Photovoltaic Sensitivity Analysis of Double-Diode Model

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Abstract

Photovoltaic energy is being widely used due to its numerous benefits. To promote greater system efficiency, model-based studies must be implemented. The double-diode model is one of the most commonly used and was applied in this work through sensitivity analysis and parameter estimation using the Mean-Variance Mapping Optimization algorithm to investigate which parameters have the greatest or least impact on the model. The results show that the diode reverse saturation current of diode 1 is the parameter with the greatest impact on the model. At the same time, the shunt resistance is the parameter with the least impact and, therefore, the most difficult to estimate.

Keywords: Photovoltaic modeling, double-diode model, sensitivity analysis, parameter estimation

1. Introduction

Photovoltaic (PV) energy has become a popular, reliable, and consistent renewable source due to its wide availability, environmental benefits, and low maintenance costs (Ayyarao and Kishore, 2024). Maximizing the use of PV systems requires planning and research into modeling techniques and parameter estimation methods. Accurate estimation of unknown PV parameters is essential, making it a relevant topic of growing interest among researchers (Qaraad et al., 2024). Two models stand out in the literature: the single-diode (SDM) and the double-diode (DDM) models. Several approaches have been proposed to optimize model parameter estimation, categorized into three types: numerical techniques, analytical methods, and soft computing approaches. The latter aims to overcome the limitations of the other methods through metaheuristic algorithms, which search for globally optimal solutions by copying natural behaviors in their search strategies (Issa et al., 2024). This study presents a sensitivity analysis (SA) of the DDM, conducted using the estimated parameters of a PV cell, obtained through the Mean-Variance Mapping Optimization (MVMO) metaheuristic algorithm. The objective is to identify which parameters have the greatest and least impact on the PV model's behavior, as this topic is little explored in the literature.

2. PV modelling

The DDM is represented by an electrical circuit, as shown in Fig. 1, consisting of a current source, two diodes, and two resistors. One diode acts as a rectifier, while the second diode accounts for losses due to charge carrier recombination and other non-ideal aspects of PV cells, enabling the modeling of the photovoltaic system's behavior under low solar irradiation (Issa et al., 2024).

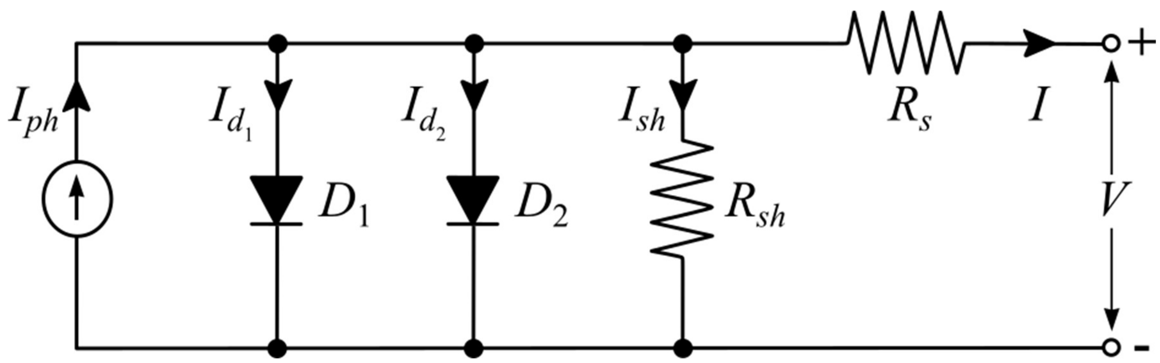

Fig. 1: Double-diode model electric circuit.

