Rethinking solar photovoltaic parameter estimation: global optimality analysis and a simple efficient differential evolution method

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Abstract—A large variety of sophisticated metaheuristics have been proposed for photovoltaic parameter extraction. Our aim is not to develop another metaheuristic method but to investigate two practically important yet rarely studied issues: (i) whether existing results are already globally optimal; (ii) whether a significantly simpler metaheuristic can achieve equally good performance. We take the two widely used I-V curve datasets for case studies. The first issue is addressed using a branch and bound algorithm, which certifies the global minimum rigorously or locates a fairly tight upper bound, despite its intolerable slowness. These values are useful references for the evaluation and development of metaheuristics. Next, extensive examination and comparison reveal that, perhaps surprisingly, an elementary differential evolution (DE) algorithm can either attain the global minimum certified above or obtain the best-known result. More attractively, the simple DE algorithm takes only a fraction of the runtime of state-of-the-art metaheuristic methods and is particularly preferable in time-sensitive applications. This novel, unusual finding also indicates that the employment of increasingly complicated metaheuristics might be somewhat overkilling for regular PV parameter estimation. Finally, we discuss the implications for future research and suggest the simple DE method as the first choice for industrial applications.

Index Terms—Photovoltaic modeling, parameter identification, metaheuristic algorithms, global optimization, differential evolution, time efficiency

I. INTRODUCTION

SOLAR energy can be exploited via photovoltaic (PV) power generation using a solar PV system composed of many PV cells connected in series or parallel [1], [2]. Accurate modeling of PV systems is necessary for their effective design, simulation, power forecasting, and optimal control [1]–[4]. The dominating method to describe solar PV systems depends on an analogous electrical circuit model [5], which has been further specialized to the single-diode model (SDM), the double-diode model (DDM), or even the less commonly used three-diode model [6]. Despite the intuitiveness of these circuit models, the main difficulty lies in the accurate determination of unknown parameters in the model [3], [5], [7]–[9].

There are two kinds of data sources for PV parameter estimation, either datasheets provided by manufacturers or experimentally measured I-V (current-voltage) curves [4], [8]–[10]. We focus on the latter in this study since it typically contains more data points and probably yields higher accuracy [11]. PV parameter estimation is commonly formulated as a nonlinear optimization problem from the perspective of I-V curve fitting. The problem has been widely attempted with various metaheuristic algorithms. Most metaheuristics are population-based by exploiting a swarm of interacting agents to search the solution space efficiently [3], [12]. Since metaheuristic algorithms are mostly not problem-specific, any metaheuristic optimizer may be applied to PV parameter estimation in principle [12]. It is unsurprising that a large number of metaheuristic methods have been proposed for PV parameter estimation. Some recent examples include guaranteed convergence particle swarm optimization [13], improved JAYA optimization [14], performance-guided JAYA [15], self-adaptive ensemble-based differential evolution [16], teaching-learning-based optimization [1], [17], grey wolf optimizer and cuckoo search based hybrid method [18], and wind-driven optimization [6], among many others (see, e.g., [2], [3], [8] for detailed reviews). A limited number of studies approach the problem from a different angle, for instance, Lambert W function based analytical method [19], unknown variable reduction with a new characteristic equation [20], and combination of the analytical and optimization methods with datasheet data [4]. Since these methods’ rationales are distinct from metaheuristic optimization methods and depend on certain technical assumptions, we exclude them from comparison. Despite the increasing interest in such metaheuristics, none of them can guarantee or identify the discovery of the global optimum [7]. Moreover, the minimal root mean square error (RMSE) of curve fitting attained by different metaheuristics has suffered from stagnation with no further reduction in recent studies (see [1, Table 3], [15, Table 3], and Table VII). Thus, one may wonder naturally whether the best-known result is already the global minimum such that we can avoid futile efforts by designing more advanced metaheuristics blindly. If the answer is yes, researchers should look into other aspects of PV parameter identification such as algorithmic robustness and speed rather than devote all efforts to accuracy enhancement. Also, since a variety of metaheuristics can get the same RMSE value, another natural query is how sophisticated a metaheuristic has to be to achieve effective PV parameter estimation. An industrial practitioner desires certainly an effective yet simple and fast algorithm. In particular, the algorithm’s efficiency is critical for time-sensitive applications, for example, the real-
time monitoring of solar cell degradation via photovoltaic curves telemetry using a microprocessor on a satellite [21], and the real-time effective MPPT control of solar PV systems.

