)
1	−0.2057	0.764
2	−0.1291	0.762
3	−0.058	0.7605
4	0.00057	0.7605
5	0.06460	0.76
6	0.1185	0.759
7	0.1678	0.757
8	0.2132	0.757
9	0.2545	0.7555
10	0.2924	0.754
11	0.3269	0.7505
12	0.3585	0.7465
13	0.3873	0.7385
14	0.4137	0.728
15	0.4373	0.7065
16	0.459	0.6755
17	0.4787	0.632
18	0.496	0.753
19	0.5119	0.499
20	0.5265	0.413
21	0.5398	0.3165
22	0.5521	0.2120
23	0.5633	0.1035
24	0.5736	−0.0100
25	0.5833	−0.1230
26	0.5900	−0.2100

Table 2.
Real data from RTC [38].

4. Hybrid optimization-based method

Hybrid optimization-based algorithms have become the modern choice for resolving challenging problems [41–43]. A compromise is gotten in this work, from a combination of a traditional numeric optimization-based with a metaheuristic swarm-based method.

The estimation/identification process can be gotten in three major steps, such as the initial step of prediction through the use of least-squares mean (LSM), the getting of optimal PV parameters values through Levenberg-Marquardt (LM), and the optimization of a dominant factor through GWO as detailed below.

4.1 Least squares mean (initial phase of prediction)

Prediction of initial PV parameters values using LSM [44, 45] for the two parts of the introduced real experimental points of I-V curve characteristics as described below.

- For the linear part:

The prediction in the linear part [46, 47] of the model can be obtained simply through the use of the following expressions.

$$I_{Model}(i) = a * V_{Model}(i) + b \quad (3)$$

$$Error(i) = I_{Real}(i) - I_{Model}(i) \quad (4)$$

$$J(i) = J(i-1) + error(i)^2 \quad (5)$$

where a and b are constants depending on a determinant and others constants introduced by user.

- For the nonlinear part:

The prediction in the nonlinear part [19, 48] of the model can be obtained with a logarithmic way through the use of the following logarithmic expression.

$$I_{Model}(i) = C_0 + C_1 * I_{Model}(i) + C_2 * \log\left(1 - \frac{I_{Real}(i)}{b}\right) \quad (6)$$

$$Error(i) = I_{Real}(i) - I_{Model}(i) \quad (7)$$

$$J(i+1) = J(i) + error(i)^2 \quad (8)$$

where C_0 , C_1 , C_2 and b are constants depending on a determinant, on the hessian and other constants introduced by the user.

Once obtaining initial values of PV parameters values, we introduce them on the LM in order to optimize their values, as explained in the following subsection.

4.2 Levenberg Marquardt (get of optimal PV parameter values)

The traditional Levenberg-Marquardt approach is a gradient order from Steepest-Descent (SD) in its first step and from Gauss-Newton (GN) in its second step [48–50]. It is mainly based on an optimization of the error between real data and data from the model through the following expression.

$$Ecart - Quad = \sum_{i=1}^N Error(i)^2 \quad (9)$$

where N is the number of measured I-V data.

$$Error = I_{Real}(i) - I_{Model}(i) \quad (10)$$

The real and simulated data are denoted by I_{Real} and I_{Model} , respectively. While I_{Model} is the objective function given as Eq. (2),

$$I_{Model}(i) = f(I, V, \theta) \quad (11)$$

Evaluate the objective function $f(\theta)|_{\theta = \theta_k}$. Here, θ is considered as the PV parameters vector.

$$\theta = \{I_L, I_{ds}, n, R_s, R_{sh}\} \quad (12)$$

Calculus of Jacobian of $f(I, V, \theta)$ for θ_k , as the derivative calculation of I (Eq. (2)) with respect to parameters:

$$J = - \left[\frac{\partial f(\theta)}{\partial \theta} \right]_{\theta = \theta_k} \quad (13)$$

For (damping optimized) update θ_k . The PV parameters to be found are updated at each iteration by the use of the expression below.

$$\theta_{k+1} = \theta_k - \left[\frac{J' * \varepsilon}{J' * J + \lambda_k * I} \right]_{\theta = \theta_k} \quad (14)$$

The dominant factor λ is considered as responsible parameters for switching from SD to GN in the LM process [19].

