

Comparative Assessment of Differential Evolution-Based and Analytical Parameter Extraction for Single-Diode PV Models Using Measured Data

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Abstract:

This paper compares a single-diode model (SDM) parameter extraction method based on differential evolution (DE) with the analytical Villalva method, using a selected set of current-voltage (I-V) curves from the publicly available Sandia flash test dataset. The paper examines the methods' applicability to experimentally measured curves from commercial photovoltaic (PV) modules. The SDM DE method analytically eliminates parameters from five to three, uses a Newton-Raphson solver for the implicit I-V characteristic, and minimises an objective function based on the error at the maximum power point. The results show that the proposed method achieves a lower root mean square error (RMSE) and normalized root mean square error (NRMSE) than the Villalva method across all tested curves, though at a higher computational cost.

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1. INTRODUCTION

Solar PV power has become the fastest-growing source of new renewable generation capacity worldwide [1]. Driven by the global transition toward decarbonized energy systems and the continuing decline in module manufacturing costs, PV capacity additions have consistently outpaced those of other renewable technologies in recent years, with utility-scale, commercial and residential installations expanding across nearly every region [2]. As PV systems are increasingly integrated into national grids and distributed energy networks, their reliable and predictable performance becomes essential not only for individual system owners but also for grid stability and long-term energy planning. This rapid deployment increases the need for accurate, computationally effective models of PV module behaviour, both for system design under non-standard operating conditions and for the diagnostic and performance monitoring tools required at scale.

The physical basis of these models traces back to the ideal diode equation derived by Shockley [3] for p-n junctions, which underlines the equivalent-circuit representation used to describe the current-voltage (I-V) characteristic of a PV cell module today.

Estimation of equivalent circuit parameters of a PV module is crucial for reliable performance modeling, fault diagnosis, and degradation assessment during operation [4, 5]. The SDM is the most commonly used because of its compromise between physical accuracy and computational simplicity, since it describes the I-V characteristic sufficiently well with five parameters (photocurrent I_{ph} , diode saturation current I_0 , series resistance R_s , parallel or shunt resistance R_{sh} , and diode ideality factor n) [6].

Methods for extracting SDM parameters fall into two broad categories. Analytical methods derive parameters from datasheet values: current at short-circuit conditions I_{sc} , voltage at open-circuit conditions V_{oc} , voltage at maximum power point V_{mp} , and current at maximum power point I_{mp} , using a system of equations based on simplifying

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assumptions. There are also metaheuristic methods, which determine parameters by optimizing an objective function based on datasheet values or by using measured or synthesized full I-V curves [5, 7]. Villalva et al. [8] proposed one of the most cited analytical methods, which uses datasheet values as input parameters, making the method computationally simple. De Soto et al. [9] proposed an alternative analytical formulation that incorporates explicit irradiance and temperature dependence for all five parameters. Further analytical variants include the early dP/dV based formulation of Xiao et al. [10], the simplified parametrization of Mahmoud et al. [11], and the two-step iterative method of Stornelli et al. [12], each trading off closed-form simplicity against accuracy across different operating ranges.

On the other hand, metaheuristic methods do not constitute a single group. Some use datasheet values exclusively, in the same way that the analytical methods use, but the parameters are determined by an optimization search of parameters instead of using the closed system of equations as in the iterative refinement proposed by Silva et al. [13]. Other methods determine the parameters by directly fitting the entire measured or digitized I-V curve, minimizing the error across all points of the curve [7]. Differential evolution (DE) [14] is a common choice for the optimization algorithm in both cases because of its robustness against local minima, albeit at the cost of higher computational demand and sensitivity to the definition of the objective function and search boundaries [15]. Other metaheuristics reported for the problem include particle swarm optimization (PSO) [16] and genetic algorithms [17], while recent DE variants have targeted faster convergence through improved mutation strategies [18] or hybridization with local gradient-based solvers such as Newton-Raphson [19]. Additional nature-inspired algorithms, such as the Kangaroo Escape Optimizer, have also been proposed for the same problem [20].

While hybrid approaches combining analytical reasoning with metaheuristic optimization have been explored, there remains room for alternative parameter-reduction strategies aimed at improving accuracy. The proposed method in this paper combines both approaches; it analytically eliminates I_o and I_{ph} from the boundary conditions, which narrows down the DE search from five to three parameters, which are then determined through optimization based on the same nominal operating points, using a Newton-Raphson solver

[21] for the implicit I-V characteristic. The DE optimization and array computations were implemented in Python using SciPy [22].