In this study, we attempt to answer the above two questions through extensive investigations using the two most broadly studied benchmark datasets (mainly to facilitate comparison) [22]. We have obtained some novel (and somewhat surprising) findings and deep insights that are valuable to both the research community and industrial practitioners. It should be emphasized that the purpose of this study is not to develop another new method for PV parameter estimation. Instead, we try to show to the research community that this specific problem may probably not need so advanced and largely complicated metaheuristics prevalent in the literature, while some classic and simple metaheuristic algorithm can be competent.

The main contributions of this paper are listed below.

- The global minimum RMSE of the SDM has been certified on both datasets for the first time using an interval arithmetic based branch and bound method. Besides, a useful upper bound of the global minimum for the DDM is obtained. These values can serve as valuable references for the assessment and development of metaheuristics.
- We show that an intentionally simple differential evolution (DE) algorithm is adequate to attain the global minimum for the SDM and achieve equally high accuracy for the DDM compared with a variety of sophisticated metaheuristics. Moreover, the DE algorithm stands out with high performance stability and incomparable time efficiency thanks to its simplicity, which renders itself particularly suitable for real-time applications.
- Based on our findings and comparison with state-of-the-art methods, we recommend the simple DE to solar industry engineers as the first choice in practical applications, especially time-sensitive ones. Besides, we provide useful suggestions for researchers to refresh viewpoints on PV parameter estimation and to refrain from possible over-engineering in designing overcomplicated metaheuristics.

The remainder of this paper is organized as follows. Common PV models are first introduced in Section II, followed by the optimization problem formulation. The two optimization methods are described in Section III. We then apply the two methods to two benchmark datasets, report the results, and conduct a detailed comparison in Section IV. Finally, in Section V, we give concluding remarks on our findings and suggest promising work in the future.

II. SYSTEM MODELING AND PROBLEM FORMULATION

This section introduces briefly the two most widely used circuit models for PV systems, namely the single diode model (SDM) and the double diode model (DDM). We refer readers to [5], [11] for more details of the underlying physical principles. Then, the formulation of the nonlinear optimization problem for PV parameter identification is presented.

A. Modeling of PV systems

The electrical circuit corresponding to the SDM is shown in Fig. 1(a). Specifically, the circuit contains a current source $I_{ph}$, which refers to the photocurrent generated by the PV cell, a diode flowing current $I_d$, and two resistors with resistance $R_p$ and $R_s$, respectively. We can calculate the diode current $I_d$ using the Shockley equation as follows,

$$I_d = I_0 \left[ \exp \left( \frac{q(V + IR_s)}{nkT} \right) - 1 \right],$$

where $I_0$ is the reverse saturation current of the diode, $n$ is the ideality factor, $T$ is the temperature in Kelvin, and $V$ is the output voltage of the cell. The other terms are just physical constants: the electron charge $q = 1.60217646 \times 10^{-19}$ C and the Boltzmann constant $k = 1.3806503 \times 10^{-23}$ J/K.

The output current $I$ is computed using first principles by

$$I = I_{ph} - I_0 \left[ \exp \left( \frac{q(V + IR_s)}{nkT} \right) - 1 \right] - \frac{V + IR_s}{R_p}. \tag{2}$$

There are five unknown parameters in (2), which are collected into a parameter vector $\theta_S = [I_{ph}, I_0, n, R_s, R_p]$.

Despite the simplicity and usefulness of the above SDM, it does not consider the effect of recombination current loss in the depletion region [2], [8]. An additional diode can be introduced into the circuit to compensate for this specific loss to attain higher accuracy. The equivalent circuit of the DDM is illustrated in Fig. 1(b). In analogy to the SDM (2), the DDM is derived straightforwardly as follows:

$$I = I_{ph} - I_{d1} - I_{d2} - I_p$$

$$= I_{ph} - I_{01} \left[ \exp \left( \frac{q(V + IR_s)}{n_1kT} \right) - 1 \right] - \frac{V + IR_s}{R_p},$$

$$= I_{ph} - I_{02} \left[ \exp \left( \frac{q(V + IR_s)}{n_2kT} \right) - 1 \right] - \frac{V + IR_s}{R_p}, \tag{3}$$

where $I_{01}$ and $I_{02}$ are the reverse saturation current of the two diodes, and $n_1$ and $n_2$ denote the ideality factor of the two diodes, respectively. The DDM has seven parameters in total, denoted by $\theta_D = [I_{ph}, I_0, I_{01}, I_{02}, n_1, n_2, R_s, R_p]$.

