A combination of Newton-Raphson method and heuristics algorithms for parameter estimation in photovoltaic modules

Patrick Juvet Gnetchejo a,*, Salomé Ndjakomo Essiane a, b, Abdouramani Dadje c, Pierre Ele a, d

a Laboratory of Technologies and Applied Sciences, University of Douala, Cameroon
b Signal, Image and Systems Laboratory, Higher Technical Teacher Training College of Ebolowa, University of Yaounde 1, Cameroon
c School of Geology and Mining Engineering, University of Ngaoundéré, Ngaoundéré, Cameroon
d Laboratory of Electrical Engineering, Mechatronic and Signal Treatment, National Advanced School of Engineering, University of Yaounde 1, Yaoundé, Cameroon

Keywords: Solar energy modelisation Parameters identifications Photocells Photovoltaic modules Optimization of drone units Heuristics algorithms

A B S T R A C T

Parameters extraction is instrumental to standard PV cells design. Reports indicates that heuristic algorithms are the most effective methods for accurately determining the values of parameters. However, local concentration is against recent heuristic methods, and they are inhibited producing optimal results. This paper seeks to show that combining the heuristics algorithms with the Newton Raphson method can considerably increased the accuracy of results. An inspired artifact technique from the drone squadron simulation from control center is proposed for the extraction of the best constitutive parameters. This study equally provides clarifications on the approaches recently reported and proposed to build objective function. Furthermore, comparative evaluation of the current ten best heuristics algorithms that are published in the PV estimation domain is also undertaken. Moreover, this study investigates the convergence of algorithms when points of the number of current-voltage characteristics are varied. The results from this study highlight the differences between the two formulation, and it shows the best formulation accuracy. The results obtained from seven study cases that are considered in this present study, with the combined Newton Raphson performance method and Drone Squadron optimisation, were employed to extract precise PV module parameters. The study of the numbers of points reveals that the algorithm converges and is more precise when the numbers of points of the I-V characteristic are reduced. However, if these points are minimal, the algorithm will be hindered from returning optimal results.

1. Introduction

Electricity production from solar energy has undergone continuous changed in the 21st century [1]. The increase in solar energy production is attributed to advanced field research and to the free availability of solar energy in the day time in many countries in Africa and elsewhere [2]. Therefore, field development is important for an accurate design of cells and PV modules that can predict the power delivery from the PV system [3, 4].

PV modeling takes into account, well-known parameters such as the ideality factor of diode, the current saturation, photocurrent generation, series resistance and shunt resistance [5]. The drawn PV cell equivalent circuit and mathematic model enable the understanding of information provided from a basic technical data sheet, to estimate unknown parameters and generate maximum power. These data sheets present the open circuit voltage (Voc), the short-circuit current (Isc), voltages at points of maximum power (Vmp), the current at the point of maximum power (Imp) and the power at the point of maximum power (Pmp). Different techniques (analytic, numeric, metaheuristic and hybrids) have been used in the literatures for different parameters extractions. Metaheuristic algorithms have been considered as the best method [4]. The modelling of PV uses sets of nonlinear equations to find the unknown values of PV cell. A detailed literature review on extraction techniques is summarized by [7] which shows that PV equations can be modelled using three different approaches, namely: analytic, numeric and progressive computational techniques [7].

Precise results are gotten from the prime method with little computation time. Analytic method are very simple and more often, just an iteration is necessary to obtain the desired result. A develop method of approximation, which serves as explicit model capitalizing for VI characteristics and estimation of single PV model of diode parameters has been proposed by [8]. Others methods like Lambert's W-function [9], the

* Corresponding author.
E-mail address: patrijuvet@univ-douala.com (P.J. Gnetchejo).

https://doi.org/10.1016/j.heliyon.2021.e06673
Received 26 September 2020; Received in revised form 6 December 2020; Accepted 29 March 2021
2405-8440/© 2021 The Author(s). Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).
expansion of Taylor series [10], set of approximate explicit equations [11] and curve-fitting approaches [12] have been considered in the literature. Some methods enable 5 parameters estimation and others extract just series resistance and shunt resistance [11]. Major weakness of this analytical method is that they suit only the condition of standard test and collapse with conditions variations. Numerical methods with techniques of curve fitting are best than analytic and various considered algorithms of these methods enable acquisition of results accuracy by the assessment of all PV-IV curves points using the algorithm of Levenberg to get solar cell parameters [13]. Method of Newton Raphson implies large computing times and memories; it fails for inaccurate initial guess convergence even though the method to delay the convergence is efficient [14]. PV parameters estimation include constraints optimization was carried out using metaheuristic. These algorithms are mainly nature inspired, following natural environmental processes. These algorithms are considered the best, because they give optimal results whatever the conditions. Numerous available algorithms in literatures portray different modelling techniques such as conventional GA and basic progressive computing techniques. Double PV parameters estimation for diode model was done using: improved the Optimization of Harris hawks (HHO) [15], improved adapted differential and evolution with repairing crossover rate (RecrJADE) [16], genetic algorithm (GA) [17], algorithm of the enhanced vibration of particles system (EVPS) [6], artificial algorithm of bee swarm optimizations (ABSO) [18] and algorithm optimization of the improved JAYA (IJAYA) [19]. In addition we have the use of self-adaptive learning-based optimization (SATLBO) [20], improved optimization of whale algorithm (IWAO) [21] algorithm of the improved shuffled and complex evolutions (ISCE) [22], algorithm of hybrid pollination of flower (GOFPANM) [23] and grasshopper optimization algorithm (GOA) [24], the improved teaching and learning based optimization (ITLBO) [25], the algorithm of hybrid cuckoo search (HBCS) [26]. There is also improved algorithm of opposition-based cosine (ISCA) [27], the algorithm of hybrid reflective of trust-region (ABC-TRR) [28], teaching-learning artificial based bee colony photovoltaic estimation of parameters (TLABC) [29] and the algorithm of hybrid differentia-evolution with the optimization of whale (DE/WOA) [30]. Other algorithm used are algorithm of enhanced shuffled and complex evaluation by opposition-based learning improvement (ESCE OBL) [31] and the advanced onlooker-ranking based and improved adaptive and differential evolution (OReJADE) [32], the optimization of cat swarm algorithm (CSO) [33], the algorithms of firefly hybrid search pattern (HFAPS) [34] and the improved mothflame (IMFO) [35]. The mimic adaptive and differential evolution (MADE) [36], algorithm of Coyote optimization (CAO) [37], algorithm of multiple learning and back-tracking search (MLBSA) [38], symbiotic-organisms-search (SOS) [39], success area algorithm discretization (SDA) [40], algorithm of hybrid adaptive and nelder-mead simplex (EHA-NMS) [41, 42], nonhomogeneous algorithm cuckoo search (NoCuSa) [43] and analytical-sunflower algorithm optimization (SPO) [44] were used. Guided JAYA performance (PGJAYA) [45] and improved adaptive and differential evolution algorithm (IADE) [46]. PSO was proven limited in areas of selecting initial parameters as well as high numbers of iteration. The modified PSO proposed to subdue these limitations: Heterogeneous-Chaotic, comprehensive and learning particle optimizer of swarm (C-HCLPSO) [47], the swarm intelligence collaborative (WDOWOAPSO), the enhanced optimization leader particle of swarm (ELPSO) [48], mutation particle with swarm adaptive optimisation (MPSO) [49] and time variation acceleration (TVA) and evolutionary particle optimization (TVAAPSO) [50]. Recent studies investigated other aspects of PV parameters [51], authors investigated on the identification of PV parameters in operation conditions instead of standard. The determined shunt resistance and series resistance in working condition with a few point of IV characteristics around power maximum point. Other authors [52] investigate on influence of the degradation on PV parameters where they used an explicit method to identify single model of diode parameters [53] using current and voltage, temperature coefficient with three specific points include open circuit point, power maximum point, and short circuit point, to extract a solar cell’s best parameter. The method enable PV performance under standard reporting conditions prediction. In [54], a new multispiral leader’s particles swarm was used to boost PSO convergence while estimating PV parameters. In [55], Boosted Harris Howk’s optimization was proposed to determine stable and accurate results [56]. Investigate the different methods used for the estimate of PV parameters, and then they proposed an exact based method on Lambert W-function.