For this reason, it is important to get an optimal value of this damping factor by the use of another optimization-based method, our choice was for the recent swarm-based method called GWO, through the following idea:

$$Ecart - Quad(I, V, \theta, \lambda) \rightarrow Ecart - Quad(\lambda)|_{\theta = \theta_k} \quad (15)$$

In addition, it is mentioned that at each iteration of the LM process that the damping factor must be found and is considered as crucial factor for the convergence process of the algorithm. Therefore, its value must be optimized by the use of another approach such as the GWO approach.

4.3 Grey Wolf optimizer (optimization of damping factor's value)

In this subsection, our focus is on the evolution of the function $f(I,V,\theta,\lambda)$ indicated by $f(\lambda)$ for θ fixed at θ_k , as regards with various varied values of the damping factor, at each iteration of the LM. As it is observed that at each iteration different local minimums values of $f(\lambda)$ exist. So, for obtaining the global minimum of $f(\lambda)$, which correspond to the best minimal value of the objective function $f(I,V,\theta)$, we suggest using the swarm-based meta-heuristic GWO method.

The meta-heuristic methods are known for their simplicity, flexibility, derivation free process and the ability to find the global optimal solution. They are also appropriate for a diversity of problems without changing on their main structure. These methods can be based on a single solution or on population of solutions. The basic concepts can be obtained through exploration (exploring all of the search space and thus avoiding local optimum) and exploitation (investigating process in detail of the promising search space area).

Swarm-based intelligence (SI) methods, which derive from meta-heuristics, are based on the smart collective behavior of decentralized and self-organized swarms to ensure some biological needing such as food or security. A detailed discussion about the recent smart swarm-based algorithm, known as GWO is presented as follow.

Grey Wolf optimizer (GWO) algorithm, developed by Mirjalili in 2014, is a recent smart swarm-based meta-heuristic approach [50–52]. This algorithm mimics the leadership hierarchy and hunting process of Grey wolves in the wildlife. The following points represent the hierarchy in a wolf's group, which is about 5 to 12 members.

1. The alphas wolves (α): are the leading wolves that are responsible for managing and making decisions. These are the first level of the wolves' social hierarchical structure. This later is presented in **Figure 4**.
2. The betas wolves (β): represent the second level. Their main job is to help and support alpha's decisions.
3. The deltas wolves (δ): represent the third level in the pack and are called subordinates. They use to follow alpha and beta wolves. The delta wolves can divide their tasks into five categories as follows:

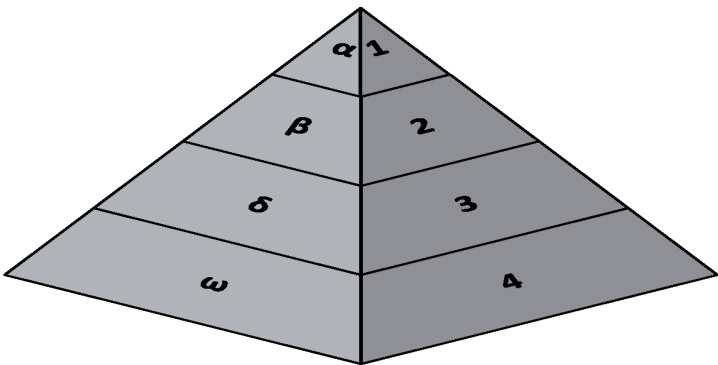


Figure 4.
The social hierarchical structure of Grey wolves (dominance decreases from the top-down) [51].

- Scouts: used to control the boundaries of the territory and alert the pack in case of danger.
- Sentinels: protect and guarantee the safety of the pack.
- Elders: among these strong and mature wolves, some of them become either alpha or beta.
- Hunters: help alpha and beta in the hunting prey, providing food to the pack.
- Caretakers: responsible for caring the ill, wounded and weak wolves.