In the available literature extraction methods for single-diode and double-diode models are mostly validated on a small number of standard benchmark cases [20, 23-30], using the historical R.T.C. France cell, Photowatt PWP201 module or synthetic curves reconstructed from the manufacturer's datasheet using digitalizing tools.

While useful for isolating method behaviour under controlled conditions, this validation does not establish whether the same conclusion generalizes to real modules of different manufacturers, technologies and degradation states. Publicly available I-V measurement datasets, such as Sandia National Laboratories flash-test dataset [31], allow the generalization to be tested directly.

This paper therefore makes the comparison between the proposed SDM DE method with the Villalva analytical approach on a selected subset of real I-V curves from the publicly available Sandia dataset.

The remainder of the paper is organized as follows. Section 2 describes the SDM formulation and the parameter-extraction procedure for both methods. Section 3 describes the dataset. Section 4 presents the results and discusses the findings, and Section 5 concludes the paper.

2. SINGLE-DIODE MODEL

SDM represents the PV cell or a module with an equivalent circuit that consists of a current source dependent on illumination (photocurrent I_{ph}), a diode connected in parallel, a series resistance R_s , and a parallel (shunt) resistance R_{sh} [32]. The diode current is described by the Shockley Eq. [3], and the module current is given by an implicit expression:

$$I = I_{ph} - I_o \left[\exp \left(\frac{V + IR_s}{nN_s v_t} \right) - 1 \right] - \frac{V + IR_s}{R_{sh}}, \quad (1)$$

where I is the terminal current, V is the terminal voltage, I_o is the diode saturation current, n is the ideality factor of the diode, N_s is the number of cells of a module connected in series.

The thermal voltage v_t depends on the temperature of the cell T , the Boltzmann constant k , and the electron charge q . The model thus contains five unknown parameters: I_{ph} , I_o , R_s , R_{sh} , and n .

$$v_t = \frac{kT}{q} \quad (2)$$

Due to the implicit dependence of the current I on itself (appearing on both the left and the right sides of the equation), the expression cannot be solved analytically for I at a given voltage V ; instead, it requires a numerical iterative procedure, like the Newton-Raphson method.

Fig. 1 shows the equivalent circuit of an SDM representing a PV module.

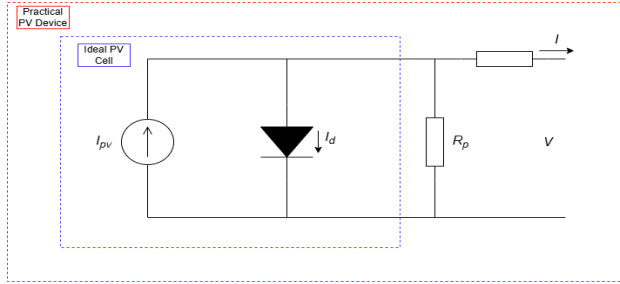


Fig. 1. Schematic of the equivalent circuit of the SDM

3. MATERIALS AND METHODS

This study employs a quantitative, computational modeling approach with empirical validation. It combines analytical and metaheuristic approaches for SDM parameter extraction, using boundary-condition analysis to reduce the dimensionality of the parameter space. DE is applied as the metaheuristic optimization technique, and a Newton-Raphson solver is used to resolve the implicit I-V characteristic. The proposed method is implemented in Python using the SciPy library, and its performance is validated against the analytical Villalva method using a real measured I-V curve from the publicly available Sandia National Laboratories flash-test dataset. To quantify the accuracy of the modeled I-V characteristics, the RMSE and NRMSE between the measured and modeled current values were used as the evaluation metrics.

3.1. Villalva Analytical Method

Villalva et al. [8] analytical method determines SDM parameters exclusively from the datasheet values (V_{oc} , I_{sc} , I_{mp} , V_{mp}) without needing the data from the full I-V curve. The ideality factor n is typically fixed (in the range of 1.0 to 1.5, depending on the cell technology), which leaves four unknown parameters: I_{ph} , I_0 , R_s and R_{sh} .