Even with the improvement of these algorithms to date, there is no algorithm for answering all the problems of optimization; moreover, as expressed earlier in the theorem of "no-free-lunch", solving optimization problems with new algorithms are always welcome. That is why we proposed a new method, which is DSO in combination with the method of Newton Raphson, for PV parameters extraction. This algorithm is different from metaheuristics, which are nature inspired; the DSO algorithm is of human and scientific development.

The objective function used by many authors is reducing errors between current measurements and estimation. Studies carried out by researchers in 2019 have proposed method of checking best accuracy results from PV parameters extraction. The obtained results pointed out that some proposed methods found in literatures were not accurate [3]. Nevertheless, the given answer of these authors reveal some inaccuracies in two distinct formulations that had always been presented in literature as similar [57]. This current paper aims firstly to provide insights on the two reported current estimated (accuracy and approximation formulation), and then hybrid methods related to Newton Raphson and self-adapting algorithm is proposed. The DSO is a simulation technique of drone squadron from control station [58], that is used here for the extraction of the best PV modules and cells parameters. At the end, the study also investigates on the convergence of the algorithm when the number of points of the current voltage characteristic is varied.

This paper contributes to:
- the clarification of current estimation of two formulations.
- the two analogue formulations that are often used in literatures were introduced and compare with recently published ten algorithms.
- the application of self-adapting algorithm in combination with the method of Newton-Raphson considered as first time applied method for best PV cells and PV modules parameters extraction.
- the investigation on the convergence of the algorithms when the number of points of the current voltage characteristics are varied.
Where:

\[ V_t = \frac{N_s \cdot K \cdot T}{q} \]  

(2)

N_s is the number of cells connected in series; k is the constant of Boltzmann [J/K], T the temperature [K] and q the charge of electron [C].

For dual diode model, output current is expressed by:

\[ I = I_{ph} - I_0 \left[ \exp \left( \frac{V + I R_p}{n_1 V_t} \right) - 1 \right] - I_0 \left[ \exp \left( \frac{V + I R_p}{n_2 V_t} \right) - 1 \right] - \frac{V + I R_p}{R_s} \]  

(3)

3. Objective function

In order to implement heuristic algorithm to obtain a photovoltaic cell's intrinsic parameters, we should express the problem as optimization problem. Some authors used root mean square errors (RMSE) defined by [18, 34]:

\[ \text{Min} \left( F(\theta) \right) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (I_i - I_{est}(\theta))^2} \]  

(4)

\( F(\theta) \) is the objective function to minimize; \( I_i \) the set of experimental number of I-V pairs; \( I_{est}(\theta) \) data set of current estimated; \( \theta \) represents the vector of parameters to be estimated; \( \theta = [I_0, I_{ph}, n_1, R_p, R_s] \) represents single diode vector of parameters estimated \( \theta = [I_0, I_{ph}, I_{int}, n_1, n_2, R_p, R_s] \) for dual diode model.

Results from literatures and their implementation in this research reveals two formulations for current estimation: formulation of approximation and formulation of accuracy.

3.1. Approximation formulation

For output current complexity at Eq. (1), many of the authors [25, 33] have chosen to use the approximation formulation for current estimation described by Eq. (5):

\[ I_{est} = I_{ph} - I_0 \left[ \exp \left( \frac{V + I R_p}{n_1 V_t} \right) - 1 \right] - \frac{V + I R_p}{R_s} \]  

(5)

The expression of the objective function estimating five parameters from single model of diode is given by:

\[ \text{Min}(F(\theta)) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left( I_i - I_{est} \left[ \exp \left( \frac{V + I R_p}{n_1 V_t} \right) - 1 \right] - \frac{V + I R_p}{R_s} \right)^2} \]  

(6)

\[ \text{Min}(F(\theta)) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left( I_i - I_{est} \left[ \exp \left( \frac{V + I R_p}{n_1 V_t} \right) - 1 \right] - \frac{V + I R_p}{R_s} \right)^2} \]  

(7)

For the double diode, the objective function is given by the expression:

\[ \text{Min}(F(\theta)) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left( I_i - I_{est} \left[ \exp \left( \frac{V + I R_p}{n_1 V_t} \right) - 1 \right] - \frac{V + I R_p}{R_s} \right)^2} \]  

(8)
With $V_i$ and $I_i$ representing measured voltage and current respectively;
The major advantage of the approximation formulation is that it focuses directly on obtaining the least square error and parameters from the listed optimization algorithms. However, the results determined are not reliable; they are presented at section 5.

### 3.2. The best formulation

The estimated characteristic of I-V is very close to the experimental measurements, for the experimental use set $(V_i, I_i)$ using $V_i$, the estimated current by the formulation of a single and dual diode respectively and

\[
\text{Min}(F(\theta)) = \left[ \frac{1}{N} \sum_{i=1}^{N} \left( I_i - I_{\text{ph}}, I_{\text{n}} \left[ \exp \left( \frac{(V_i + I_{\text{ext}} R_s)}{n V_i} \right) - 1 \right] + I_{\text{inc}} \left[ \exp \left( \frac{(V_i + I_{\text{ext}} R_s)}{n V_i} \right) - 1 \right] + \frac{V_i + I_{\text{ext}} R_s}{R_p} \right)^2 \right]
\]

\[\text{(9)}\]

\[
I_{\text{ext}} = I_{\text{ph}}, I_{\text{n}} \left[ \exp \left( \frac{(V_i + I_{\text{ext}} R_s)}{n V_i} \right) - 1 \right] - \frac{V_i + I_{\text{ext}} R_s}{R_p} - I_{\text{inc}} - V_i \left[ \exp \left( \frac{(V_i + I_{\text{ext}} R_s)}{n V_i} \right) - 1 \right]
\]

\[\text{(10)}\]

Non-linear Eqs. (9) and (10) can not be solve to determine a precise solution: which is a limit solving this equation. Lambert function (W) and digital methods are applied to overcome this limitation [59].

Eq. (9) is then rewritten as Eq. (11)

\[f(I_{\text{ext}}) = I_{\text{ph}}, I_{\text{n}} \left[ \exp \left( \frac{(V_i + I_{\text{ext}} R_s)}{n V_i} \right) - 1 \right] - \frac{V_i + I_{\text{ext}} R_s}{R_p} - I_{\text{inc}} \]

\[\text{(11)}\]

We determine $I_{\text{ext}}$ by solving $f(I_{\text{ext}}) = 0$ with Newton Raphson’s method described in Figure 3.

And:

\[\Delta f(I_{\text{ext}}) = \frac{df(I_{\text{ext}})}{dI_{\text{ext}}} = \text{derivative from Eq. (11)} \text{ which is expressed by:}
\]

\[\Delta f(I_{\text{ext}}) = \frac{I_{\text{ph}}, I_{\text{n}} }{n V_i} \left[ \exp \left( \frac{(V_i + I_{\text{ext}} R_s)}{n V_i} \right) \right] \frac{R_s}{R_p} 1
\]

\[\text{(12)}\]

$I_{\text{ext}}$ is a total estimation of current output; the stops criterion in obtaining better precision value to be chosen $10^{-5} \leq \epsilon \leq 10^{-10}$.

Then comes set of $I_{\text{ext}}$ which corresponds to measures of $(V_i, I_i)$, a final objective formulation as function of single and dual diode models expressed by Eqs. (13) and (14) respectively

\[\text{Min}(F(\theta)) = \left[ \frac{1}{N} \sum_{i=1}^{N} \left( I_i - I_{\text{ph}}, I_{\text{n}} \left[ \exp \left( \frac{(V_i + I_{\text{ext}} R_s)}{n V_i} \right) - 1 \right] + I_{\text{inc}} \left[ \exp \left( \frac{(V_i + I_{\text{ext}} R_s)}{n V_i} \right) - 1 \right] + \frac{V_i + I_{\text{ext}} R_s}{R_p} \right)^2 \right]
\]

\[\text{(13)}\]

\[\text{Min}(F(\theta)) = \left[ \frac{1}{N} \sum_{i=1}^{N} \left( I_i - I_{\text{ph}}, I_{\text{n}} \left[ \exp \left( \frac{(V_i + I_{\text{ext}} R_s)}{n V_i} \right) - 1 \right] + I_{\text{inc}} \left[ \exp \left( \frac{(V_i + I_{\text{ext}} R_s)}{n V_i} \right) - 1 \right] + \frac{V_i + I_{\text{ext}} R_s}{R_p} \right)^2 \right]
\]

\[\text{(14)}\]

### 4. Optimization of Drone Squadron

#### 4.1. Inspiration

Algorithms of Drones Squadron are influenced by drones navigation at controlled space or command center. It was originally developed by Melo and Banzhaf in 2018 [58]. Like many other flying devices, the DSO is made up of a squadron of drones from different teams and control center. The control center do maintain partial surveillances and information collected to develop new firmware (Figure 4).