4. The omegas wolves (ω): represent the lowest level. They have to follow alpha, beta and delta wolves.

When a pack of wolves sees a prey such as (gazelle, rabbit or a buffalo) they attack it in three steps and do not recede, **Figure 5**.

These three steps of the hunting process can be mentioned as follows.

- Encircling, tracking, chasing, and approaching the prey (**Figure 5: A, B**).
- Pursuing, encircling, and harassing the prey until it stops moving (**Figure 5: C**).
- Attacking the prey (**Figure 5: D, E**).

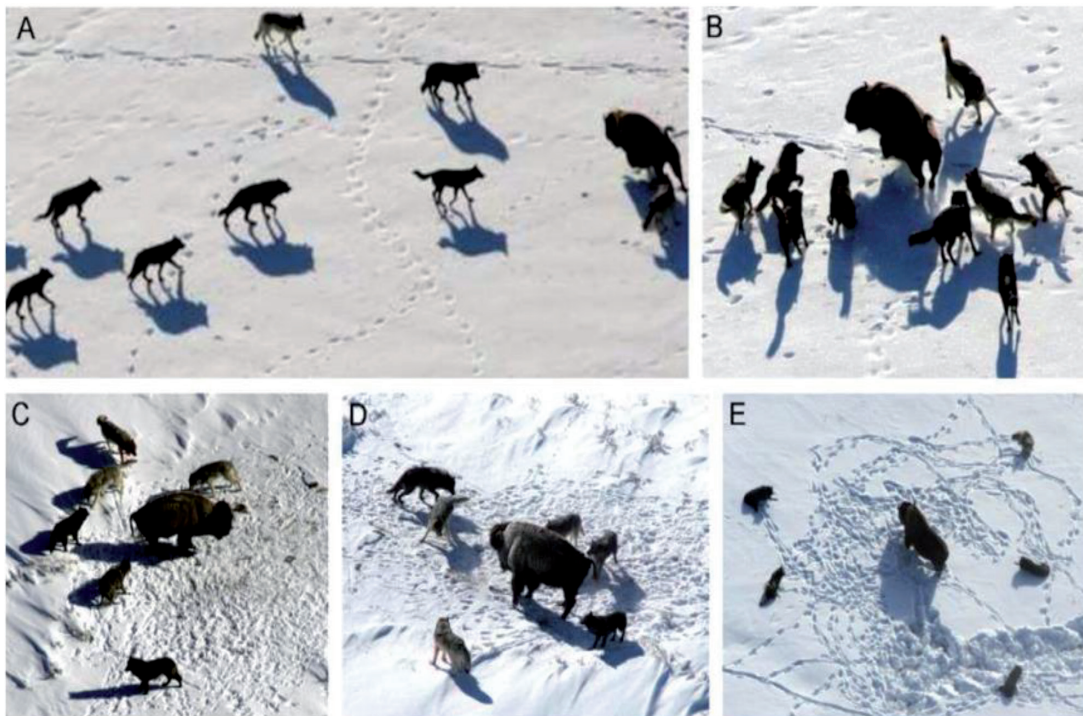


Figure 5.
The process of hunting prey by a group of wolves [51].

The mentioned above social hierarchy and hunting process of Grey wolves have been mathematically modeled in GWO, as follows [51, 52]:

- The first, second and third best solutions are considered as α , β and δ wolves, respectively.
- The rest of the candidate solutions are considered as ω .

The following equations are used to model the encircling first step of Grey wolves hunting process:

$$\vec{D} = |\vec{C} * \vec{X}_p(i) - \vec{X}(i)| \quad (16)$$

$$\vec{X}(i+1) = \vec{X}_p(i) - \vec{A} * \vec{D} \quad (17)$$

where i represents the current iteration. X and X_p represent the position vectors of the wolves and the prey, respectively. A and C are the coefficients and are calculated as follows:

$$\vec{A} = 2 * \vec{a} * \vec{r}_1 - \vec{a} \quad (18)$$

$$\vec{C} = 2 * \vec{r}_2 \quad (19)$$

where a is linearly decreasing from 2 to 0 throughout iterations, and r_1, r_2 are random values in an interval from 0 to 1. In GWO, decreasing the values of A , from 2 to 0 during the optimization process, simulates the prey approach and provides the exploration ability of the algorithm. Besides, the exploitation ability of the GWO comes from the random value of C .

