Highlights

Estimation of parameters for solar cells with S–shaped current–voltage characteristics using meta–heuristic algorithms

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- Proposed deep learning-based method to predict iron contamination in Si-SC by using IV curve.
- The simulated IV characteristics are used to create training and test datasets.
- The DNN's configurations are proposed.
- The mean squared relative error of prediction is up to 0.005.

Estimation of parameters for solar cells with S–shaped current–voltage characteristics using meta–heuristic algorithms

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ABSTRACT

Defect-assisted recombination processes frequently limit the photovoltaic device performance. The low-cost and express methods of impurity contamination control are in demand at solar cell manufacturing. In this paper, we applied deep learning-based approach to extract the iron concentration in silicon solar cell from an ideality factor values.

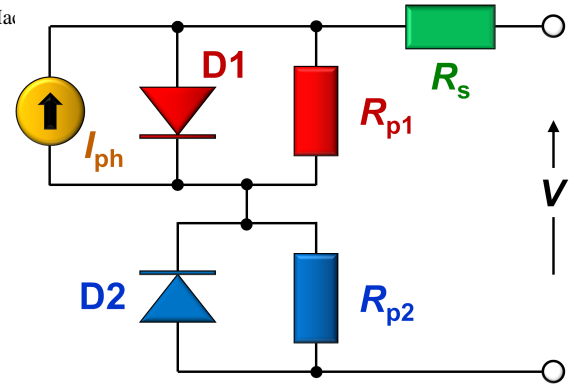

Figure 1: The opposed two–diode equivalent–circuit model of a solar cell.

1. Introduction

[1]

2. Problem definition

2.1. Solar cell model

Fig. 1 vividly reveals the structure of the used model [2]. It can be seen from the figure that model contains a current source accompanied by a diode D1, a shunt resistor R_{p1} to show the leakage current, and a series resistor R_s to consider the losses associated with the load current. Besides, the second diode D2 with a second parallel resistance R_{p2} is placed opposite to the first one and is essential to simulate the non-ideal effects of the active layer/cathode interface. In this model, D1 is responsible for the exponential behavior of the I–V curve, the main contribution of D2 is to simulate the S–shape. The analytical solution $V(I)$ of the opposed two–diode equivalent circuit model was obtained [3] using Lambert W-function [4]:

$$\begin{aligned} V = {} & (I+I_{ph}+I_{01})R_{p1} \\ & -\frac{n_1kT}{q}W\left\{\frac{qI_{01}R_{p1}}{n_1kT}\exp\left[\frac{qR_{p1}(I+I_{ph}+I_{01})}{n_1kT}\right]\right\} \\ & +\frac{n_2kT}{q}W\left\{\frac{qI_{02}R_{p2}}{n_2kT}\exp\left[-\frac{qR_{p2}(I-I_{02})}{n_2kT}\right]\right\} \\ & +(I-I_{02})R_{p2}+IR_s\,, \end{aligned} \tag{1}$$

where I_{01} and I_{02} are the saturation currents and n_1 and n_2 are the ideality factors for D1 and D2 respectively, and I_{ph} is the ideal photocurrent. Thus, the model employs eight lumped parameters (I_{01}, n_1, R_{p1}, I_{02}, n_2, R_{p2}, R_s, and I_{ph}) that need to be determined from the I-V curve. Thus, from an optimization perspective, the dimension of the problem is $D = 8$.

The expression (1) has a drawback in that it tends to stray from the range of numbers that can be accommodated by the standard 64-bit floating-point format owing to the presence of exponential functions for larger numbers. To overcome this drawback, the use of the g–function $g(x) = \ln(W(\exp(x)))$ was suggested [5]. The analytical solution $V(I)$ using the g–function is as follows [5]

$$\begin{aligned} V(I) = {} & IR_s+\frac{n_1kT}{q}g(x_1)-\frac{n_2kT}{q}g(x_2) \\ & -\frac{n_1kT}{q}\ln\left[\frac{qI_{01}R_{p1}}{n_1kT}\right]+\frac{n_2kT}{q}\ln\left[\frac{qI_{02}R_{p2}}{n_2kT}\right], \end{aligned} \tag{2}$$

with

$$x_1 = \ln\left(\frac{qI_{01}R_{p1}}{n_1kT}\right)+\frac{q(I+I_{ph}+I_{01})R_{p1}}{n_1kT}\,, \tag{3}$$

and

$$x_2 = \ln\left(\frac{qI_{02}R_{p2}}{n_2kT}\right)-\frac{q(I-I_{02})R_{p2}}{n_2kT}\,. \tag{4}$$