The drones must be sectioned in teams and size for a good update of drone firmware [62]. Drone’s mission consist of searching to locate landscaped targets.

#### 4.2. Command and control center

Considering parts of intelligent DSO that orders tasks to be performed through commands of drones from the control center is controlled.

#### 4.3. Firmware

The firmware plays the role, that of generating only by disturbance, new test coordinates (TC) [58]; The following relationships are used to randomly generate the firmware disturbance pattern:

\[P = \text{Departure} + \text{Offset}() \]

\[\text{(15)}\]
TC = calculate(P)

(16)

Where P is the complete perturbation formula which returns trial co-ordinates, Departure the solution point in the search space (the coordinate) and Offset() a function that returns the actual perturbation movement.

4.4. Drones movements

In calculating targets positions, drones used autonomous system to redirect information to the control center. Scalable techniques of optimization are applied to calculate targets positions.

---

**Algorithm 1**: DSO algorithm.

1: **Input**: objective function, problem bounds (LB, UB), user defined constants, number of teams (t), number of drones per team (N), maximum number of iterations (MaxIt), maximum number of iterations without improvement (MaxStagnation), options for the firmware.

2: **Output**: Best solution (GBC) and best Objective function value (GBOFV).

3: Initialize the Command Center, drones and teams in TeamCoords, where TeamCoords are sets of teams containing the drones’ coordinates.

4: Send the drones to scan the landscape at (t × N) random coordinates.

5: Select the N best coordinates to be CBC.

7: while stopping criteria are not met do

9: Procedures performed by the Teams

10: for each team ∈ [1, 2, ..., t] do

11: for each drone ∈ [1, 2, ..., N] do

12: Generate TC using the perturbation scheme of the current team.

13: Choose the recombination method and apply it to combine TC with CBC_drone, resulting in the TmC_drone,team.

14: Choose out-of-boundary correction method and apply it to TmC_drone,team saving the violations that occurred.

15: Move to new coordinate (TmC_drone,team), scan the landscape, and set TmOFV_drone,team = objective function value.

16: end for

17: end for

18: Procedures performed by the Command Center.

19: Select the best coordinates found by the teams in the current iteration.

20: Set improved = 0.

21: for each drone ∈ [1, 2, ..., N] do

22: Rank TmC_drone,team according to TmOFV_drone,team.

23: Set bestIds = index of the best TmOFV_drone,team.

24: if TmOFV_drone,bestIds < CBOFV_drone then

25: Set CBOFV_drone = TmOFV_drone,bestIds.

26: Set CBC_drone = TmC_drone,bestIds.

27: if TmOFV_drone,bestIds < GBOFV_drone then

28: Set improved = improved + 1.

29: Set GBOFV = TmOFV_drone,bestIds.

30: Set GBC = TmC_drone,bestIds.

31: end if

32: end if

33: end for

34: if improved == 0 then

35: Check and apply stagnation control.

36: end if

37: Set TeamQuality as the average rank plus boundary violations.

38: Update the firmware, considering TeamQuality.

39: end while
Table 1. Parameters of commercialized silicon PV cells RTC France.

| Parameters | Isc(A) | Voc(V) | Imp(A) | Vmp(V) | Ns | Ki for Isc (%/C) | T(°C) | G (W/m²) |
|------------|--------|--------|--------|--------|----|-----------------|-------|----------|
| Values     | 0.760  | 0.573  | 0.691  | 0.450  | 1  | 0.0350          | 33    | 1000     |

Table 2. Best results of approximation formulation from ten algorithms.

| Algorithms | Best parameters | Iph(A) | Io(μA) | n | Rs(Ω) | Rp(Ω) | Best RMSE x 10⁻⁴ |
|------------|-----------------|--------|--------|---|-------|-------|------------------|
| GAMS[3]    | 0.760775        | 0.323020 | 1.481183 | 0.036377 | 53.718524 | 9.860218 |
| MADE [36]  | 0.760775        | 0.323020 | 1.481183 | 0.036377 | 53.718538 | 9.860218 |
| ITLBO[25]  | 0.760775        | 0.323020 | 1.481183 | 0.036377 | 53.718523 | 9.860218 |
| TVACPSO[50]| 0.760775        | 0.323020 | 1.481183 | 0.036377 | 53.718524 | 9.860218 |
| LIAYA [19] | 0.760875        | 0.322847 | 1.481168 | 0.036281 | 52.218878 | 9.860751 |
| EVPS [6]   | 0.760772        | 0.325040 | 1.481811 | 0.036352 | 53.896023 | 9.860934 |
| IMFO [35]  | 0.760774        | 0.323468 | 1.481322 | 0.036371 | 53.760868 | 9.860255 |
| CAO [37]   | 0.760775        | 0.323018 | 1.479167 | 0.036377 | 53.718289 | 9.860218 |
| SOS [39]   | 0.760775        | 0.322467 | 1.481013 | 0.036379 | 53.571905 | 9.860547 |
| MLBSA[38]  | 0.760775        | 0.323020 | 1.481183 | 0.036377 | 53.718523 | 9.860218 |

Table 3. Best results from 10 algorithms of accuracy formulation.

| Algorithms | Best parameters | Iph(A) | Io(μA) | n | Rs(Ω) | Rp(Ω) | Best RMSE x 10⁻⁴ |
|------------|-----------------|--------|--------|---|-------|-------|------------------|
| GAMS[3]    | 0.760788        | 0.310684 | 1.477268 | 0.036547 | 52.889789 | 7.730062 |
| MADE [36]  | 0.760787        | 0.310684 | 1.475258 | 0.036546 | 52.889790 | 7.730062 |
| ITLBO[25]  | 0.760787        | 0.310684 | 1.475258 | 0.036544 | 52.904381 | 7.730066 |
| IMFO [35]  | 0.760787        | 0.310684 | 1.475258 | 0.036546 | 52.889790 | 7.730062 |
| MLBSA[38]  | 0.760787        | 0.310684 | 1.475258 | 0.036546 | 52.890001 | 7.730062 |
| LIAYA [19] | 0.760822        | 0.305965 | 1.473717 | 0.036634 | 52.920663 | 7.731828 |
| CAO [37]   | 0.760787        | 0.310684 | 1.475258 | 0.036546 | 52.889778 | 7.730062 |
| SOS [39]   | 0.760786        | 0.310641 | 1.475244 | 0.036548 | 52.905131 | 7.730076 |
| EVPS [6]   | 0.760780        | 0.317061 | 1.477295 | 0.036458 | 53.337698 | 7.764575 |

Table 4. Statistics of ten algorithms.

| Methods       | Best RMSE x 10⁻⁴ | Mean RMSE x 10⁻⁴ | Worst RMSE x 10⁻⁴ | std | Best Cpu time (S) |
|---------------|------------------|------------------|-------------------|-----|------------------|
| Approximate formulation: | | | | | |
| GAMS [3]      | 9.860218         | 9.860218         | 9.860218          | 0   | 0.016            |
| MADE [36]     | 9.860218         | 9.860218         | 9.860218          | 3.207e-15 | 0.17             |
| ITLBO [25]    | 9.860218         | 9.860218         | 9.860218          | 1.49e-17 | 0.36             |
| TVACPSO [50]  | 9.860218         | 9.860218         | 9.860218          | 2.381e-7  | 2.61             |
| LIAYA [19]    | 9.860751         | 9.933388         | 10.072718         | 6.22e-6  | 1.32             |
| CAO [37]      | 9.860218         | 9.860218         | 9.860218          | 1.316e-05 | 0.71             |
| SOS [39]      | 9.860218         | 9.860218         | 9.860218          | 6.929e-5  | 4.44             |
| EVPS [6]      | 9.860218         | 9.860218         | 9.860218          | 1.086e-16 | 1.53             |
| Accurate formulation: | | | | | |
| GAMS [3]      | 7.730062         | 7.730062         | 7.730062          | 0   | 0.032            |
| MADE [36]     | 7.730062         | 7.730062         | 7.730062          | 4.187e-15 | 0.22             |
| ITLBO [25]    | 7.730062         | 7.730062         | 7.730062          | 1.431e-17 | 0.98             |
| IMFO [35]     | 7.730066         | 7.7352115        | 7.772781          | 9.890e-7  | 1.32             |
| MLBSA [38]    | 7.730062         | 7.730062         | 7.730062          | 1.086e-16 | 1.53             |
| TVACPSO [50]  | 7.730062         | 7.730063         | 7.730072          | 3.01e-10  | 5.12             |
| LIAYA [19]    | 7.731828         | 7.756194         | 7.854054          | 2.864e-6  | 1.14             |
| CAO [37]      | 7.730062         | 7.755962         | 8.195525          | 1.036e-5  | 4.05             |
| SOS [39]      | 7.730076         | 7.730048         | 7.731448          | 4.36e-8   | 7.67             |
| EVPS [6]      | 7.764575         | 7.762812         | 7.785691          | 1.52e-6   | 1024             |
The goal is generating better position for each drone/team (TmCteam, drone). With the travelling of drones within spaces boundaries, Eq. (17) is applied as correction for each exterior reference point.