To mathematically simulate the second step of the Grey wolves hunting process, we suppose that the alpha (best candidate solution), beta and delta have a better knowledge about the potential location of the prey [53]. Therefore, the first three best solutions obtained so far are saved and oblige the other search agents (including the omegas) to update their positions according to the position of the best search agents. In this regard, the following formulas are used.

$$\vec{D}_{\alpha,\beta,\delta} = |\vec{C}_{1,2,3} * \vec{X}_{\alpha,\beta,\delta} - \vec{X}| \quad (20)$$

$$\vec{X}_{1,2,3} = \vec{X}_{\alpha,\beta,\delta} - \vec{A}_{1,2,3} * \vec{D}_{\alpha,\beta,\delta} \quad (21)$$

$$\vec{X}(i+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (22)$$

The final third step is the hunting process as attacking the prey as soon as it stops moving.

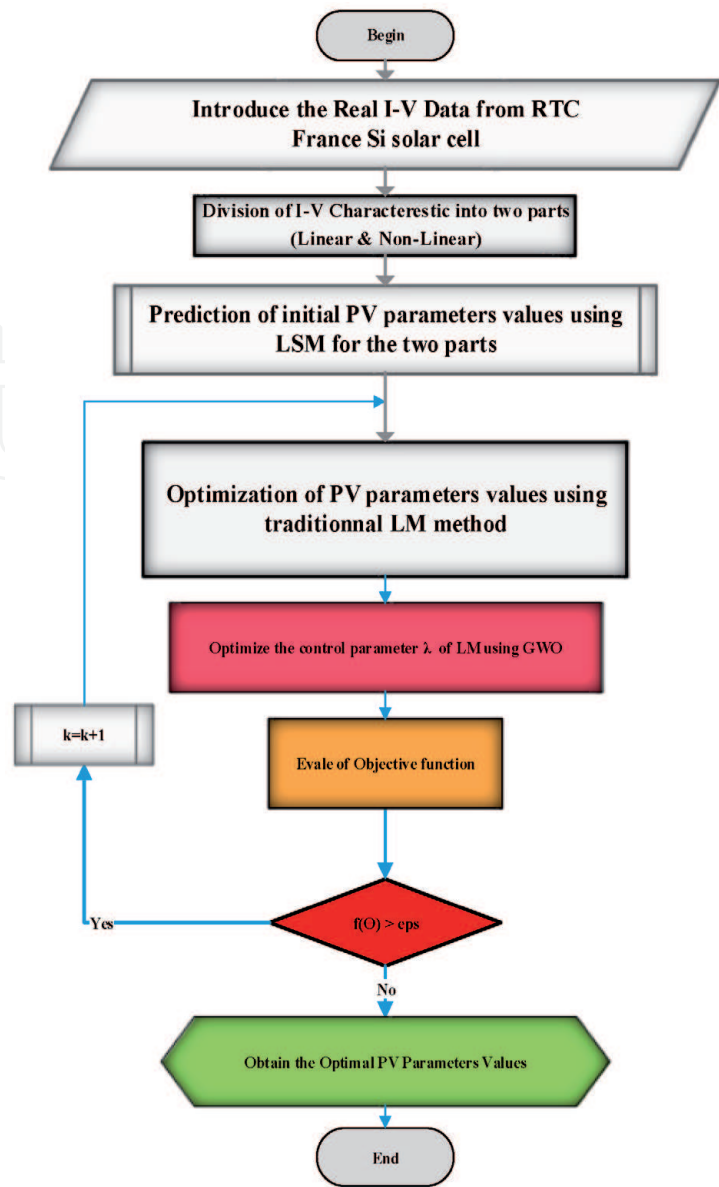


Figure 6.
PV parameters identification steps using the hybrid LM approach with GWO approach.