The method begins with an initial estimate of R_{sh} from the slope of the I-V curve near the short-circuit point, approximated using datasheet values:

$$R_{sh,0} = \frac{V_{mp}}{I_{sc} - I_{mp}} - \frac{V_{oc} - V_{mp}}{I_{mp}} \quad (3)$$

while R_s is initialized at 0. Photocurrent I_{ph} and diode saturation current I_0 at every iteration step are calculated analytically from the current values of R_s and R_{sh} , by applying the boundary conditions at short-circuit and open-circuit:

$$I_{ph} = \frac{R_{sh} + R_s}{R_{sh}} \cdot I_{sc} \quad (4)$$

$$I_0 = \frac{I_{ph} \frac{V_{oc}}{R_{sh}}}{e^{nV_{oc}} - 1} \quad (5)$$

The core of the method is an iterative loop that gradually increases R_s in small steps, while R_{sh} is recalculated at each step so that the model reproduces the datasheet power value at the maximum power point P_{mp} by solving the implicit SDM equation at $V=V_{mp}$. The loop terminates when the modeled power at the maximum power point (MPP) converges to the datasheet value within a specified tolerance. Since R_{sh} is calculated in each iteration using the photocurrent I_{ph} , which itself depends on the R_s and R_{sh} values from the previous step, the update loop directly affects the convergence and the final parameter values. Therefore, it is essential to strictly follow the calculation order described in the original paper during implementation.

Fig. 2 shows the block diagram of the reconstructed SDM algorithm based on the Villalva et al. method [8].

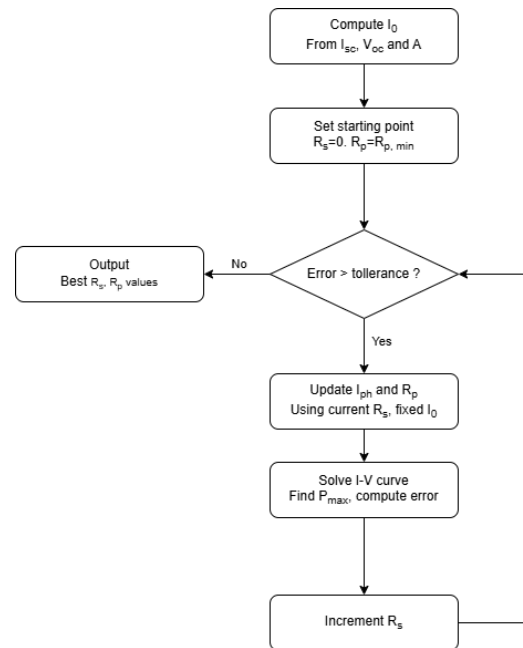


Fig. 2. The block diagram of the reconstructed SDM algorithm

Due to its exclusive reliance on four scalar datasheet values, the method is computationally very inexpensive (typically requiring only a few dozen iterations to converge) and does not require a measured I-V curve; however, its accuracy outside the MPP is not explicitly optimized but derives solely from the analytical boundary conditions used during initialization.

3.2. Proposed SDM DE Method

The proposed method analytically eliminates I_0 and I_{ph} from the I_{sc} and V_{oc} boundary conditions, reducing the number of unknown parameters the DE algorithm must search from five to three (R_s , R_{sh} , n). Boundary conditions of current when $V=V_{oc}$ and voltage when $I=I_{sc}$ are applied to the SDM equation to get a system of two equations with two remaining unknowns (I_0 , I_{ph}).

For each candidate combination (R_s , R_{sh} , n) within the DE search, I_0 and I_{ph} are calculated directly, thereby avoiding the need to include them in the optimization space.

The model's MPP is localized with a two-stage search along the voltage axis. A coarse grid of 50 points around the datasheet value of $V_{mp} \pm 3$ V first identifies the approximate location of the maximum power point, after which a fine grid of 100 points between adjacent coarse points is used for more precise localization. The current at each voltage point is obtained by solving the implicit $I(V)$ equation using the Newton-Raphson method, with an initial current estimate linearly interpolated

between I_{sc} and zero, a limit of 200 iterations, and a stopping criterion of max step size $|\Delta I| < 1 \cdot 10^{-11}$.

The DE algorithm uses the *bestbin* strategy, with a population size of 15, mutation rate (0.5, 1.0), tolerance of the stopping criterion of $1 \cdot 10^{-8}$, and a maximum number of iterations set at 1000.