\[
\text{violation}_{\text{team}} = \sum_{i=1}^{N} \sum_{j=1}^{D} \left| \text{TmC}_{\text{team, drone}, j} - UB_{j} \right| + \left| LB_{j} - \text{TmC}_{\text{team, drone}, j} \right|
\]

Where:

- N: drones number/team,
- D: dimensions
- UB: upper bounds
- LB: lower bounds.

4.5. Firmware upgrade and update

Algorithms could possibly end with this step. For the assessment of the quality of parameters/team, two elements are evaluated from the control center: target classified algorithm value and level of violations generated algorithm [58]. Eq. (18) determines each team quality.

\[
\text{TeamQuality}_{i} = \text{Rank}_i + \text{violation}_i
\]

The drones can during landscape exploration, generate two coordinates or identical information. For this purpose, a stagnation in relation to Eq. (19) is established [62].

\[
\text{if} \left( \text{TmOFV}_{\text{drone, best}} < \text{CBOFV}_{\text{drone}} \text{ or } \text{U}(0, 1) < P_{\text{acc}} \right) \text{ then } \left( \text{CBC}_{\text{drone}} = \text{TmC}_{\text{drone, best}} \right)
\]

Where:

- \( \text{TmOFV} \): objective team’s function
- \( \text{CBC} \) : best current coordinates
- \( \text{CBOFV} \) : objective function of the best current coordinates
- \( \text{TmC} \) : details of teams coordinates
- \( \text{U}(0, 1) \) : uniform random distribution within the interval of 1 and 0
- \( P_{\text{acc}} \) : accepting solution probability

Melo in 2017 described the complete DSO algorithm [62] and the detailed description of all DSO steps determined by the relationship described by Melo and Banzhaf in 2018 [58].

5. Experiments carried out and results

This section presents various experiments results including the approximation formulation, the accurate formulation results that are presented in section 5.1 and Section 5.2 respectively, and the 10 recent algorithms published: EVPS [6], TVACPSO [50], IMFO [35], IJAYA [19], ITLBO [25], CAO [37], SOS [39], MLBSA [38], MADE [36], GAMS [3]. The experiment of these algorithms was made based on the well known set of RTC France solar cell, with various parameters presented at Table 1. Irradiation and temperature are 1000W/m² and 33 °C respectively. The starting parameters of these algorithms were mentioned in each paper, which are set as follows:

- EVPS: number of agents or population (NP) = 50; maximum iterations (MaxIt) = 1000;
- SOS: Np = 50; the maximum number of function evaluations (Max_FEs) = 50,000
- COA: number of groups (NP) = 10; number of coyotes (Nc) = 10; MaxIt = 1000.
- TVAPSO: Np = 1000; MaxIt = 100
- IJAYA: NP = 20; Max_FEs = 50,000;
- MLBSA: NP = 50; Max_FEs = 50,000;
- IMFO: Np = 100; Max_FEs = 50,000;
- DONE: NP = 50; Max_FEs = 50,000;
- ITLBO: Np = 50; Max_FEs = 50,000;
- GAMS: MaxIt = 100; Max_FEs = 188.

The DSO is valid for six different cases, taking into account single and double diode model. Selected algorithms are executed on software Matlab 2017b, installed on a computer with Intel (R) Core (TM) i7-2670QM CPU @ 2.20GHz, RAM 8.0GB, in an operating system Windows10.

5.1. Results combination of 10 algorithms for approximation formulation

Table 2 shows best results from twenty tests from different independent algorithms. We observe the nearly similar results from 10 algorithms with best RSME lying between 9.860 * 10-4. Results of determined parameters are more or less similar to the ones obtained by the different authors in their publication with the exception of TVACPSO [50], which applied best formulations.

| Parameters       | Best solutions |
|------------------|----------------|
| Rs(\Omega)       | 0.310684       |
| Rg(\Omega)       | 52.889786      |
| OF(RMSE \times 10^{-4}) | 7.730062     |
5.2. Results combination of 10 algorithms for precision formulation

Table 3 shows the best results of the precision formulation of 20 independent tests from the different algorithms. Table 3 shows best results of precision formulation of twenty independent tests of different algorithms. From there, we observe that the RMSE values of 9.86 \times 10^{-4} from the approximate formulation is now 7.73 \times 10^{-4}. We observe a significant error reduction, that also provides a good precision in various parameters extracted. Table 4 gives summary statistics and performances of two formulations based on algorithms considered.

Table 4 shows the statistics of results from twenty independent tests obtained from 10 algorithms of two formulations with:
- Best: representing minimum values of RMSE from twenty tests;
- Average: RMSE average of 20 tests;
- Worst: optimal RMSE value from twenty tests.

From Table 4, we can concluded that the computation time of the approximation formulation is reduced compared to that of the accurate formulation.

5.3. Case study I

The essential step of this case is the consideration DSO for single diode model of RTC France. Table 5 shows 5 parameters with best values. Figures 5 and 6 present IV and PV curves measurements and estimations respectively.

Table 5 shows a better RMSE achieved by DSO. The comparison of values with the ones determined at Table 2 and Table 3 clearly shows the better results of DSO compared to other proposed methods.

### Table 6. Best results from RTC-France DD in relation to recent literature.

| Algorithms | Iph(A) | Io1(\mu A) | Io2(\mu A) | n1 | n2 | Rs(\Omega) | Rp(\Omega) | Best RMSE × 10^{-4} |
|------------|--------|------------|------------|----|----|------------|------------|---------------------|
| DSO        | 0.760813 | 0.086953   | 2.177280   | 1.371206 | 1.9999 | 0.038033   | 58.371326 | 7.325513            |
| MPSO [49]  | 0.760812 | 0.089797   | 2.136189   | 1.373644 | 2   | 0.037994   | 58.24134   | 7.3257              |
| C-HILPSO-IIIB [47] | 0.76081 | 0.08797 | 0.97376 | 1.3795 | 1.817 | 0.037640 | 56.54905 | 7.4365 |
| TVACPSO [50] | 0.760809 | 0.040446 | 0.992746 | 1.327160 | 1.735315 | 0.037973 | 56.54905 | 7.4365 |
| ELPSO [48] | 0.76080 | 1e-6 | 0.099168 | 1.380691 | 1.835767 | 0.037551 | 55.920471 | 7.4240 |