A PV module contains multiple PV cells connected in series or parallel. It is standard to assume the same parameter values for all cells for computational tractability purposes. We can thus lump all cells into a single, functionally equivalent cell [10], [15], [22], [23]. An identical procedure is used to fit either the SDM (2) or the DDM (3) to the I-V curve of a PV module, just like a PV cell, though most studies consider the SDM exclusively due to the increased parameterization difficulty of the DDM when dealing with PV modules [11] (refer to Section IV-D for more details).

B. Optimization problem formulation

The fundamental principle of parameter estimation via I-V curve fitting is to find appropriate parameter values such as

\[ I = I_{ph} - I_{d1} - I_{d2} - I_p = I_{ph} - I_{01} \left[ \exp \left( \frac{q(V + IR_s)}{n_1kT} \right) - 1 \right] - \frac{V + IR_s}{R_p} = I_{ph} - I_{02} \left[ \exp \left( \frac{q(V + IR_s)}{n_2kT} \right) - 1 \right] - \frac{V + IR_s}{R_p}, \]
that the current values calculated with either the SDM (2) or the DDM (3) match the measurement values for a set of data points [2], [6]. Without loss of generality, we discuss below the problem formulation using the SDM (2), termed \( f_S \) hereafter, with parameters \( \theta_S \), whose principle can be transplanted to the DDM case seamlessly.

Note that we cannot write down a simple closed-form solution \( I = f_S^{-1}(V) \) for the model \( f_S \) (2) to compute \( I \) given \( V \). As a workaround, given a measurement \((V_m, I_m)\) and a tentative parameter vector \( \theta_S \), the majority of metaheuristic-based studies compute the predicted current with the model approximately but computationally economically as

\[
I \approx f_S(V_m, I_m; \theta_S),
\]

(4)

and try to reduce the deviation between \( I \) and \( I_m \) by adjusting \( \theta_S \) (see [1], [15], and [23] among others).

The root mean square error (RMSE) is widely used to quantify the difference between computed current values and the measurement values [16], [21]. Supposing there are \( N \) data points in the I-V curve, we get the following constrained optimization problem, which is known widely as nonlinear least-squares regression in the literature.

\[
\text{minimize} \quad J(\theta) = \sum_{i=1}^{N} (f(V_i^{m}, I_i^{m}; \theta) - I_i^{m})^2, \quad (5a)
\]

subject to \( \theta \in \Theta \),

(5b)

where \( f \) refers to either the SDM \( f_S \) (2) or the DDM \( f_D \) (3), and \( \theta \) is the corresponding parameter vector \( \theta_S \) or \( \theta_D \). \((V_i^{m}, I_i^{m})\) is the \( i \)-th data point in measurement. \( \Theta \) denotes the specified bound constraints of \( \theta \) that take physical reality into consideration (see Table I for examples).

### III. Optimization methods

To address the two concerns in Section I, we attempt to (i) determine rigorously the global minimum or at least a reasonably tight bound of the global minimum for the problem (5) and (ii) show that an intentionally simple metaheuristic can effectively attain the global minimum or the best-known minimum in the literature. To measure the solution optimality rigorously in task (i), we apply a branch and bound (B&B) based deterministic global optimization technique. For task (ii), we choose deliberately a simple stochastic optimization algorithm, differential evolution (DE).

**A. Deterministic global optimization with an interval arithmetic based branch and bound algorithm**

The fundamental task of deterministic global optimization (DOG) is to determine rigorously (i.e., with theoretical guarantees) the global minimum of an objective function \( f \) subject to a set of constraints [24]. However, finding the global minimum for a general nonconvex optimization problem like (5) has been proved to be NP-hard [24]. We are practically more interested in identifying a solution sufficiently close to the true global minimum, called the \( \epsilon \)-global minimum:

**Definition 1:** [24] Consider the minimization of \( f(x), x \in S \). A feasible solution \( \bar{x} \in S \) is an \( \epsilon \)-global minimum if \( f(\bar{x}) \geq f(x) - \epsilon, \forall x \in S \), where \( \epsilon \geq 0 \) is a small tolerance.

The most popular algorithmic framework of DGO is arguably the branch and bound (B&B) method and its variants like branch and reduce [24], whose general principle is intuitive. The search space is divided recursively into smaller subspaces and forms accordingly a tree structure of subproblems. One crucial factor to success lies in determining the proper bounds of each subproblem, usually via convex or concave relaxation. The consequential pruning of search space is performed by eliminating subproblems whose lower bound is no better than the best upper bound found so far. Interval analysis is a handy tool to estimate the lower and upper bounds of regions/branches of the search space, whose technical details are presented in [25] and omitted here.

