IEICE TRANSACTIONS

on Electronics

DOI:10.1587/transele.2024OMS0004

Publicized:2024/10/31

This advance publication article will be replaced by the finalized version after proofreading.

A PUBLICATION OF THE ELECTRONICS SOCIETY

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BRIEF PAPER

Bayesian Estimation of Photovoltaic Cell Circuit Parameters from S-shaped *I*-*V* Characteristics with Affordable Computational Cost

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SUMMARY S-shaped current (I)-voltage (V) characteristics are routinely observed in emerging photovoltaic cell research. The opposed two-diode equivalent circuit model can reproduce such characteristics. The present study demonstrates Bayesian estimation of equivalent circuit parameters of a photovoltaic cell from S-shaped I-V characteristics with affordable computational cost below 15 min. The demonstration codes have been made publicly available on GitHub to cultivate transparency and facilitate reproducibility. This initiative aims not only to advance the understanding of photovoltaic cell behaviors but also to provide a practical, accessible tool for researchers in the field.
key words: *photovoltaic cell, equivalent circuit model, parameter extraction, Roberts g-function, Bayesian estimation*

1. Introduction

Pursuing the sustainable development of society accelerates the research of renewable energy technologies. The photovoltaic cells beyond Si technology including organic and perovskite photovoltaic cells are major targets of such research activity. Equivalent circuit models of photovoltaic cells are not only important for optimizing systems with photovoltaic cells, but useful for understanding the power loss mechanism in photovoltaic cells. This makes the extraction of equivalent circuit parameters from experimental current (I)-voltage (V) characteristics an active research field for decades. [1]–[3]

S-shaped I-V characteristics are often observed in emerging photovoltaic cell research such as organic photovoltaics. [4], [5] The opposed two-diode circuit model shown in Fig. 1 is the simplest one that reproduces such characteristics. [6], [7] However, the ample number of parameters allows completely different sets of parameters to produce indistinguishably similar curves over the voltage range scanned in the experiment. Therefore, it is difficult to uniquely determine a set of equivalent circuit parameters from experimental I-V data by point estimation using nonlinear least squares or other methods.

The author recently advocated for the utilization of Bayesian estimation to derive equivalent circuit parameters from the I-V characteristics of photovoltaic cells [8]. Unlike traditional methods such as nonlinear least squares, Bayesian estimation offers probability distributions instead of single point estimates for the parameters, effectively capturing the uncertainty inherent in experimental data. Moreover, it eliminates the need for guessing initial parameter values and provides information on the errors associated with the parameter estimates.

However, it is worth noting that Bayesian estimation comes with a computational cost, primarily due to its reliance on the sampling-based Markov Chain Monte Carlo (MCMC) method. A prior study demonstrated that employing a cutting-edge sampling mothod significantly expedites the parameter extraction process for photovoltaic cells exhibiting standard I-V characteristics, reducing the time required by an order of magnitude [9]. Building upon this, the present report demonstrates the applicability of a similar approach in efficiently extracting circuit parameters, specifically focusing on the opposed two-diode circuit model.

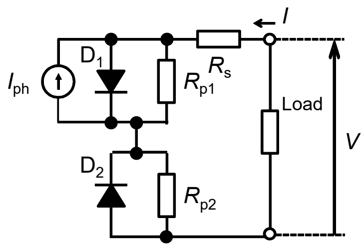

Fig. 1 Opposed two-diode equivalent circuit model of a photovoltaic cell.

Table 1 Prior distributions of the parameters.

Parameter	Prior density
I_{ph} [mA]	$Unif(1\times10^{-3}, 1\times10^{2})$
R_{p1} [Ω]	$Unif(1\times10^{1}, 1\times10^{4})$
I_{01} [pA]	$Unif(1\times10^{-4}, 1\times10^{7})$
n_1	$Unif(5\times10^{-1}, 1\times10^{2})$
R_{p2} [Ω]	$Unif(1\times10^{1}, 1\times10^{4})$
I_{02} [pA]	$Unif(1\times10^{2}, 1\times10^{10})$
n_2	$Unif(5\times10^{-1}, 1\times10^{2})$
R_s	0 (fixed)*

* Preliminary calculations showed the poeterior distribution of R_s peaked at zero. [16]

2. Model and methods

The upper part of the model corresponds to a healthy photovoltaic cell and consists of a current source I_{ph}, a diode D_1, a parallel resistance R_{p1}, and a series resistance R_s. The lower corresponds to a deficiency such as an imper-