### Table 7. Best Photo Watt-PWP201 SD module results compared to actual methods.

| Algorithms | Iph(A) | Io(\mu A) | n | Rs(\Omega) | Rp(\Omega) | Best RMSE × 10^{-4} |
|------------|--------|------------|---|------------|------------|---------------------|
| DSO        | 1.03257 | 2.496596   | 1.314835 | 1.240547   | 748.3209   | 2.039992            |
| MPSO [49]  | 1.032230 | 2.552134   | 1.31884 | 1.238450   | 762.9058   | 2.041               |
| WDOWOAPSO [34] | 1.032382 | 2.512991 | 1.317304 | 1.239288 | 744.71435 | 2.046535 |
| GCPSO [50] | 1.032382 | 2.512992 | 1.317305 | 1.239288 | 744.71663 | 2.046535 |
| TVACPSO [50] | 1.031435 | 2.6386 | 1.321018 | 1.235611 | 821.59514 | 2.0530 |
| SDA [40] | 1.030517 | 3.481614 | 1.349970 | 1.201288 | 981.59961 | 2.425074 |
| EHA-NMS [41] | 1.030514 | 3.482263 | 1.35119 | 1.201271 | 981.98225 | 2.425075 |
| DE-WAO [30] | 1.030514 | 3.482263 | 1.35119 | 1.201271 | 981.98224 | 2.425075 |
| ABC-TRR [28] | 1.030514 | 3.482263 | 1.35119 | 1.201271 | 981.98223 | 2.425075 |
| ISCE [22] | 1.030514 | 3.482263 | 1.35119 | 1.201271 | 981.98228 | 2.425075 |
| PGJAYA [45] | 1.0305 | 3.4818 | 1.351177 | 1.2013 | 981.8545 | 2.425075 |
| HFAPS [34] | 1.0305 | 3.4842 | 1.351247 | 1.2013 | 984.2813 | 2.4251 |
| TLABC [29] | 1.03056 | 3.4715 | 1.35087 | 1.20165 | 972.93567 | 2.42507 |
| GOPPANM [23] | 1.030514 | 3.482263 | 1.35119 | 1.201271 | 981.98232 | 2.425075 |
| ORcr-UADE [32] | 1.030514 | 3.482263 | 1.35119 | 1.201271 | 981.98224 | 2.425074 |
| (IWAO) [21] | 1.0305 | 3.4717 | 1.350669 | 1.2016 | 978.6771 | 2.4251 |

std: standard of deviation.
Cpu: the optimum calculation time of 20 tests.

From Table 4, we can concluded that the computation time of the approximation formulation is reduced compared to that of the accurate formulation.

5.3. Case study I

The essential step of this case is the consideration DSO for single diode model of RTC France. Table 5 shows 5 parameters with best values. Figures 5 and 6 present IV and PV curves measurements and estimations respectively.

Table 5 shows a better RMSE achieved by DSO. The comparison of values with the ones determined at Table 2 and Table 3 clearly shows the better results of DSO compared to other proposed methods. Characteristics
of IV and PV curves in Figure 5 and Figure 6 are plotted from the determined DSO parameters, representing data measurements and estimations. We observe on each curve, measured data, which correspond to estimated data: this clearly points to the precision parameters of DSO algorithm.

5.4. Case study 2

The case study concerns dual diode model from RTC France combined with DSO. Best results from 7 estimated RTC France parameters were compared to recent literatures presented at Table 6. Best values determined are observed from Table 6. DSO provides best values from 17 recently known algorithms. Statistic at Table 7 shows for each independent tests, the algorithm accuracy. This second phase of case study concerns the dual diode model for DSO and RTC France. Table 6 shows best estimation results for the seven parameters from RTC France in comparison to recent literature. Observation from Table 6 shows that out of 17 recently proposed algorithms, best values were determined by DSO algorithm. The statistics at Table 7 equally show for each individual test, precision of the algorithm.

5.5. Case study 3

The present case study has for reference model of PV module Photo Watt-PWP201. In series having 36 cells with environmental conditions such as G = 1000W/m², and T = 51 °C. The electrical characteristic and the set of parameters have been taken from [25]. Table 8 shows the best results obtained for five parameters evaluated from STM6- 40/36 PV module of recent literature. These parameters determined by DSO compared to 11 propositions of recent algorithms is observed from Table 8. These parameters are very close to those determined [16] and [40]. RMSE = 1.72192 × 10⁻³ is better compared to the one of 11 propositions of algorithms. Table 9 presents the statistics of the recent literatures of RTC-France SD and DD, Photo Watt-PWP201 and STM6- 40/36 SD specifying DSO stability for PV parameters estimation. Results determined from 20 independent tests are: the minimum reached RMSE best values; the highest value is the worst RMSE value; the average RMSE shows average value after 20 tests with standard of deviation (std). The smallest standard deviation values for each case expresses DSO algorithm reliability.

5.6. Case study 4

This case refers to monocrystalline PV module STM6-40/36 which consists of 36 cells in series. The environmental measurement conditions are G = 1000W/m², and T = 51 °C. The electrical characteristic and the set of measured parameters have been taken from Tables 11 and 12, show estimated low and high RMSE best values; the highest value is the worst RMSE value; the average RMSE shows average value after 20 tests with standard of deviation (std). The smallest standard deviation values for each case expresses DSO algorithm reliability.

5.7. Case study 5

The fifth case study therefore concerns experimental PV module data of Sharp ND-R250A5 [59]. Two models composed of single and dual diode used to express DSO performance. Table 10 presents electrical characteristics for PV module Sharp ND-R250A5 at STC. The measured data are available in [42], [59]. The limit of lower and upper bound of Ip, Io, n, Rs, Rp is available in [59] Tables 11 and 12 show the best single and dual diode parameters of Sharp ND-R250A5 PV-module from different irradiances. Figures 8 and 9 present characteristics of IV and PV curves at various operating conditions. Observation from these figures shows that measured data merge with estimated data under various irradiation and temperature. RMSE value observed from each condition in Figures 8 and 9 present characteristics of IV and PV curves at various operating conditions. Observation from these figures shows that measured data merge with estimated data under various irradiation and temperature. RMSE value observed from each condition in Figures 8 and 9 present characteristics of IV and PV curves at various operating conditions.

Table 8. Compared recent methods of literatures.

| Algorithms    | Best parameters | Rs (mΩ) | Rp(Ω) | Best RMSE × 10⁻³ |
|---------------|-----------------|---------|-------|-----------------|
| DSO           | 1.663903        | 1.741245| 1.51839| 153.640         | 573.53392 | 1.721921 |
| SDA [40]      | 1.663949        | 1.702581| 1.51783| 156.421         | 570.22744 | 1.729645 |
| ReiLuADE [16] | 1.663904        | 1.738656| 1.52030| 153.8557        | 573.41858 | 1.729813 |
| HBCS [26]     | 1.66390         | 1.7386   | 1.5203  | 153.72          | 573.418   | 1.7298   |
| NoCuSa [43]   | 1.66390         | 1.73866  | 1.5203  | 153.72          | 573.418   | 1.7298   |
| ELSO [48]     | 1.666268        | 45.9614  | 1.40162| 0.5             | 497.74731 | 2.1803   |
| TVACP50 [50]  | 1.666268        | 45.96154| 1.40162| 0.5             | 497.74866 | 2.1803   |
| HFAPS [34]    | 1.6663          | 1.0703   | 1.47266| 0.24849         | 490.03    | 1.97     |
| EHA-NMS [41]  | 1.663904        | 1.738656| 1.52030| 4.273771        | 573.418   | 1.729813 |
| MADE [36]     | 1.6639          | 1.7387   | 1.5203  | 154.8           | 573.4186  | 1.7298   |
| ISCE [22]     | 1.663904        | 1.738656| 1.52030| 4.273771        | 573.418   | 1.729813 |
| TLABC [29]    | 1.66317         | 2.14043  | 1.54354| 130.68          | 621.34272 | 1.80612  |
Table 9. Statistics of RTC-France SD and DD, Photo Watt-PWP 201, STM6-40/36 SD in recent literature.