The general B&B framework with interval arithmetic is depicted in Algorithm 1, where \( [x] \) denotes an \( n \)-dimensional interval vector (also known as an interval box, whose components are intervals). Applying a function \( f : \mathbb{R}^n \rightarrow \mathbb{R} \) to \([x] \) yields another interval termed \( f([x]) = [f(\bar{x})], f([\bar{x}]) \) where \( f(\bar{x}) \) and \( f([\bar{x}]) \) denote the lower and upper bounds respectively and are calculated rigorously with interval analysis [25]. Each iteration is composed of three main components: box selection (Line 5), box contracting (Line 6), and box splitting (Line 12). In particular, the purpose of contracting is to delete subboxes inside \([x] \) that cannot contain a globally optimal solution to reduce search space [25, Chapter 12]. In order to be included in \( L_S \), a box \([x] \) must satisfy two conditions that are checked in Line 9:

\[
\text{width}(\bar{x}) \leq \epsilon_x, \text{width}(f([\bar{x}])) \leq \epsilon_f, \quad (6)
\]

where \( \text{width}(\cdot) \) denotes the width of a box defined by its largest diameter [24], \( \epsilon_x \) and \( \epsilon_f \) are two tolerance parameters provided by the user, often known as the precision. After the main loop finishes, we post-process the solution list \( L_S \) in Line 15 to discard boxes which cannot contain the global minimum \( x^* \) according to the latest knowledge of \( \tilde{f} \).

At the end of Algorithm 1, we get the (usually very tight) bounds of the global minimum \( f^* \in [f, \tilde{f}] \). It is guaranteed that \( \tilde{f}(\bar{x}) - f^* \leq 2\epsilon_f, \forall \bar{x} \in L_S \) [25]. Definition 1 tells
that any $x$ inside the remaining boxes $L_S$ becomes an $e$-global minimum with $e = 2\epsilon_f$ in this case. Though the exact global minimum $x^*$ and $f^*$ are still unknown and remain computationally intractable, a reasonably tight bound by setting small $\epsilon_f$ and $\epsilon_e$ in Algorithm 1 is usually enough for practical purposes. Note that Algorithm 1 only sketches out the basic skeleton of interval B&B algorithms. We resort to a dedicated interval analysis library ibexopt (http://www.ibex-lib.org (v2.8)) in actual implementation. Interested readers may refer to the monograph [25] for more details.

B. Stochastic global optimization with a simple DE

Though an interval B&B algorithm can ascertain the global optimum rigorously in theory, it is generally much more computationally expensive than metaheuristic algorithms, rendering itself impractical in industrial applications [7]. We will report its intolerably long running time in Section IV-B. In many engineering applications, it is either unnecessary or computationally intractable to obtain the exact global minimum [24], and metaheuristic methods are particularly useful in these scenarios. In view of the abundance of metaheuristics (recall Section I), we take an elementary differential evolution (DE) algorithm [26] on purpose to investigate whether highly complicated metaheuristics are really necessary for PV parameter estimation. Again, we would like to emphasize that our objective is not to develop yet another new metaheuristic but to investigate whether a fundamental one is empirically sufficient for practical PV parameter estimation tasks.

DE follows the Darwinian principle to evolve a population of solutions (called vectors), and each iteration of DE comprises three key steps: selection, crossover, and mutation. The distinguishing feature of DE is its mutation with difference vectors [26], [27]. To minimize a function $f : \mathbb{R}^n \rightarrow \mathbb{R}$ with bound constraints $X \subset \mathbb{R}^n$, we outline the classical and simple DE in Algorithm 2, whose main body includes only five lines of code in agreement with its simplicity. The initial population $P$ comprises $N_p$ vectors, and each initial vector $x^0_{i,0}$, $i \in [1, N_p]$ is generated randomly by

$$x^0_{i,j} = \bar{x}_j + \epsilon_j \cdot (\bar{b}_j - \bar{b}_j),$$

where $x^0_{i,j}$ denotes the $j$-th component of $x^0_i$, $\bar{b}_j$ and $\bar{b}_j$ represent the lower and upper bound of the $j$-th variable respectively, $j \in [1, n]$. Besides, rand$(0, 1)$ generates a random number between 0 and 1.

Several mutation strategies have been developed for DE [26], [27]. Here we adopt the most commonly used one called the “DE/rand/1” scheme. For each vector in the $g$-th iteration, a donor vector $v^g_i$, $i \in [1, N_p]$, is produced by

$$v^g_i = x^g_a + F(x^g_b - x^g_c), \quad a \neq b \neq c \neq i,$$

where three indices $a, b, c \in [1, N_p]$ are randomly chosen, and $F$ is the scaling factor typically in the range $[0.4, 1]$ [27].