The objective function of the DE algorithm minimizes the weighted sum of squared relative errors at the maximum power point:

$$\mathcal{L} = 5\left(\frac{P_{mp} - P_{mp}^{model}}{P_{mp}}\right)^2 + 2\left(\frac{V_{mp} - V_{mp}^{model}}{V_{mp}}\right)^2 + 2\left(\frac{I_{mp} - I_{mp}^{model}}{I_{mp}}\right)^2, \quad (6)$$

where P_{mp}^{model} , V_{mp}^{model} and I_{mp}^{model} are values from the modeled I-V curve. The MPP represents the operationally most relevant point of panel behaviour. Therefore, the larger weight on the power term in Eq. (6) reflects the priority given to P_{mp} accuracy as the primary criterion, while the smaller weights on V_{mp} and I_{mp} (2, 2) prevent solutions that match the MPP value but with an incorrect voltage-current split.

The lower bound for R_s is set to 0.001Ω to exclude the physically degenerate case of zero series resistance while allowing very low-loss panels. The search range for R_{sh} is set to $[10, 3500] \Omega$, where the lower bound excludes panels with excessive leakage and the upper bound corresponds to near-ideal junctions with negligible shunt resistance losses. The ideality factor n is constrained to $[1.0, 1.3]$, consistent with the theoretical range for the SDM in which diffusion current dominates.

Fig. 3 shows the block diagram of the proposed SDM DE method.

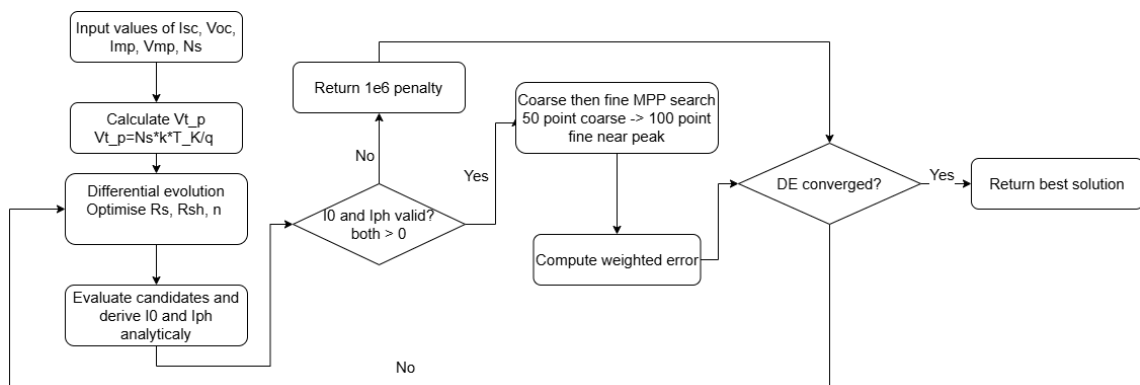


Fig. 3. Block diagram of the proposed SDM DE method

4. DATASET

4.1. Sandia Flash Test I-V Dataset

Field-measured I-V curves used in this paper were obtained from the publicly available Sandia National Laboratories dataset [31], which contains

flash test measurements of 28 models from 17 manufacturers. This dataset includes 613 sets of corresponding I-V trace flash test data from 438 unique modules. These modules were removed from field systems in Albuquerque (New Mexico, USA) and subsequently measured in the laboratory after 0 to 5 years of outdoor exposure. The number

of series-connected cells for each module was retrieved from metadata associated with the raw I-V files, having been determined during a prior deduplication and quality-check process based on an assessment of the physical plausibility of the voltage per cell.

This paper uses 11 curves from the dataset. All selected modules have no outdoor exposure to ensure no atmospheric or degradation impact on PV module behaviour. The curves used have a nameplate power of 400 W, making them the highest-output-power PV modules in the dataset and better representing contemporary commercially manufactured PV modules; this makes the results more representative of present-day deployment scenarios than lower-power legacy panel data also present in the dataset.

4.2. Curve Smoothing and Operating Point Extraction

Raw I-V points of every module, before being used as input for parameter extraction, are processed using a smoothing procedure to minimize the impact of measurement noise on subsequently calculated characteristic parameters. For each module, data points are loaded from a separate CSV file named according to the model identifier, which corresponds to the index in the associated metadata table, and then sorted in ascending order by voltage.

