Highlights

main title

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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.

main title

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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.

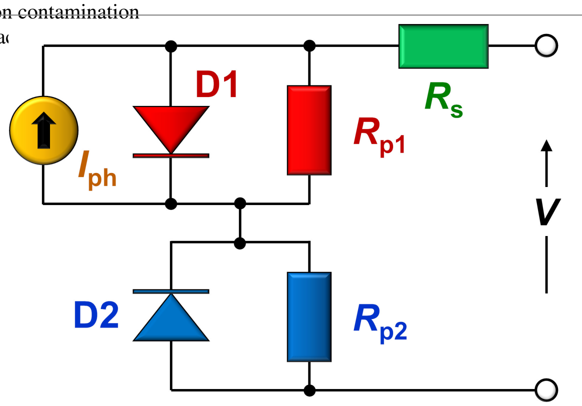

Figure 1: The opposed two–diode equivalent–circuit model of a solar cell.

1. Introduction

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]:

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

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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.

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]

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

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 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]: 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

Table 1

conduct of collections of flocks or communities found in nature), chemical & physical-based methods (simulate physical phenomena or chemical laws existed in the universe), human-society-based methods (inspired by human beings, including physical and non–physical activities such as thinking and social behavior), and math-based methods.

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