Note that the donor vector $v^g_i$ in (8) may lie outside the bounded region $X$. We adopt a simple bounce-back strategy [26], [27] to handle bound constraints in Line 5, which relocates each infeasible component between the bound it violates and the corresponding value of the target vector $x^g_i$:}

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Algorithm 2 Simple differential evolution

**Input:** objective function $f : \mathbb{R}^n \rightarrow \mathbb{R}$ and bound constraints $X \subset \mathbb{R}^n$, control parameters $N_p, C_r, F, G$

**Output:** the best vector $\hat{x}$ and the function value $\hat{f}$

1: $g \gets 0$
2: $g^* \leftarrow \{g^*_i\}_{i=1}^N$ with (7)
3: for $g$ from 0 to $G - 1$ do
4:    for each vector $x^g_i \in \mathbb{R}^p$ do
5:       $v^g_i \leftarrow$ bounce-back($v^g_i$) by (9)
6:       $u^g_i \leftarrow$ crossover($v^g_i$, $x^g_i$) by (10)
7:       $x^{g+1}_i \leftarrow$ select($u^g_i$, $x^g_i$) by (11)
8:    end for
9: end for
10: $\hat{x} \leftarrow$ the best vector in $P^G$ and $\hat{f} \leftarrow f(\hat{x})$
```

In DE, the donor vector $v^g_i$ and the target vector $x^g_i$ mate to produce a new vector $u^g_i$ named the trial vector. The binomial crossover scheme is widely used as follows:

$$u^g_{i,j} = \begin{cases} v^g_{i,j} & \text{if} \quad \text{rand}(0, 1) \leq C_r \\ x^g_{i,j} & \text{otherwise} \end{cases},$$

where $\beta \in [1, n]$ is a random integer that is generated anew for each $i$ and $C_r$ is the user provided crossover rate [27]. Eq. (10) says each entry of $u^g_i$ comes from either $v^g_i$ or $x^g_i$.

Finally, DE imposes elitism by selecting the better one between the target vector $x^{g+1}_i$ and the trial vector $u^g_i$ as the $i$-th vector into the next generation according to their fitness:

$$x^{g+1}_i = \begin{cases} u^g_i & \text{if} \quad f(u^g_i) \leq f(x^g_i) \\ x^g_i & \text{otherwise} \end{cases}.$$
TABLE I: Parameter search range in numerical experiments.

| Parameter      | RT       | PW       | Lower | Upper | Lower | Upper |
|----------------|----------|----------|-------|-------|-------|-------|
| $I_{ph}$ (A)   | 0.760779120136 | 1.03052020484 |
| $I_{0}$, $I_{01}$, $I_{02}$ (µA) | 0.322873926858 | 3.48287904343 |
| $n$            | 1.48113747635 | 48.6435574734 |
| $R_n$ (Ω)      | 0.0363792207867 | 1.20123682021 |
| $R_p$ (Ω)      | 53.7009537057 | 981.263690780 |
| RMSE           | [9.860250417458982E-4, 2.4250765995320144E-3] |
| Gap            | 1.950333050615427E-12 | 1.212332907351913E-12 |
| Time (s)       | 13547 | 38924 |

TABLE II: Optimization results for SDM using interval B&B.

| Variable | RT       | PW       |
|----------|----------|----------|
| $I_{ph}$ (A) | 0.760815738919 | 1.0339286971 |
| $I_{0}$ (µA) | 0.217867184041 | 1.8657574201E-23 |
| $I_{01}$ (µA) | 0.781454995330 | 0.535399234849 |
| $R_n$ (Ω) | 1.44827388213 | 9.58860778809 |
| $R_p$ (Ω) | 1.98183166760 | 42.6724488388 |
| RMSE       | [0, 9.83581875679E-4] | [0, 1.61865668151E-3] |
| Gap        | 55.8931982861 | 607.690281231 |
| Time (s)   | 86400 | 43200 |

B. Global optimality analysis via interval B&B

Despite the large number of metaheuristics for PV parameter estimation (like those in Table 1 of [19]), none of them can certify the finding of the global minimum even if they have essentially found it. Besides, a notable observation is that the minimum RMSE attained so far remains 9.8602E-4 for the case “SDM+RT” in the past few years. A natural speculation is whether 9.8602E-4 is the global minimum. Similar observations exist for the DDM and the PW dataset. This section presents results regarding global optimality.

1) SDM results: Note that a B&B algorithm is generally computationally intensive. Following [7], we limited the runtime of ibexopt to 20000 seconds for “SDM+RT”. On the other hand, unlike [7], we did not use the default absolute and relative precision but set them to smaller values (1E-13 and 1E-9) in order to obtain tighter bounds of the global minimum. The results are reported in Table II. The optimization results for “SDM+RT” are reported in the first column of Table II. In particular, the bounds of the RMSE enjoy a negligible gap. Note that the results reported in existing studies are mostly truncated to five significant digits. Hence, we can certify safely, for the first time, that 9.8602E-4 is indeed the global minimum RMSE value of “SDM+RT”, which agrees with the literature. The parameter values in Table II correspond to the upper bound of RMSE, and those values match closely to results acquired with various metaheuristics (like [19, Table 1]).