4.4 LMGWO

The main steps of the used hybrid LMGWO method applied for the PV parameters obtaining values are presented in **Figure 6**.

5. Results and discussions

The following **Table 3** presents PV parameters results for the all classified optimization-based method discussed in Section 2.

From the above **Table 3** it is clear that for the traditional methods, the LM is more accurate than Newton’s method, which in turn outperforms Kashif’s method. Then, for the metaheuristic methods for each of their category as follow.

- Evolution-based:

It is observed that ISCE, Rcr-IJADE, and PCE outperform PS, which in turn is better than GA and SA.

Methods	Parameters	I_L (A)	$I_{ds}(\mu A)$	n	$R_s(\Omega)$	$R_{sh}(\Omega)$	RMSE
Traditional	Kashif [16]	0.760300	2.624738e-09	1.200000	0.014000	19.000032	7.090000e-02
	LM [19]	0.760782	3.166611e-07	1.479182	0.036461	53.271523	9.8680e- 4
	Newton [17]	0.7608	0.3223	1.4837	0.0364	53.7634	9.70E-03
Meta-heuristics	Evolution-based						
	GA [25]	0.7619	0.8087	1.5751	0.0299	42.3729	0.019
	SA [26]	0.762	0.4798	1.5172	0.0345	43.1034	0.019
	PS [21]	0.7617	0.998	1.6	0.0313	64.1026	0.0149
	ISCE [27]	0.760776	0.32302	1.48118	0.03638	53.7185	9.8602E-04
	Rcr-IJADE [28]	0.760776	0.32302	1.48118	0.03638	53.7185	9.8602E-04
	PCE	0.760776	0.323021	1.481074	0.03638	53.7185	9.8602E-04
	Swarm-based						
	PSO [35, 36]	0.76077	0.32454	1.48165	0.03636	53.8550	9.8606E-04
	ABSO [38]	0.7608	0.30623	1.47583	0.03659	52.2903	9.9124E-04
	BMO [37]	0.76077	0.32479	1.48173	0.03636	53.8716	9.8608E-04
	CSO [41]	0.76078	0.323	1.48118	0.03638	53.7185	9.8602E-04
	CWOA [40]	0.76077	0.3239	1.4812	0.03636	53.7987	9.8602E-04
	Human-based						
	BFA [31]	0.7602	0.8000	1.6951	0.0325	50.8691	0.029
	HS [30]	0.7607	0.305	1.4754	0.0366	53.5946	9.95E-04
	STLBO [32]	0.76078	0.32302	1.48114	0.03638	53.7187	9.8602E-04
	Physic-based						
	EFO [29]	0.760776	0.323022	1.481184	0.036377	53.718646	9.860219E-04
	GSA [29]	0.760977	0.847206	1.585214	0.032130	82.871489	2.166195E-03
	EMA [29]	0.760590	0.329155	1.483019	0.036365	57.025188	9.972880E-04
	WSA [29]	0.754454	1.000000	1.607072	0.027957	97.854073	7.702232E-03
Hybrid	LM-GWO	0.760776	0.32306	1.48118	0.03637	53.7222	9.8601E-04
	LMSA [19]	0.7608	0.3185	1.4798	0.0364	53.3264	9.86E-04
	EHA-NMS [27]	0.760776	0.32302	1.48118	0.03638	53.7185	9.8602E-04
	ABC-TRR [43]	0.760776	0.32302	1.48118	0.03638	53.7185	9.8602E-04
	ABC-DE [43]	0.76077	0.32302	1.47986	0.03637	53.7185	9.8602E-04
	NM-MPSO	0.76078	0.32306	1.4812	0.03638	53.7222	9.8602E-04
	TLABC [43]	0.76078	0.32302	1.48118	0.03638	53.7164	9.8602E-04

Table 3.
Parameter extraction results for 57-mm diameter R.T.C. France commercial silicon solar cell using the single diode model.