| Algorithms | Best RMSE $\times 10^{-4}$ | Mean RMSE $\times 10^{-4}$ | Worst RMSE $\times 10^{-4}$ | std |
|------------|-----------------------------|-----------------------------|-----------------------------|-----|
| **RTC FRANCE SD** | | | | |
| DSO        | 7.730062                    | 7.730062                    | 7.730062                    | 1.272E-16 |
| TVACPSO [50] | 7.7301                      | 7.7301                      | 7.7301                      | 5.580E-10 |
| C-HCLPSO-III [47] | 7.7306                      | NA                          | NA                          | 8.235E-10 |
| EHA-NMS [41] | 9.824848                    | 9.826829                    | 9.860219                    | 5.190E-07 |
| DE-WAO [30] | 9.860219                    | 9.860219                    | 9.860219                    | 3.545E-10 |
| ABC-TRR [28] | 9.86021                      | 9.86021                      | 9.86021                      | 6.150E-17 |
| ISCE [22] | 9.860219                    | 9.860219                    | 9.860219                    | 3.98E-17 |
| CSTO [33] | 9.8602                      | 9.8602                      | NA                          | 5.49E-9 |
| **RTC FRANCE DD** | | | | |
| DSO        | 7.325513                    | 7.488326                    | 7.638173                    | 1.385E-05 |
| MPSO [49] | 7.3257                      | NA                          | NA                          | 5.549E-11 |
| C-HCLPSO-III [47] | 7.4259                      | NA                          | NA                          | 9.549E-11 |
| TVACPSO [50] | 7.4365                      | 7.5883                      | 7.8476                      | 1.104E-05 |
| ELPSO [48] | 7.4240                      | 7.5904                      | 7.9208                      | 9.749E-06 |
| EHA-NMS [41] | 9.824848                    | 9.825566                    | 9.860219                    | 5.190E-07 |
| DE-WAO [30] | 9.82484                      | NA                          | NA                          | 4.950E-11 |
| ABC-TRR [28] | 9.824849                    | 9.827740                    | 9.861992                    | 4.610E-07 |
| ISCE [32] | 9.82485                     | 9.83800                     | 9.86685                     | 1.538E-06 |
| PGJAYA [45] | 9.8263                      | 9.85821                     | 9.949852                    | 2.537E-06 |
| HFAPS [34] | 9.8248                      | NA                          | NA                          | 9.82485 |
| TLABC [29] | 9.84145                     | 10.5535                     | 15.0482                     | 1.550E-04 |
| GOPPANM [23] | 9.82484                     | 9.9548                      | 1.34053                     | 6.518E-05 |
| Orcr-IJADE [32] | 9.824858                    | NA                          | NA                          | 9.824858 |
| IWAO [8, 21] | 9.8255                      | 9.9693                      | 10.889                      | 1.929E-07 |
| CSO [33] | 9.8252                      | 9.9619                      | 3.467E-05                   | 3.467E-05 |
| ABSO [18] | 9.8344                      | NA                          | NA                          | 9.8344 |
| **Photo Watt-PWP 201 SD** | | | | |
| DSO        | 2.039992                    | 2.039992                    | 2.039992                    | 2.704E-12 |
| MPSO [49] | 2.041                      | NA                          | NA                          | 2.041  |
| WIDOWAOPSO [34, 42] | 2.046535                    | 2.046535                    | 2.046535                    | 1.267E-12 |
| GCPSO [59] | 2.046535                    | 2.046535                    | 2.046536                    | 1.105E-10 |
| TVACPSO [50] | 2.0530                      | 2.0530                      | 2.0537                      | 1.340E-07 |
| SDA [40] | 2.425074                    | NA                          | NA                          | 2.425074 |
| EHA-NMS [41] | 2.425075                    | 2.425075                    | 2.425075                    | 5.530E-17 |
| DE-WAO [30] | 2.425075                    | 2.425075                    | 2.425075                    | 6.270E-08 |
| ABC-TRR [28] | 2.425075                    | 2.425075                    | 2.425075                    | 9.680E-17 |
| ISCE [22] | 2.425075                    | 2.425075                    | 2.425075                    | 2.470E-17 |
| PGJAYA [45] | 2.425075                    | 2.425144                    | 2.426764                    | 3.071E-07 |
| HFAPS [34] | 2.4251                      | NA                          | NA                          | 2.4251 |
| TLABC [29] | 2.425075                    | 2.42647                     | 2.44584                     | 3.998E-06 |
| GOPPANM [23] | 2.425075                    | 2.425075                    | 2.425075                    | 2.918E-16 |
| Orcr-IJADE [32] | 2.425074                    | NA                          | NA                          | 2.425074 |
| IWAO [21] | 2.4251                      | 2.4269                      | 2.4335                      | 2.236E-06 |
| CSO [33] | 9.8344                      | NA                          | NA                          | 9.8344 |
| **STM6-40/36 SD** | | | | |
| DSO        | 1.721921                    | 1.721921                    | 1.721921                    | 5.983E-16 |
| SDA [40] | 1.729645                    | 1.729813                    | 1.729813                    | 1.180E-14 |
| Orcr-IJADE [16] | 1.729813                    | 1.729813                    | 1.729813                    | 4.059E-04 |
| BHCS [26] | 1.72981                     | 1.83648                     | 3.29885                     | 9.222E-02 |
| NoCuSa [43] | 1.72981                     | 4.12985                     | 3.10757                     | 9.222E-02 |
| ELPSO [48] | 2.1803                      | 2.2503                      | 3.7160                      | 2.921E-4 |
| TVACPSO [50] | 2.1803                      | 2.1803                      | 2.1803                      | 6.374E-9 |
| HFAPS [34] | 1.97                       | 1.729813                    | 1.729813                    | 2.300E-17 |
| EHA-NMS [41] | 1.729813                    | 1.729813                    | 1.729813                    | 8.490E-14 |
| MADE [36] | 1.72981                     | 1.72981                     | 1.72981                     | 2.430E-17 |
| ISCE [22] | 1.729813                    | 1.729813                    | 1.729813                    | 8.767E-05 |
| TLABC [29] | 1.80612                     | 1.97321                     | 2.21357                     | 8.767E-05 |
5.8. Case study 6

This case study concerns STP6-120/36 module, PV module (STE 4/100) and the Leybold solar module (LEYBOLD 664 431). PV module STP6-120/36 consists of 36 monocrystalline cells connected in series has environmental measurement conditions \( G = 1000\, \text{W/m}^2, T = 25^\circ\,\text{C} \). The electrical characteristics and the set of measures of (STE 4/100) and Leybold Solar Module (LEYBOLD 664 431) have been taken from [63]. Table 13 shows the best-estimated results of 5 parameters for each PV module from the current literature. The RMSE as well as the determined parameters confirm DSO algorithm reliability hypothesis, which gives best precision for PV modules parameters.

Table 10. Module parameter of Sharp ND-R250A5.

| Parameters | Values |
|------------|--------|
| \( I_{sc} \) | 8.68 |
| \( V_{oc} \) | 37.6 |
| \( I_{mp} \) | 8.10 |
| \( V_{mp} \) | 30.9 |
| \( N_s \) | 60 |

Table 11. Results of SD model of ND-R250A5.

| Irradiation/temperature | Best parameters |
|------------------------|-----------------|
| \( G = 1040\,\text{w/m}^2 \) \( T = 59^\circ\,\text{C} \) | \( I_{ph} \) (A) 9.144865 0.995881 \( n \) 1.204937 0.591870 \( R_s \) (\( \Omega \)) 5000 \( R_p \) (\( \Omega \)) 7.697717 |
| \( G = 924\,\text{w/m}^2 \) \( T = 68^\circ\,\text{C} \) | 8.151384 1.46680 1.199462 0.590546 5000 7.72753142 |
| \( G = 743\,\text{w/m}^2 \) \( T = 67^\circ\,\text{C} \) | 6.560009 0.180341 1.078311 0.633776 5000 8.93948385 |
| \( G = 544\,\text{w/m}^2 \) \( T = 53^\circ\,\text{C} \) | 4.771023 6.089760e-2 1.105081 0.615500 5000 4.828055534 |

Table 12. Result of different SD models of ND-R250A5.

| Irradiation/temperature | \( I_{ph} \) (A) | \( I_{o1} \) (\( \mu \)A) | \( n_1 \) | \( n_2 \) | \( R_s \) (\( \Omega \)) | \( R_p \) (\( \Omega \)) | Best RMSE \( \times 10^{-3} \) |
|------------------------|-----------------|-----------------|--------|--------|--------|--------|-----------------|
| \( G = 1040\,\text{w/m}^2 \) \( T = 59^\circ\,\text{C} \) | 9.144865 1.91425E-6 | 9.9584E-1 | 1.204905 | 1.204937 | 0.591870 | 4999.9999 | 7.697717191 |
| \( G = 924\,\text{w/m}^2 \) \( T = 68^\circ\,\text{C} \) | 8.151384 2.849850 | 1.466799 | 1.199462 | 1.199462 | 0.590546 | 5000 | 7.727531 |
| \( G = 743\,\text{w/m}^2 \) \( T = 67^\circ\,\text{C} \) | 6.560009 1.5959E-1 | 2.07428E-2 | 1.078311 | 1.078311 | 0.633776 | 5000 | 8.939483 |
| \( G = 544\,\text{w/m}^2 \) \( T = 53^\circ\,\text{C} \) | 4.771023 4.679367E-2 | 1.4103E-2 | 1.105081 | 1.105081 | 0.615500 | 4999.9999 | 4.828055 |

5.9. Case study 7

This case refers to model GL-100 PV module containing 36 cells. The study was done on a PV module and a string containing 6 PV modules. The study aims at showing convergence of the method when numbers of points \( N \) of the characteristic is varied. The \( I-V \) characteristic's initial number of points \( N = 113 \) was obtained in [28]. Points were reduced to obtain different following values: \( N = 72 \); \( N = 36 \); \( N = 20 \);

Figure 8. I-V curves measurement and estimation of the characteristics.