2) DDM results: The DDM is more challenging due to its two extra parameters. This fact, in addition to the widened search range of PW in Table I, may explain why the DDM is rarely applied to a PV module. We decided to allow ibexopt more time (24 hours) to get hopefully tighter optimality bounds. The overall workflow is identical to the SDM case above. The results are reported in Table III. Unfortunately, the lower bound remains zero, even if we run ibexopt for another 5 hours. This failure is probably caused by the cluster effect, a pain that B&B methods often suffer from, which states roughly that increasingly small boxes keep accumulating due to excessive splitting with no real progress [24], [28].

Despite the zero lower bound, the revealed upper bound of the RMSE is still informative since it is very close to the best-known result, e.g., 9.8248E-4 for the “DDM+RT” case (see [15, Table 3]). The upper bound 9.8358E-4 in Table III implies that 9.8248E-4 is likely to be the global minimum though there is no theoretical guarantee. We did not find results reported for “DDM+PW” that are compatible with our analysis here. Nonetheless, the result of “DDM+PW” in Table III looks reasonable by comparing with the SDM counterpart in Table II: the RMSE upper bound of DDM is even smaller than the lower bound of SDM since, as expected, the DDM can better fit the data because of its two additional parameters [16].

Fig. 2: Measured and estimated I-V curves using parameter values optimized by interval B&B. (a) RT; (b) PW. The result of the simple DE is visually almost identical and thus omitted.

TABLE III: Optimization results for DDM using interval B&B.

| Variable | RT       | PW       |
|----------|----------|----------|
| $I_{ph}$ (A) | 0.760815738919 | 1.0339286971 |
| $I_{0}$ (µA) | 0.217867184041 | 1.8657574201E-23 |
| $I_{01}$ (µA) | 0.781454995330 | 0.535399234849 |
| $n$ | 1.44827388213 | 9.58860778809 |
| $R_n$ (Ω) | 1.98183166760 | 42.6724488388 |
| $R_p$ (Ω) | 55.8931982861 | 607.690281231 |
| RMSE | [0, 9.83581875679E-4] | [0, 1.61865668151E-3] |
| Gap | 86400 | 43200 |
TABLE IV: Control parameters of simple DE in Algorithm 2.

|          | N_p | C_v | F | G  |
|----------|-----|-----|---|----|
| SDM      | 50  | 0.6 | 0.9| 800 |
| DDM      | 50  | 0.6 | 0.9| 2000 |

Nonetheless, since the RMSE values of both models are pretty small, it is hard to differentiate visually the two estimated I-V curves, which are highlighted in Fig. 2.

In summary, the above case studies conclude rigorously that: (i) the global minimum of RMSE for “SDM+RT” and “SDM+PW” is certified as 9.8602E-4 and 2.4250E-3, respectively; (ii) the upper bound of the global minimum RMSE for “DDM+RT” and “DDM+PW” is 9.8358E-4 and 1.6186E-3, respectively. To our best knowledge, this conclusion is drawn for the first time. These numbers can serve as important references for future algorithm development and evaluation.

Recall the large number of boxes accumulated during B&B, which implies probably a flat region around the global minimum. The selection scheme of the simple DE in (11) can help particularly overcome this challenge by replacing the target vector \(x^g\) with the trial vector \(u^g\) even if they have the same fitness such that the DE vectors can move over flat fitness landscapes across generations [27]. Besides, in view of the distinct scales of parameters in Table I, the mutation with difference vectors in (8) helps adapt the step size of each variable to its own scaling automatically without manual specifications. The autonomous adaption has empirically proved to notably improve the convergence of the algorithm [27].

C. Optimization via simple differential evolution (DE)

The interval B&B algorithm is not suitable for regular PV parameter estimation applications due to its excessively long execution time. By contrast, various metaheuristic methods can obtain a reasonably good solution in a far shorter time. However, an interesting, practically important, yet rarely studied problem is whether normal PV parameter estimation really demands the increasingly complicated metaheuristics prevailing in the recent literature. In this section, we try to get some empirical insights by examining whether the intentionally simple DE in Algorithm 2 can achieve comparable performance. Starting with the canonical values recommended in [27, Section III], we quickly determined appropriate control parameter values for the simple DE and list them in Table IV.