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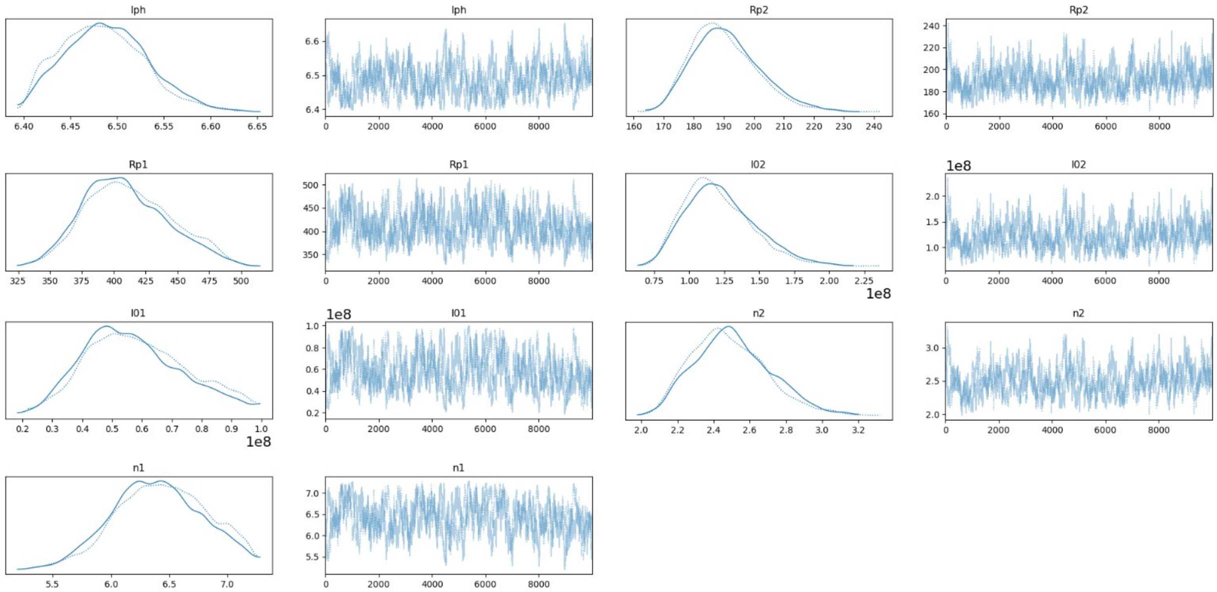

Fig. 2 Posterior distributions (right panels) and trace plots (left panels) of the parameters obtained using Numpyro. Solid and dotted lines show different chains.

Table 2 Summary of Bayesian estimation of parameters and computation time with various sampling methods.

Sampling method	I_{ph} [mA]		R_{p1} [Ω]		I_{01} [pA]		n_1	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
PyMC native	6.49	4.40×10^{-2}	4.07×10^{2}	3.18×10^{1}	5.61×10^{7}	1.56×10^{7}	6.38	0.380
nutpie	6.49	4.70×10^{-2}	4.11×10^{2}	3.52×10^{1}	5.83×10^{7}	1.75×10^{7}	6.43	0.413
Numpyro	6.49	4.40×10^{-2}	4.11×10^{2}	3.34×10^{1}	5.79×10^{7}	1.65×10^{7}	6.42	0.387

Sampling method	R_{p2} [Ω]		I_{02} [pA]		n_2		Computation time [s]
	Mean	SD	Mean	SD	Mean	SD	
PyMC native	1.92×10^{2}	1.18×10^{1}	1.24×10^{8}	2.64×10^{7}	2.52	0.215	39,489
nutpie	1.91×10^{2}	1.22×10^{1}	1.22×10^{8}	2.75×10^{7}	2.50	0.227	6,632
Numpyro	1.91×10^{2}	1.11×10^{1}	1.22×10^{8}	2.49×10^{7}	2.50	0.208	783

fect metal/semiconductor interface and consists of a diode D_2 in the opposite direction of D_1 with a parallel resistance R_{p2}. Since a diode D_i is characterized by a reverse saturation current I_{0i} and an ideality factor n_i, the model has 8 parameters. Although an exact analytical expression of $V(I)$ of the model was initially obtained by using Lambert W-function [10]. However, it easily causes an overflow in numerical calculation. To avoid this, we choose the expression using Roberts g-function $g(x)$ and the thermal voltage V_t as follows. [11]