We used Eqs. (2)–(4) both for simulation IV curves and during the approximation procedure. The g–function was evaluated by using iterative procedure [5].

2.2. Synthetic IV curves

The research involved the parameter estimation of solar cells using meta-heuristic algorithms based on synthetic IV characteristics simulated using the opposed two–diode model. This approach allows for assessing the accuracy of the employed optimization methods, as the simulation was performed using known parameter values.

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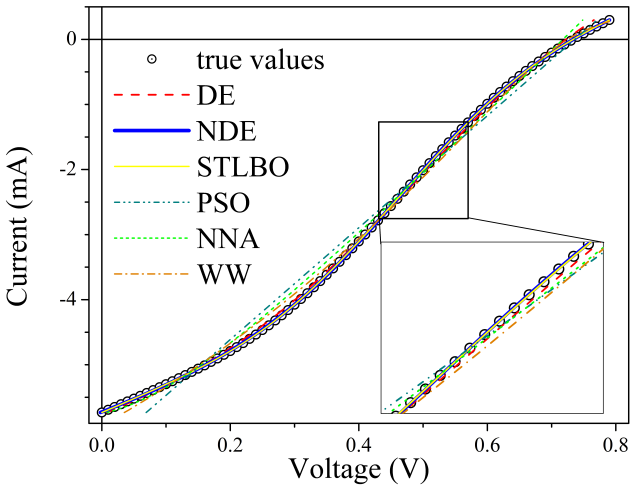

Figure 2: Fitting results (lines) for the simulated current-voltage characteristic (symbols). The values from Sec. 2.2.1 were assumed under simulation.

In one part of the study, a detailed analysis was conducted on a single IV curve, evaluating the performance of meta–heuristic algorithms for parameter estimation in a one-time application. Additionally, the suitability of employing two different fitness functions was examined. In the second part, we simulated a set of IV characteristics and evaluated the average performance metrics of various algorithms.

2.2.1. Single–IV case

Previous studies have demonstrated [6, 7] that when the ideality factor of D2 is either equal to or significantly larger than n_1, ($n_1 = n_2 = 1.92$ or $n_1 = 1.00$, $n_2 = 3.00$) the nonlinear least–squares method successfully determines a set of equivalent circuit parameters that accurately replicate the experimental data of an organic photovoltaic cell. Therefore this approach does not allow for distinguishing between similar IV curves obtained from solar cells with different parameters. To overcome this issue, Tada [7] successfully employed Bayesian estimation of parameters. To assess the capabilities of meta-heuristic methods in overcoming additional similar challenges, they were applied to a IV curve corresponding to such a problematic case. The parameter values were taken from [7] ($I_{01} = 1.6 \cdot 10^{-6}$ mA, $n_1 = 1.92$, $R_{p1} = 190\ \Omega$, $I_{02} = 0.16$ mA, $n_2 = 1.92$, $R_{p2} = 190\ \Omega$, $R_s = 45\ \Omega$, $I_{ph} = 8$ mA), and the IV curve was simulated over a range of 0-0.8 V with step 10 mV at $T = 300$ K. The simulation result is presented on Fig. 2 by symbols.