Figure 9. P-V curves measurement and estimation of the characteristics of SD model of ND-R250A5.
We also notice that the number of points does not influence the pace and slopes of the characteristic. However, if these points are minimal, the algorithm will converge and is more precise when the number of points of the I-V characteristic is reduced. However, if these points are minimal, the algorithm will have difficulty reaching its optimal result, as seen in cases where NP = 9 (T = 33.7°C). These results show how important is the choice of the I-V characteristic numbers of points N. From Table 14, by choosing a reduced number of points, one obtains a faster execution time and an optimal result. We also notice that the number of points does not influence the pace and slopes of the characteristic.

### 6. Conclusion

This article describes assumptions made as well as the clarifications of two formulations for best parameters of photovoltaic estimation: formulation of approximation and formulation of precision. Ten current published algorithms have been implemented based on the two formulations. Algorithm convergence studies carried out considering the numbers of points of variation of voltage current characteristics. The determined results of these formulations present accuracy precision formulation. The new self-adaptation algorithm called DSO was proposed.
for simulation of squadron of drones of a control center to determine the best cell and photovoltaic module parameters. A comparative study of results determined from different studies cases based on the description of methods in literatures. This makes it possible to clarify DSO performance in extracting cell, module, and array PV parameters. From results of 10 algorithms and DSO, it was observed that precision formulation is the most recommended for the rest of the work. It should be noted that the proposed solutions in this article would allow scientific communities to choose a better formulation for PV parameters estimation. In addition, combining DSO and method of Newton Raphson is of great advantage in seeking optimal solution to the problems in power systems. The combine DSO and the method of Newton Raphson could be used for precise parameter extraction. Besides, accurate results can also be determined by combing Newton Raphson’s method with any heuristic algorithm.

Declarations

Author contribution statement

Patrick Juvet Gnetchejo: Conceived and designed the experiments; Contributed reagents, materials, analysis tools or data; Wrote the paper. Salomé Ndjakomo Essiane & Pierre Ele: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.

Abdouraman Dédié: Performed the experiments; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Funding statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data availability statement

Data included in article/supp. material/referenced in article.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

References

[1] T.M. David, P.M. Silva Rocha Rizol, M.A. Guerreiro Machado, G.P. Buccieri, Future research tendencies for solar energy management using a bibliometric analysis, 2006–2019, Heliyon 6 (7) (Jul. 2020), e04452.
[2] C. Hajjai, et al., Degradation and performance analysis of a monocrystalline PV system without EVA encapsulating in semi-arid climate, Heliyon 6 (6) (Jun. 2020), e04079.
[3] P.J. Gnetchejo, S. Ndjakomo Essiane, P. Ele, R. Wamkeue, S. Perahi Ngoffe, Important notes on parameter estimation of solar photovoltaic cell, Energy Convers. Manag. 197 (Jan. 2020) 111870.
[4] Patrick Juvet Gnetchejo, et al., A Self-adaptive algorithm with Newton Raphson method for parameters Identification of photovoltaic modules and array, Trans. Electr. Electron. Mater. (March 2021).
[5] Z. Chen, Y. Chen, L. Wu, S. Cheng, P. Lin, L. You, Accurate modeling of photovoltaic modules using a 1-D deep residual network based on I-V characteristics, Energy Convers. Manag. 186 (Apr. 2019) 168–187.
[6] P.J. Gnetchejo, S.N. Essiane, P. Ele, R. Wamkeue, D.M. Wapet, S.P. Ngoffe, Enhanced vibrating particles system Algorithm for parameters estimation of photovoltaic system, JPEE 7 (8) (2019) 1-26.
[7] P.A. Kumari, P. Geethanjali, Parameter estimation for photovoltaic system, JPEE 7 (8) (2019) 1147-159.
[8] S. Chen, Y. Chen, L. Wu, S. Cheng, P. Lin, L. You, Accurate modeling of photovoltaic systems using a 1-D deep residual network based on I-V characteristics, Energy Convers. Manag. 186 (Apr. 2019) 168–187.
[9] A.M. Beigi, A. Maroosi, Parameter identification of solar cell models, Appl. Energy 102 (Feb. 2013) 943–949.
[10] G. Petrone, G. Spagnuolo, Parameter identification of the single-diode model for amorphous photovoltaic panels, in: 2015 International Conference on Clean Electrical Power (ICCEP), Taormina, Italy. Jun. 2015, pp. 105–109.
[11] V. Lo Bruno, G. Cuilla, An efficient analytical approach for obtaining a five parameters model of photovoltaic modules using only reference data, Appl. Energy 111 (Nov. 2013) 894–903.
[12] A.K. Tossa, Y.M. Soro, Y. Azoumah, D. Yamegueu, A new approach to estimate the performance and energy productivicty of photovoltaic modules in real operating conditions, Sol. Energy 110 (Dec. 2014) 543–560.
[13] J. Appelbaum, A. Peled, “Parameters extraction of solar cells – a comparative examination of three methods, Sol. Energy Mater. Sol. Cell. 122 (Mar. 2014) 164–173.
[14] H. Chen, S. Jiao, M. Wang, A.A. Heidari, X. Zhao, Parameters identification of photovoltaic cells and modules using diversification-enhanced Harris hawks optimization with chaotic drifts, J. Clean. Prod. 244 (Jan. 2020) 118778.
[15] Q. Li, Z. Cai, Parameter extraction of solar cell models using repaired adaptive differential evolution, Sol. Energy 94 (Aug. 2013) 209–220.
[16] G. Petrone, M. Luna, G. La Tona, M. Di Piazza, G. Spagnuolo, Online identification of photovoltaic source parameters by using a genetic algorithm, Appl. Sci. 8 (1) (Dec. 2017) 9.
[17] A. Askarzadeh, A. Rezaazadeh, Artificial bee swarm optimization algorithm for parameters identification of solar cell models, Appl. Energy 102 (Feb. 2013) 943–949.
[18] S. Li, W. Gong, X. Yan, C. Hu, D. Bai, L. Wang, Parameter estimation of photovoltaic models using an improved whale optimization algorithm, Energy Convers. Manag. 150 (Oct. 2017) 742–753.
[19] K. Yu, X. Chen, X. Wang, Z. Wang, Parameters identification of photovoltaic models using self-adaptive teaching-learning-based optimization, Energy Convers. Manag. 145 (Aug. 2017) 233–246.
[20] G. Xiong, J. Zhang, D. Shi, Y. He, Parameter extraction of solar photovoltaic models using an improved whale optimization algorithm, Energy Convers. Manag. 174 (Oct. 2018) 388–405.
[21] X. Gao, et al., Parameter extraction of solar cell models using improved shuffled complex evolution algorithm, Energy Convers. Manag. 157 (Feb. 2018) 466–479.
[22] S. Xu, X. Wang, Parameter estimation of photovoltaic modules using a hybrid flower pollination algorithm, Energy Convers. Manag. 144 (Jul. 2017) 53–68.
[23] J. Montano, A.F. Tobón, J.P. Villegas, M. Durninga, Grasshopper optimization algorithm for parameter estimation of photovoltaic modules based on the single diode model, Int. J. Energy Environ. Eng. 11 (3) (Sep. 2020) 367–375.
[24] S. Li, et al., Parameter extraction of photovoltaic models using an improved teaching-learning-based optimization, Energy Convers. Manag. 186 (Apr. 2019) 293–305.
[25] X. Chen, K. Yu, Hybridizing cuckoo search algorithm with biogeography-based optimization for estimating photovoltaic module parameters, Sol. Energy 180 (Mar. 2019) 192–206.
[26] H. Chen, S. Jiao, A.A. Heidari, M. Wang, X. Chen, X. Zhao, An opposition-based sine cosine approach with local search for parameter estimation of photovoltaic models, Energy Convers. Manag. 195 (Sep. 2019) 927–942.
[27] L. Wu, et al., Parameter extraction of photovoltaic models from measured I-V characteristics curves using a hybrid trust-region reflective algorithm, Appl. Energy 232 (Dec. 2018) 36–53.
[28] X. Chen, B. Xu, C. Mei, Y. Ding, K. Li, “Teaching–learning–based artificial bee colony for solar photovoltaic parameter estimation, Appl. Energy 212 (Feb. 2018) 1576–1588.
[29] G. Xiong, J. Zhang, X. Yuan, D. Shi, Y. He, G. Yao, Parameter extraction of solar photovoltaic models by means of a hybrid differential evolution with white optimization algorithm, Sol. Energy 176 (Dec. 2018) 742–761.
[30] Y. Chen, Z. Chen, L. Wu, C. Long, P. Lin, S. Cheng, Parameter extraction of PV models using an enhanced shuffled complex evolution algorithm improved by opposition-based learning, Energy Proc. 158 (Feb. 2019) 991–997.
[31] N. Muangkote, K. Sureti, S. Chiewchuchawatana, S. Kaivinunt, An advanced onlooker-ranking based adaptive differential evolution to extract the parameters of solar cell models, Renew. Energy 134 (Apr. 2019) 1129–1147.
[32] L. Guo, Z. Meng, Y. Sun, L. Wang, Parameter identification and sensitivity analysis of solar cell models with cat swarm optimization algorithm, Energy Convers. Manag. 108 (Jan. 2016) 520–528.
[33] A.M. Beigi, A. Marosini, Parameter identification for solar cells and module using a hybrid firefly and pattern search algorithms, Sol. Energy 171 (Sep. 2018) 435–446.
[34] H. Shen, et al., Parameters extraction of photovoltaic models using an improved moth-flame optimization, Energies 12 (18) (Sep. 2019) 3527.
[35] S. Li, W. Gong, X. Yan, C. Hu, D. Bai, L. Wang, Parameter estimation of photovoltaic models with memetic adaptive differential evolution, Sol. Energy 190 (Sep. 2018) 465–474.
[36] M.H. Qais, H.M. Hasanien, S. Alghuwainem, A.S. Nouh, Coyote optimization algorithm for parameters extraction of three-diode photovoltaic models of photovoltaic modules, Energy 187 (Nov. 2019) 116001.
[37] K. Yu, J.J. Liang, B.Y. Qu, Z. Cheng, H. Wang, Multiple learning backtracking search algorithm for estimating parameters of photovoltaic models, Appl. Energy 226 (Sep. 2018) 408–422.
[38] W. Gong, Z. Zhang, X. Yuan, D. Shi, Y. He, Application of symbiotic organisms search algorithm for parameter extraction of solar cell models, Appl. Sci. 8 (11) (Nov. 2018) 2155.
[40] D.T. Cotfas, A.M. Deaconu, P.A. Cotfas, Application of successive discretization algorithm for determining photovoltaic cells parameters, Energy Convers. Manag. 196 (Sep. 2019) 545–556.