Since DE is a stochastic algorithm, we follow the convention (e.g., [15], [23]) to execute DE 30 times for each case and report the statistic characteristics. For illustration purposes, we list the DE results in a typical run in Table V, whose estimated I-V curves are visually almost identical to Fig. 2 (since all RMSE values are likewise tiny) and thus omitted here. The convergence curves of this simple DE for RT using both models in a typical run are shown in Fig. 3. The DE usually takes far fewer generations to converge than the conservative value \(G\) in Table IV. The convergence curves of DE with the PW dataset share a similar character and is omitted here.

The statistics of RMSE in the 30 runs are reported in Table VI. Overall, the performance of our DE algorithm is remarkably stable despite its stochasticity in nature. When applying to the SDM on both datasets and to “DDM+PW”, the DE algorithm always yields the same minimal RMSE in all 30 trials. Even in the worst “DDM+RT” case, the gap between the maximum and minimum RMSE values in 30 runs is still minor, as implied by the slight standard deviation in Table VI.

Recall Table II and III above. Table VI tells that the simple DE managed to find the global minimum RMSE for both SDM cases. As for the more challenging DDM cases, DE achieved the best-known result for “DDM+RT”, i.e., 9.8248E-4. However, the RMSE attained by DE for “DDM+PW” is still above the identified upper bound (2.4250E-3 vs 1.6186E-3). The main reason is presumably attributed to the extraordinarily small value of \(I_{01}\) in the potential optimal solution (around 1.86E-23 in Table III). It is quite difficult for DE or any metaheuristic to pinpoint such a tiny number within the large search range due to roundoff errors (which is handled properly by interval arithmetic though [25]). Besides, since no existing studies have reported compatible results for “DDM + PW”, we examine additionally two sophisticated metaheuristics and get the same results as our DE (see Table VII below).

D. Comparison with existing algorithms

We compare the performance of the simple DE (Algorithm 2) with more sophisticated metaheuristics, inspecting both accuracy and efficiency. We select state-of-the-art algorithms of distinct methodology and pick particularly DE variants for a comprehensive comparison. The existing results have been listed as they appear in four latest articles: [1, Table 12], [15, Table 3], [23, Table 9], and [16, Table 9]. All results are listed in Table VII. Since the hardest case “DDM+PW” were not considered in these papers, we run the original source code of two recent studies [15], [16] (see https://github.com/cilabzzu) and report their results for fair comparisons. The statistics of the RMSE values in 30 runs are listed in Table VII.

To examine the statistical significance of performance difference between the simple DE and the other methods, we

Fig. 3: Convergence curves of DE with RT: (a) SDM (b) DDM.
TABLE VI: Statistics of RMSE values by DE in 30 runs.

| Method          | RMSE | U test |
|-----------------|------|--------|
|                 | Min  | Mean   | Max  | Std   |
| MLBSA [29]      | 9.8602E-4 | 9.8602E-4 | 9.8602E-4 | 7.0800E-11 | +   |
| TLABC [17]      | 9.8602E-4 | 9.9417E-4 | 1.0308E-3 | 1.1896E-5 | +   |
| IJAYA [14]      | 9.8602E-4 | 9.8605E-4 | 9.8684E-4 | 1.4931E-7 | +   |
| PGIAYA [15]     | 9.8602E-4 | 9.8602E-4 | 9.8603E-4 | 2.8029E-9 | +   |
| SATLBO [30]     | 9.8602E-4 | 9.8879E-4 | 1.0097E-3 | 4.8133E-6 | +   |
| SGDE [23]       | 9.8602E-4 | 9.8602E-4 | 9.8603E-4 | 2.4746E-9 | -   |
| SEDE [16]       | 9.8602E-4 | 9.8602E-4 | 9.8603E-4 | 4.2000E-17 | –   |
| CoDE [31]       | 9.8602E-4 | 9.8602E-4 | 9.8602E-4 | 2.3100E-17 | –   |
| Simple DE       | 9.8602E-4 | 9.8602E-4 | 9.8602E-4 | 2.9464E-17 | +   |

Table VII: Comparison of results of various algorithms in four cases. From top to bottom: “SDM+RT”, “SDM+PW”, “DDM+RT”, and “DDM+PW”.

| Method          | RMSE | U test |
|-----------------|------|--------|
|                 | Min  | Mean   | Max  | Std   |
| MLBSA           | 9.8248E-4 | 9.8506E-4 | 9.8613E-4 | 1.2400E-6 | +   |
| TLABC           | 1.0012E-3 | 1.2116E-3 | 1.9826E-3 | 2.1100E-4 | +   |
| IJAYA           | 9.8249E-4 | 1.0036E-3 | 1.5496E-3 | 1.0300E-4 | +   |
| PGIAYA          | 9.8248E-4 | 9.8289E-4 | 9.8602E-4 | 9.1700E-7 | -   |
| SATLBO          | 9.8248E-4 | 9.8289E-4 | 9.8602E-4 | 9.1700E-7 | -   |
| SEDE            | 9.8249E-4 | 1.0036E-3 | 1.5496E-3 | 1.0300E-4 | +   |