10.18086/swc.2025.03.57 Available at http://proceedings.ises.org

Applying Kirchhoff's laws to the circuit, the mathematical model is given by:

$$I_{ph} - I_{d_1} - I_{d_2} - I_{sh} - I = 0 \qquad \text{(eq. 1)}$$

where Iph is the photo-generated current, I_{d1} and I_{d2} are the diode currents 1 and 2 (Eqs. 2 and 3) respectively, Ish is the shunt resistor current provided by Eq. 4, and I is the PV output current.

$$I_{d_1} = I_{01}\left\{exp\left[\frac{q(V+R_S\,I)}{a_1\,k\,T}\right] - 1\right\} \qquad \text{(eq. 2)}$$

$$I_{d_2} = I_{02}\left\{exp\left[\frac{q(V+R_S\,I)}{a_2\,k\,T}\right] - 1\right\} \qquad \text{(eq. 3)}$$

$$I_{sh} = \frac{V + R_S\,I}{R_{sh}} \qquad \text{(eq. 4)}$$

where I_{01} and I_{02} are the reverse saturation current of diodes 1 and 2, respectively, q is the electron charge ($1.60217646 \times 10^{-19}$ C), V is the PV output voltage, a_1 and a_2 are the diode ideality factors of diodes 1 and 2, respectively, k is the Boltzmann constant ($1.3806503 \times 10^{-23}$ J/K), T is the temperature on PV cell, and R_s and R_{sh} are the series and shunt resistances, respectively. The model is defined by a function:

$$0 = f(x, y, u, p, c) \qquad \text{(eq. 5)}$$

$$\left.\begin{aligned} x &= [V] \\ y &= [I] \\ u &= [T] \\ p &= [I_{ph}, I_{01}, I_{02}, a_1, a_2, R_s, R_{sh}] \\ c &= [q, k] \end{aligned}\right\} \qquad \text{(eq. 6)}$$

where x represents the independent vector, y and u are the output and input vectors, respectively, p comprises the parameter vector and c is the constants vector.

3. Sensitivity analysis methodology

The identification of the impact of parameters on the model is carried out in two steps, as shown in Fig. 2. First, the model parameters are estimated using the MVMO algorithm, and then an SA is performed. It begins with an initialization phase, where the algorithm is configured and a population of individuals is created within defined minimum and maximum parameter limits. Each individual is then evaluated using the objective function to determine the error value (in this work, the RMSE was adopted). Next, a new individual is generated based on the mean and variance of the population (offspring generation). This new individual is evaluated by the objective function and added to the population, after which the worst-performing individual is eliminated. The algorithm runs until a maximum number of generations is reached (stopping criteria), where the parameters are considered estimated and then subjected to SA.

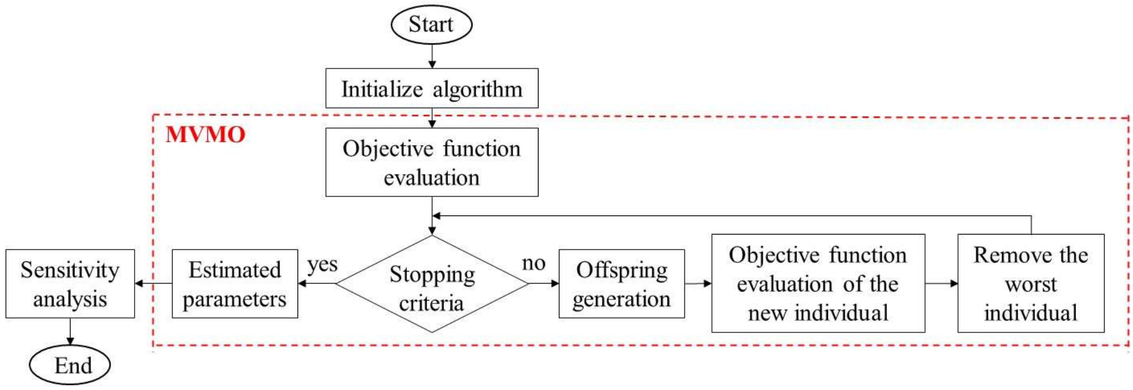

Fig. 2: Sensitivity analysis methodology.

The Root Mean Square Error (RMSE) was used as the objective function for fitting the algorithm's results, as given by:

$$J(p) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_{mea} - y_{calc})^2} \qquad \text{(eq. 7)}$$

where *J(p)* is the error associated with a given set of evaluated parameters in vector *p*. The samples number is given by n,Y_{mea} is the measured output current and Y_{calc} is the calculated output current obtained by the proposed methodology.