2.2.2. IV–set case

2.3. Meta-heuristic algorithms

In the literature, meta-heuristics are frequently categorized based on their sources of inspiration. This categorization involves incorporating elements of true simulations and principles that incorporate stochasticity, with the objective of emulating diverse characteristics observed in biological behavior, the lives of creatures in nature, human behavior, or natural phenomena. On this basis, any meta-heuristic algorithm can fall into one of the following main classes [8, 9, 10]: evolution-based methods (emulate the principles of evolutionary behavior observed in creatures in nature by relying on the concept of survival of the fittest), swarm intelligence–based methods (simulate the collective, dynamic, intelligent, and concerted gregarious conduct of collections of flocks or communities found in nature), bio–based methods (use biological processes unrelated to group behavior), chemical & physical–based methods (originate from the physical phenomena or chemical laws that exist in the universe), human-society–based methods (inspired by human beings, including various activities such as thinking and social behavior), and math–based methods (borrow the mathematical functions). Generally, there are hundreds of meta-heuristic optimization methods available. While we acknowledge that our selection may not be fully comprehensive, we utilized 14 methods, representing all classes mentioned above, to tackle the parameter estimation task within the framework of the opposed two-diode model for a solar cell. Hereafter, we provide a succinct description of each method alongside the parameters employed during the fitting process.

Differential evolution (**DE**). DE is one of the classical methods, and it is based on the natural selection law and uses the randomly generated initial population, differential mutation, and probability crossover [11]. During the implementation, we employed a penalty function suggested by Ishaque *et al* [12]. Besides, according to Wang and Ye [11], the values of mutation scaling factor $F = 0.8$, crossover rate $Cr = 0.3$, and population size $Np = 8 \times D = 64$ were used in this work.

Adaptive differential evolution with the Lagrange interpolation argument (**ADELI**). The method is based on DE, which integrates an adaptive local search scheme with Lagrange interpolation [13]. This incorporation aims to enhance the exploitation capability and accelerate the convergence speed. In ADELI, the scaling factor and crossover rate are set to self–adapting to optimize the results. We used parameter values recommended by Huang *et al* [13] during the implementation process. Additionally, we set Np to 64 for our numerical experiments.

Differential evolution with neighborhood–based adaptive evolution mechanism (**NDE**). The method uses a mutation strategy, which takes into account neighborhood and individual information, and an adaptive evolution mechanism [14]. The determination of F and Cr values is achieved through the utilization of the weighted adaptive procedure [15], and an adaptive adjustment of the population size is implemented using a simple reduction method (from $10 \times D = 80$ to 5).

Success history based DE with hybridization mutation strategies and population size reduction (**EBLSHADE**). The method is the hybridization framework between *pbest* and *ord_pbest* mutation strategies and stores a set of Cr and F values that have performed well in the recent past [16]. A linear Np reduction (from $18 \times D = 144$ to 4) is used as well.

Particle swarm optimization (**PSO**). It is another classic method based on observations of the social behavior of animals, such as bird flocking, fish schooling, and swarm theory. According to Ye et al. [17], the values of learning factors $l_1 = l_2 = 2$, the final weight and the initial weight $w_{max} = 0.9$, $w_{min} = 0.4$, and $Np = 15 \times D = 120$ are used in this work.

The *modified artificial bee colony* (**MABC**) algorithm is based on the intelligent foraging behavior of honey bee swarms [18]. The control parameters include the population size ($Np = 8 \times D = 64$) and the maximum number of generations after which each non-improved food source is to be discarded ($L_{imit} = 36$).

Chaotic Whale Optimization Algorithm (**CWOA**). WOA draws inspiration from the hunting behavior of humpback whales [19]. On the other hand, CWOA employs chaotic maps to compute and dynamically adjust its internal parameters [20]. In our study, we utilized the Singer chaotic map and set $Np = 100$ for the identification of the parameters of the solar cell.

The *Neural Network Algorithm* (**NNA**) is a meta-heuristic algorithm that draws inspiration from both biological nervous systems and artificial neural networks [21]. The recommended [21] value $Np = 50$ is used in our paper.

The *teaching learning based optimization* (**TLBO**) algorithm employs the concept of passing on knowledge within a classroom. Similar to learners acquiring knowledge from a teacher and interacting with their peers, TLBO incorporates such interactions [22]. In this study, a value of $Np = 100$ is utilized.

Generalized oppositional teaching learning based optimization (**GOTLBO**). This method integrates a concept that incorporates both the current estimate and its opposite estimate simultaneously into the original TLBO algorithm through the initialization step and generation jumping [23]. The values of jumping rate $Jr = 1.0$ and $Np = 20$ were used.