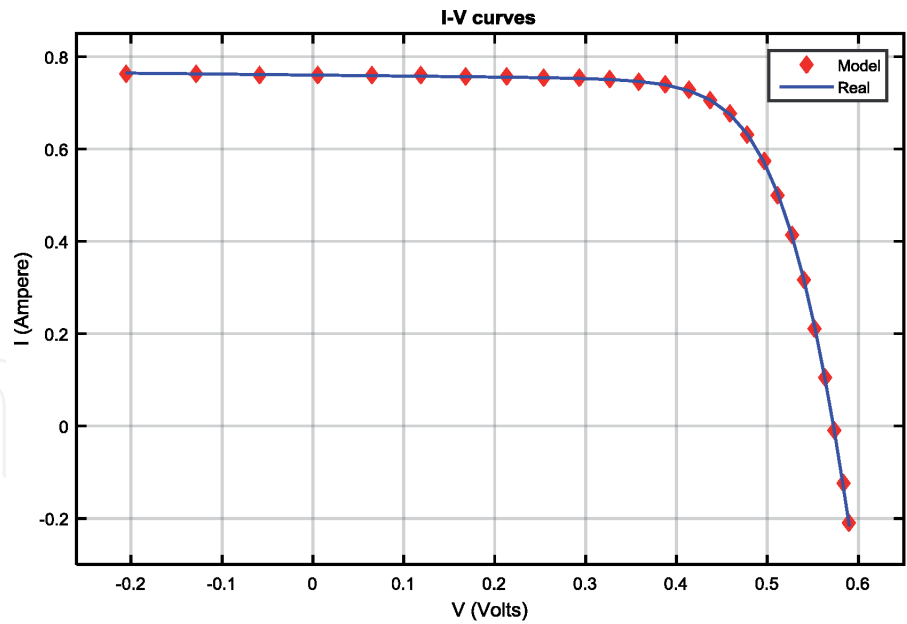


Figure 7.
Fitted I-V curve characteristic for the RTC silicon solar cell, using the hybrid LM-GWO method.

- Swarm-based:

All the swarm-based used outperform ABSO in terms of precision.

- Human-based:

CSO and STBLO outperform HS, which is better than BFA.

- Physics-based

EFO is more accurate than EMA, which is more accurate than WSA, which is more accurate then GSA.

It is mentioned that the swarm-based got the best results compared to the other metaheuristic's category.

Finally, for the hybrid methods, it is clear that all of them have achieved the highest best optimized (minimum) values for RMSE, until now with the value of (9.8601E-04).

In addition, the hybrid methods outperform the metaheuristics, which in turn outperform the traditional methods.

The fitting obtained curves of real and simulated data, using the proposed LMGWO are illustrated in **Figure 7**.

The best approximation gotten from the fitted curves in **Figure 7** has proved the effectiveness of our hybrid LMGWO method.

6. Conclusion

Since nonlinear and multi-parameter PV models are used to represent a PV cell's physical behavior, classical methods are incapable of evaluating the exact parameters' values of these models. For these reasons, the present paper presents a proposed hybrid method of obtaining the unknown electrical parameters of

solar photovoltaic cells. To do so, we applied our hybrid method, the LM combined with GWO method, after having initial guess using least squares mean, and then compared it with other previous optimization-based methods. The application of LMGWO has shown high precision for the obtained solutions' values. The LMGWO outperforms the other tested algorithms in many aspects. It is simple and accurate and converges rapidly to the optimum in every test. In addition, it has fewer parameters to set then it is easily implemented. The obtained results demonstrate the efficiency of the hybrid LMGWO approach compared to the other meta-heuristics and some of the other traditional methods.

Conflict of interest

The authors declare no conflict of interest.

Author details


Selma Tchoketch Kebir^{1,2}

1 Laboratoire de Dispositifs de Communications et de Conversion Photovoltaïque, Electronic Department, Ecole Nationale Polytechnique, 16000 El-harrach, Algiers, Algeria

2 Unité de Développement des Equipements Solaires, UDES/Centre de Développement des Energies Renouvelables, CDER, Bou-Ismaïl, 42415 W, Tipaza, Algeria

*Address all correspondence to: selma.tchoketch_kebir@g.enp.edu.dz

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