[41] Z. Chen, L. Wu, P. Lin, Y. Wu, S. Cheng, Parameters identification of photovoltaic models using hybrid adaptive Nelder-Mead simplex algorithm based on eagle strategy, Appl. Energy 182 (Nov. 2016) 47–57.

[42] H.G.G. Nunes, J.A.N. Pombo, P.M.R. Bento, S.J.P.S. Mariano, M.R.A. Calado, Collaborative swarm intelligence to estimate PV parameters, Energy Convers. Manag. 185 (Apr. 2019) 866–890.

[43] N.J. Cheung, X.-M. Ding, H.-B. Shen, A nonhomogeneous cuckoo search algorithm based on quantum mechanism for real parameter optimization, IEEE Trans. Cybern. (2016) 1–12.

[44] M.H. Qais, H.M. Hasanien, S. Alghuwainem, Identification of electrical parameters for three-diode photovoltaic model using analytical and sunflower optimization algorithm, Appl. Energy 250 (Sep. 2019) 109–117.

[45] K. Yu, B. Qu, C. Yue, S. Ge, X. Chen, J. Liang, A performance-guided JAYA algorithm for parameters identification of photovoltaic cell and module, Appl. Energy 237 (Mar. 2019) 241–257.

[46] L.L. Jiang, D.L. Maskell, J.C. Patra, Parameter estimation of solar cells and modules using an improved adaptive differential evolution algorithm, Appl. Energy 112 (Dec. 2013) 185–193.

[47] D. Youn, D. Allam, M.B. Eteiba, P.N. Segaran, ‘Static and dynamic photovoltaic models’ parameters identification using chaotic heterogeneous comprehensive learning particle swarm optimizer variants, Energy Convers. Manag. 182 (Feb. 2019) 546–563.

[48] A. Rezane Jordehi, Enhanced leader particle swarm optimisation (ELPSO): an efficient algorithm for parameter estimation of photovoltaic (PV) cells and modules, Sol. Energy 159 (Jan. 2018) 78–87.

[49] M. Merchaoui, A. Sakly, M.F. Mimouni, Particle swarm optimisation with adaptive mutation strategy for photovoltaic solar cell/module parameter extraction, Energy Convers. Manag. 175 (Nov. 2018) 151–163.

[50] A.R. Jordehi, Time varying acceleration coefficients particle swarm optimisation (TVACPSO): a new optimisation algorithm for estimating parameters of PV cells and modules, Energy Convers. Manag. 129 (Dec. 2016) 262–274.

[51] K. Lappalininen, P. Manganelli, M. Pilouigne, G. Spagnuolo, S. Valkealahti, Virtual sensing of photovoltaic module operating parameters, IEEE J. Photovoltaics 10 (3) (May 2020) 852–862.

[52] M. Pilouigne, R.A. Guejia-Burbano, G. Petrone, F.J. Sánchez-Pacheco, L. Mora-Lopez, M. Sidrach-de-Cardona, Parameters extraction of single diode model for degraded photovoltaic modules, Renew. Energy 164 (Feb. 2021) 674–686.

[53] S. Yadid, et al., Evolution of the physical parameters of photovoltaic generators as a function of temperature and irradiance: new method of prediction based on the manufacturer’s datasheet, Energy Convers. Manag. 253 (Jan. 2020) 112141.

[54] H.G.G. Nunes, P.N.C. Silva, J.A.N. Pombo, S.J.P.S. Mariano, M.R.A. Calado, Multiswarm spiral leader particle swarm optimisation algorithm for PV parameter identification, Energy Convers. Manag. 225 (Dec. 2020) 113388.

[55] H.M. Ridha, A.A. Heidari, M. Wang, H. Chen, Boosted mutation-based Harris hawks optimizer for parameters identification of single-diode solar cell models, Energy Convers. Manag. 209 (Apr. 2020) 112660.

[56] M. Calasan, S.H.E. Abdel Aleem, A.F. Zoba, On the root mean square error (RMSE) calculation for parameter estimation of photovoltaic models: a novel exact analytical solution based on Lambert W function, Energy Convers. Manag. 210 (Apr. 2020) 112716.

[57] P.J. Gnetchejo, S. Ndjakomo Essiane, P. Ele, R. Wamkue, D. Mbadjoun Wapet, S. Perabí Ngófie, ‘Reply to comment on ‘Important notes on parameter estimation of solar photovoltaic cell’, by Gnetchejo et al. Energy Conversion and Management, Energy Convers. Manag. 201 (Dec. 2019) 112132.

[58] V.V. de Melo, W. Banzhaf, Drone Squadron Optimization: a novel self-adaptive algorithm for global numerical optimization, Neural Comput. Appl. 30 (10) (Nov. 2018) 3117–3144.

[59] H.G.G. Nunes, J.A.N. Pombo, S.J.P.S. Mariano, M.R.A. Calado, J.A.M. Felippe de Souza, A new high performance method for determining the parameters of PV cells and modules based on guaranteed convergence particle swarm optimization, Appl. Energy 211 (Feb. 2018) 774–791.

[60] A. Hazra, S. Das, M. Basu, An efficient fault diagnosis method for PV systems following string current, J. Clean. Prod. 154 (Jun. 2017) 220–232.

[61] A. Elkholy, A.A. Abou El-Ela, Optimal parameters estimation and modelling of photovoltaic modules using analytical method, Heliyon 5 (7) (Jul. 2019), e02137.

[62] V.V. de Melo, A Novel Metaheuristic Method for Solving Constrained Engineering Optimization Problems: Drone Squadron Optimization, arXiv:1708.01368 [cs, math], Aug. 2017 [Online]. Available: http://arxiv.org/abs/1708.01368. [Accessed 5 December 2019].

[63] F.F. Muhammadsharif, et al., ‘Brent’s algorithm based new computational approach for accurate determination of single-diode model parameters to simulate solar cells and modules, Sol. Energy 193 (Nov. 2019) 782–798.