The MVMO and SA applications can be found in Farias et al. (2018), Santos et al. (2024), and Santos et al. (2025). SA is calculated for each parameter p_i of vector p defined by:

$$\frac{\partial y}{\partial p_i} \approx \frac{f(x,y,p_i+\Delta p_i,c,u)-f(x,y,p,c,u)}{\Delta p_i} \qquad \text{(eq. 8)}$$

where $\Delta p_i = p_i \times 10^{-4}$ is a small perturbation, the results are presented in normalized values ($\| \partial y / \partial p_i \|$).

4. Results and discussions

The RTC France cell dataset at 33° C from Issa et al. (2024) was used in this study. Its main characteristics are a power output of 0.3 W, a maximum current and voltage of 0.6894 A and 0.4507 V, respectively. The MVMO algorithm was configured with a population of 20 individuals and a maximum of 1000 generations (stopping criteria). It was run 30 times in Matlab on a PC with an Intel Core i7-8565U processor and 16 GB of RAM, with an average time per run of 9.43 seconds. The result with the lowest RMSE by MVMO was used in the SA. The values are shown in Tab. 1. For comparative purposes, estimated parameters from Issa et al. (2024) by adaptive sine–cosine particle swarm optimization (ASCA-PSO) algorithm were included.

Tab. 1: Sensitivity analysis methodology results and comparative values of parameter estimation.

Parameters	Parameter limits	Parameter estimation		Sensitivity analysis	
	Min.– Max.	**ASCA-PSO**	**MVMO**	**$\|\|\partial y/\partial p_i\|\|$**	**Influence**
I_{ph} (A)	0 – 1	0.761	0.7610	5.1	Medium
I_{01} (μA)	0 – 1	1.03	0.274	660.11 E4	High
I_{02} (μA)	0 – 1	0.0987	0.061	54.22 E4	High
a_1 (-)	1 – 2	1.838	1.4664	18.19	Medium
a_2 (-)	1 – 2	1.388	1.7661	0.23	Medium
R_s (Ω)	0 – 0.5	0.037	0.0367	9.79	Medium
R_{sh} (Ω)	0 – 100	55.93	48.7948	8.886 E-4	Low
	RMSE	0.0009	0.0008		

The results indicate that the parameters estimated by MVMO were very similar to those obtained using ASCA-PSO, although MVMO achieved a lower RMSE. The sensitivity analysis revealed that parameters I_{01} and I_{02} have the highest impact on the model output; I_{ph}, a_1, a_2, and R_s have a medium impact, and R_{sh} has the lowest impact, making it the most challenging parameter to estimate.

The measured and calculated output current and power of the RTC France Cell is present in Fig. 3 where the blue and red lines are the measured current and power respectively and the dot lines are the calculated current and power. A good fit can be observed in both cases, with the calculated curves closely matching the measured data, thereby validating the proposed methodology as an effective tool for parameter estimation in step 1.