| CoDE            | 9.8248E-4 | 9.8289E-4 | 9.8602E-4 | 9.1700E-7 | -   |
| Simple DE       | 9.8245E-3 | 2.4250E-3 | 2.4250E-3 | 1.7547E-17 | –   |

Fig. 4: Runtime comparison of different algorithms

perform the Mann-Whitney U test [16] and report results in the “U test” column of Table VII. The null hypothesis $H_0$ indicates equally good performance, and the level of significance is 0.05. In the results reported in Table VII, the symbol “+” indicates a statistically significant performance difference, i.e., rejecting the null hypothesis, while “-” means there is no statistically significant evidence to conclude the performance difference.

Overall, our simple DE (Algorithm 2) and several strong competitors like SEDE can attain the best RMSE values. Statistically, the Mann-Whitney U test indicates that the accuracy of the simple DE is on par with the selected state-of-the-art approaches such as SEDE. The result is somewhat surprising given the extreme simplicity of the simple DE. Unfortunately, such simple metaheuristics have been largely overlooked in the current literature. Note that we compare the simple DE intentionally with three more complicated DE variants: SGDE, SEDE, and CoDE. In the two SDM cases in Table VII, the four DE algorithms exhibit almost identical accuracy in terms of RMSE values, while CoDE demonstrates the highest stability measured by the standard deviation and SGDE is the least stable one. By contrast, in the more challenging DDM cases, our simple DE outperforms both CoDE and SEDE with its enhanced performance stability.

The most apparent advantage of the simple DE is its substantially reduced running time ($<1$ s). This impressive speedup is mainly brought by its extreme simplicity including only four computationally cheap equations in Algorithm 2. Besides, note that the evaluation of the objective function (5a) with a few dozens of data points is inexpensive, which implies consequently that it is usually the algorithm’s internal computation burden that dominates the overall time consumption. This claim is supported particularly by the significantly longer computation burden that dominates the overall time consumption.

As for the “DDM+PW” case in Table VII, we notice that the best RMSE value attained by the three algorithms all turns out to be 2.4250E-3, though this value is certainly not the global minimum (recall the upper bound ascertained in Table III). As mentioned in Section IV-C, this failure is possibly caused by the excessively small true value of $I_{01}$ (see Table III) that can challenge all metaheuristic methods.

V. Conclusion

In this paper, we tried to address two essential issues of PV parameter estimation that have seldom been attempted in the
current literature. With the two most widely used benchmark datasets, the globally minimum RMSE for the SDM and a reasonably tight upper bound for the DDM were certified rigorously by an interval analysis based B&B algorithm. However, the running time of this interval B&B algorithm is overly long for practical usages despite its theoretical guarantee. Next, we showed through extensive examination that, for the first time and somewhat surprisingly, a simple DE algorithm (Algorithm 2) was capable of locating the global minimum or at least attaining the best-known result. Moreover, the simple and easy-to-tune DE algorithm is distinguished by its favorable performance stability and unmatched efficiency. We suggest that a practitioner start with the simple DE as the off-the-shelf tool, especially in real-time parameter estimation scenarios, where the environment may keep changing, and estimation is repeated periodically with the latest I-V curve data.

Our findings imply that, unfortunately, many existing meta-heuristics for PV parameter estimation might be overly complicated and risk over-engineering. We suggest that forthcoming studies justify their methods with the proposed simple DE as the baseline. Moreover, future research efforts may be better put into other aspects apart from merely fitting accuracy, for instance, certification of global optimality and measurement error quantification. Finally, since our methodology is not restricted to a specific dataset, it is meaningful to validate the performance of the simple DE method with more custom I-V datasets, though we focus exclusively on the two most widely used benchmark datasets to ease comparison. Our code is available at https://github.com/ShuhuaGao/rePVest.

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