Highlights

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

Oleg Olikh

- 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

Oleg Olikh

Taras Shevchenko National University of Kyiv, 64/13, Volodymyrska Street, Kyiv, 01601, Ukraine

ARTICLE INFO

Keywords:
Ideality factor
Silicon
n^+–p–p^+ structure
SCAPS
Iron contamination
Ma

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.

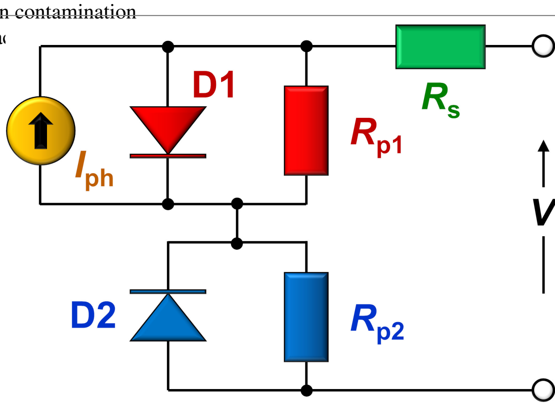

Figure 1: The opposed two–diode equivalent–circuit model of a solar cell.

1. Introduction

2. Models and Methods

2.1. Solar cell model

Fig. 1 vividly reveals the structure of the used model [1]. 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 [2] using Lambert W-function [3]:

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

olegolikh@knu.ua (Oleg Olikh)
ORCID(s):

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 [4]. The analytical solution $V(I)$ using the g–function is as follows [4]

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

with

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

and

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

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

2.2. 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 [5, 6, 7]:

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 [8]. During the implementation, we employed a penalty function suggested by Ishaque *et al* [9]. Besides, according to Wang and Ye [8], 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 [10]. 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* [10] 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 [11]. The determination of F and Cr values is achieved through the utilization of the weighted adaptive procedure [12], 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 [13]. A linear Np reduction (from $18 \times D = 144$ to 4) is used as well.

Table 1

References

[1] F. A. de Castro, J. Heier, F. A. Nüesch, R. Hany, Origin of the kink in current-density versus voltage curves and efficiency enhancement of polymer–C_{60} heterojunction solar cells, IEEE J. Sel. Top. Quantum Electron. 16 (2010) 1690–1699.

[2] B. Romero, G. del Pozo, B. Arredondo, Exact analytical solution of a two diode circuit model for organic solar cells showing S–shape using Lambert W–functions, Sol. Energy 86 (2012) 3026–3029.

[3] L. Lóczi, Guaranteed- and high-precision evaluation of the Lambert W function, Appl. Math. Comput. 433 (2022) 127406.

[4] K. Roberts, S. R. Valluri, On calculating the current-voltage characteristic of multi-diode models for organic solar cells, 2015.

[5] M. Braik, A. Hammouri, J. Atwan, M. A. Al-Betar, M. A. Awadallah, White shark optimizer: A novel bio-inspired meta-heuristic algorithm for global optimization problems, Knowledge-Based Systems 243 (2022) 108457.

[6] J.-S. Pan, L.-G. Zhang, R.-B. Wang, V. Snášel, S.-C. Chu, Gannet optimization algorithm : A new metaheuristic algorithm for solving engineering optimization problems, Math. Comput. Simulation 202 (2022) 343–373.

[7] S. Zhao, T. Zhang, S. Ma, M. Chen, Dandelion optimizer: A nature-inspired metaheuristic algorithm for engineering applications, Eng. Appl. Artif. Intell. 114 (2022) 105075.

[8] K. Wang, M. Ye, Parameter determination of Schottky–barrier diode model using differential evolution, Solid-State Electron. 53 (2009) 234–240.

[9] K. Ishaque, Z. Salam, H. Taheri, A. Shamsudin, A critical evaluation of ea computational methods for photovoltaic cell parameter extraction based on two diode model, Solar Energy 85 (2011) 1768–1779.

[10] Q. Huang, K. Zhang, J. Song, Y. Zhang, J. Shi, Adaptive differential evolution with a lagrange interpolation argument algorithm, Inform. Sci. 472 (2019) 180–202.

[11] M. Tian, X. Gao, Differential evolution with neighborhood-based adaptive evolution mechanism for numerical optimization, Inform. Sci. 478 (2019) 422–448.

[12] R. Tanabe, A. S. Fukunaga, Improving the search performance of shade using linear population size reduction, in: 2014 IEEE Congress on Evolutionary Computation (CEC), pp. 1658–1665.

[13] A. W. Mohamed, A. A. Hadi, K. M. Jambi, Novel mutation strategy for enhancing SHADE and LSHADE algorithms for global numerical optimization, Swarm Evol. Comput. 50 (2019) 100455.