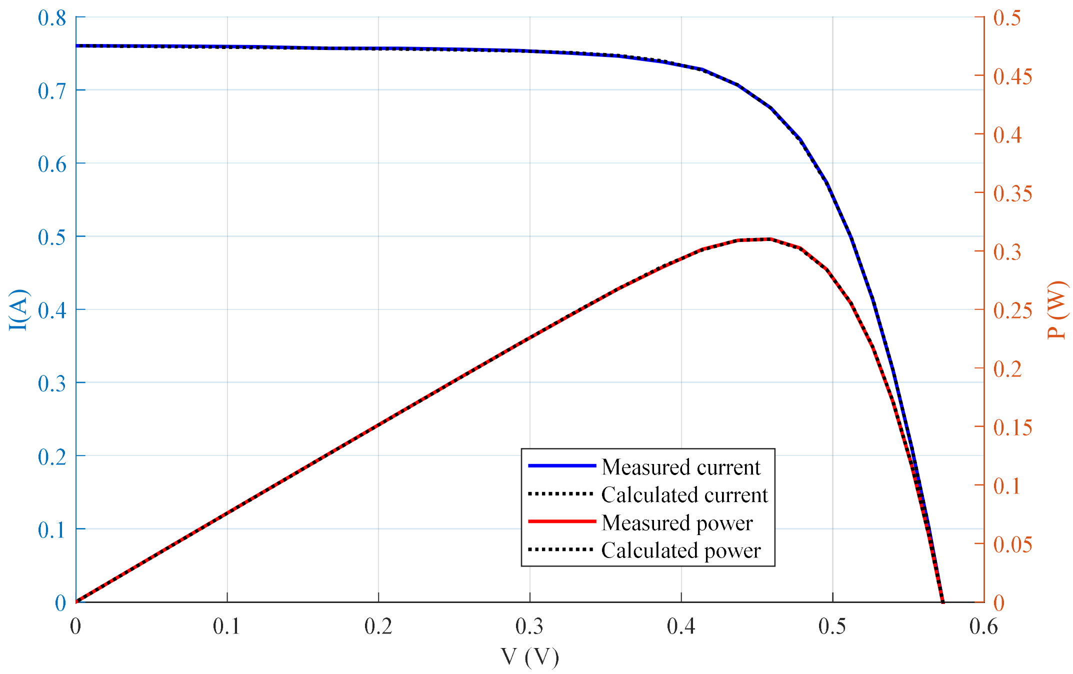

Fig. 3: RTC France I-V and P-V curves: Measured and calculated current and power.

The error evolution in Stage 1 is shown in Fig. 4, where it can be observed that the MVMO algorithm progressively reduces the error by adjusting the best sets of parameters over the iterations.

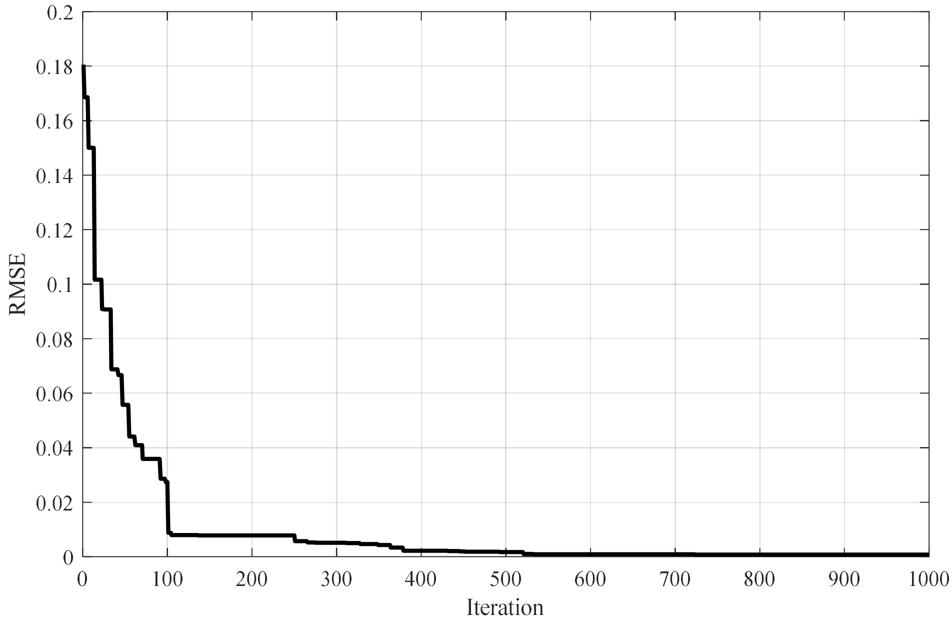

Fig. 4: Evolution of the RMSE over the iterations during the parameter fitting process by MVMO algorithm.

5. Conclusions

This study presented a sensitivity analysis of the DDM using estimated parameters from a PV cell. The results demonstrated that the reverse saturation currents of diodes 1 and 2 (I_{01} and I_{02}) are the parameters with the greatest impact on the model's output, whereas the shunt resistance (R_{sh}) showed the least impact. This low sensitivity makes R_{sh} the most difficult parameter to estimate accurately. These findings reinforce the importance of selecting appropriate estimation techniques and prioritizing the most impactful parameters in PV modeling. Moreover, the MVMO algorithm proved to be suitable for parameter estimation, achieving lower errors than those reported in the reference literature.

6. Acknowledgments

The authors thank the Federal Institute of Education, Science and Technology of São Paulo (IFSP) for the support through Call No. 64/2025 (PIPECT), which enabled the presentation of this work.

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