Simplified teaching-learning based optimization algorithm (**STLBO**). In STLBO, an elite strategy is employed to improve the searching capability, and a the chaotic map is used to enrich the uniformity of random values in the mutation phase [24]. The logistic chaotic map and $Np = 20$ were used.

Water wave optimization (**WWO**) takes inspiration from shallow water wave models and borrows ideas from wave propagation, refraction, and breaking [25]. WWO is easy to implement with a small-size population, and there are four control parameters: the maximum wave height h_{max}, the wavelength reduction coefficient α, the breaking coefficient β, and the maximum number k_{max} of breaking directions. According to Zheng [25], we used the values $h_{max} = 6$, $\alpha = 1.026$, $Np = 10$, $k_{max} = \min(12, D/2) = 4$, and β linearly decreased from 0.25 to 0.001.

Improved JAYA (**IJAYA**). Jaya algorithm is based on the concept that the solution obtained for a given problem should move toward the best solution and should avoid the worst solution and does not require any algorithm-specific parameter [26]. In IJAYA, a self-adaptive weight is introduced to adjust the tendency of approaching the best solution and avoiding the worst solution; an experience-based learning strategy is employed to maintain the population diversity and enhance the exploration ability, and a chaotic elite learning method is proposed to refine the quality of the best solution in each generation [27]. The logistic chaotic map and $Np = 4 \times D = 32$ were used.

Table 1

A	B
C	D

Improved sine cosine algorithm (**ISCA**). SCA based on simulating the behaviors of sine and cosine mathematical functions [28]. ISCA implementation included a modified position-updating equation based on inertia weight ($w_{start} = 1$, $w_{end} = 1$), a nonlinear conversion parameter strategy based on the Gaussian function ($a_{start} = 2$, $a_{end} = 0$) [29], the creation of the opposite population to jump out from the local optima with $Jr = 0.1$ [30], a greedy selection, and $Np = 30$.

The majority of the utilized algorithms demonstrate excellent performance when it comes to parameter estimation of solar cells within conventional models (single or double diode) [20, 11, 23, 27, 18, 17, 24, 22, 31, 32].

The performance of the extracted parameters is evaluated using the fitness function at every iteration. In our investigation, two fitness function were used:

$$F_{\mathrm{AE}}(Y) = \sum_{k=1}^{p} \left| V^{\mathrm{tr}}(I_k) - V^{\mathrm{cal}}(I_k, Y) \right| , \tag{5}$$

$$F_{\mathrm{SE}}(Y) = \sum_{k=1}^{p} \left[V^{\mathrm{tr}}(I_k) - V^{\mathrm{cal}}(I_k, Y) \right]^2 , \tag{6}$$

where $V^{\mathrm{tr}}(I_k)$ is the simulated value of voltage at current I_k, $V^{\mathrm{cal}}(I_k, Y)$ is the calculated values of voltage, which can be obtained by Eqs. (2)–(4), for given set of parameters (i.e. $Y = \{I_{01}, n_1, R_{\mathrm{p1}}, I_{02}, n_2, R_{\mathrm{p2}}, R_{\mathrm{s}}, I_{\mathrm{ph}}\}$) at current I_k, and p is the total number of voltage steps in the IV characteristic.

Each algorithm was run 51 times with different random seed for each simulated IV curves. The search ranges were set as follows:
$I_{01}(\mathrm{mA}) \in [10^{-13}, 1]$, $n_1 \in [0.5, 50]$, $R_{\mathrm{p1}}(\Omega) \in [10, 10^6]$, $I_{02}(\mathrm{mA}) \in [10^{-7}, 10]$, $n_2 \in [0.5, 50]$, $R_{\mathrm{p2}}(\Omega) \in [10, 5{\cdot}10^4]$, $R_{\mathrm{s}}(\Omega) \in [0.1, 1000]$, $I_{\mathrm{ph}}(\mathrm{mA}) \in [10^{-3}, 100]$.

2.4. Evaluation criteria

3. Simulation results and analysis

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