$$V(I) = I \cdot R_s + n_1 \cdot V_t \cdot \left(g(x_1(I)) - \ln\left(\frac{I_{01} \cdot R_{p1}}{n_1 \cdot V_t}\right)\right) - n_2 \cdot V_t \cdot \left(g(x_2(I)) - \ln\left(\frac{I_{02} \cdot R_{p2}}{n_2 \cdot V_t}\right)\right) \quad (1)$$

with

$$x_1(I) = \ln\left(\frac{I_{01} \cdot R_{p1}}{n_1 \cdot V_t}\right) + \frac{\left(I + I_{01} + I_{ph}\right) \cdot R_{p1}}{n_1 \cdot V_t} \quad (2)$$

$$x_2(I) = \ln\left(\frac{I_{02} \cdot R_{p2}}{n_2 \cdot V_t}\right) - \frac{(I - I_{02}) \cdot R_{p2}}{n_2 \cdot V_t} \quad (3)$$

As shown in Table 1, a uniform distribution spanning several orders of magnitude is assigned for a prior distribution of each parameter except for R_s.

A Python library PyMC [12], [13] for Bayesian statistical programming was used as the platform of the present study. The sampling methods employed were PyMC native, nutpie, [14] and Numpyro. [15] Calculations were performed on the Google Colaboratory, with 10,000 steps for both sampling and burn-in, and the number of chains (parallel calculations) is two. All calculations were executed on two 2.2 GHz Xeon cores.

3. Results and Discussion

Table 2 summarizes the outcome of Bayesian estimation of parameters and computation time with different sampling methods used. Any essential differences are found in the mean values as well as standard deviation (SD) of estimates between the sampling methods used. In all cases, the diagnostic parameter of the convergence $\hat{R}$ is found to be less than 1.05, indicating that the calculations are well converged. On the other hand, the computation time strongly

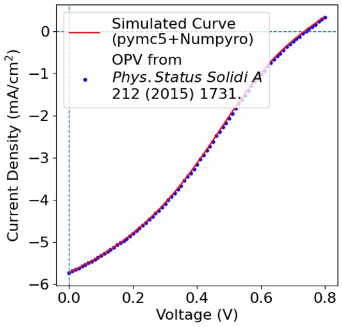

Fig. 3 Experimental *I*-*V* characteristics (symbols) and simulated curve calculated using mean values of each parameter listed in Table 2.

depends on the sampling method. PyMC native sampling method took approximately 11 h, which is comparable to a similar calculation on a PC equipped with a 3 GHz Core i9 in a previous paper. [16] In contrast, Numpyro required only 13 min, resulting in approximately 50 times acceleration. Although nutpie was reported to outperform Numpyro under the CPU environmentt, [17] it took an order of magnitude longer to compute than Numpyro. In addition, changing the runtime to a GPU did not help to accelerate the computation with Numpuro. The author considers that the computation time below 15 min is remarkable. This is because it is becoming close to the time required to measure a single *I*-*V* characteristics curve of a solar cell. This indicates that we are approaching the ”tipping point” where the Bayesian estimation can be used routinely for parameter extraction from S-shaped *I*-*V* curves of solar cells. Furthermore, we can expect to halve the computation time using 5 GHz CPUs.

Figure 2 shows the results of Bayesian estimation obtained with Numpyro. The left panels of Fig. 2 show the posterior distribution of the parameters. Different two chains result in very similar bell-shaped curves. Due to the central limit theorem, if the number of effective samples is sufficiently large, the shape of a posterior distribution approaches a normal distribution. In addition, the trace plots shown in the right panels are busily moving around a certain range. These are signatures of the favorable convergence of the calculation because the skewed posterior distributions and trace plots are usually accompanied by a deviation of $\hat{R}$ from 1.0. If the calculations do not converge well, increasing the number of burn-in and sampling steps may help.

As shown in Fig. 3, the simulated *I*-*V* curve calculated using the mean values of the prior distributions reasonably reproduces the experimental data. The present Bayesian estimation was carried out without guessing the appropriate set of initial values, which is indispensable in the traditional least-squares method.

4. Conclusions

The opposed two-diode equivalent circuit model can reproduce S-shaped *I*-*V* characteristics often observed in emerging photovoltaic cell research. Bayesian estimation of equivalent circuit parameters of such a photovoltaic cell with affordable computational cost has been demonstrated. The demonstration codes are disclosed on GitHub so that readers who have their own experimental data can readily test the present research result. [18]

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