For current I , a Savitzky-Golay filter [33] is applied using a window length of 101 points and a third-order polynomial. Unlike a standard moving average, the Savitzky-Golay filter fits a local polynomial within each window instead of simply averaging. This removes noise without introducing phase distortion or smoothing sharp curve features, which is particularly important near the knee of the I-V curve, where excessive smoothing systematically distorts the estimation of V_{mp} and I_{mp} .

Module characteristics were derived directly from the smoothed curves rather than from the manufacturer's datasheet.

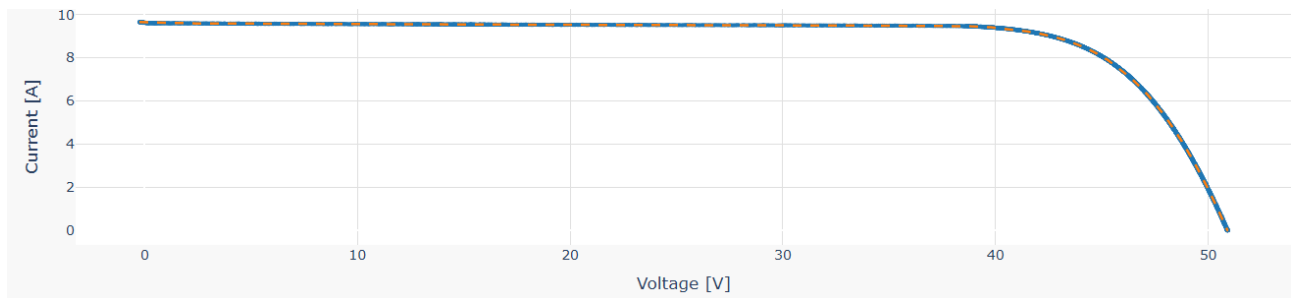
$$I_{sc} = I(V \approx 0) \quad (7)$$

$$V_{oc} = V(I \approx 0) \quad (8)$$

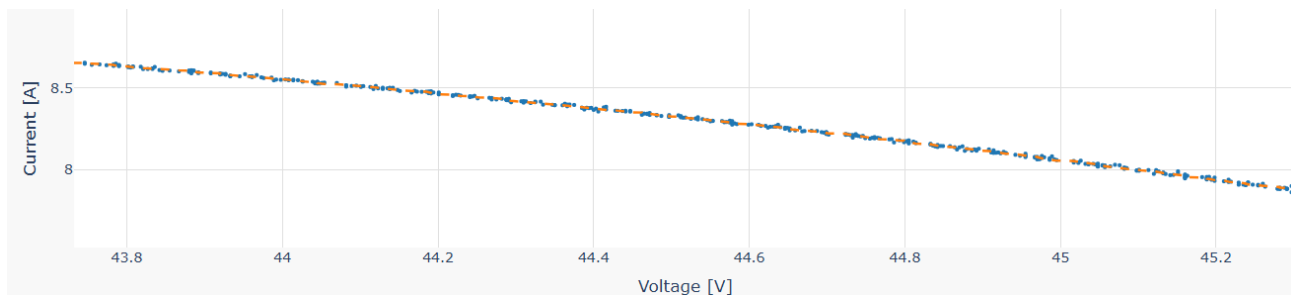
$$(V_{mp}, I_{mp}) = \max(V \cdot I(V)) \quad (9)$$

This approach ensures that the $(I_{sc}, V_{oc}, I_{mp}, V_{mp})$ values are used as input parameters for the Villalva and the proposed SDM DE method and that they are internally consistent with the smoothed curve that is subsequently used for accuracy evaluation (e.g., RMSE and NRMSE) along the entire curve), rather than obtaining the input parameters from a separate, potentially inconsistent source.

Fig. 4 shows an example of the full I-V curve and the close-up near the knee region. The smoothed curve is shown as an orange dashed line, while the original values are marked as blue dots.



a) Comparison of original and smoothed I-V curve



b) Close-up of comparison of original and smoothed I-V curve

Fig 4. Example of original and smoothed out curve

5. RESULTS AND DISCUSSION

Both tested methods were applied to 11 module curves, comparing the modeled current $I(V)$ with the current from the smoothed measured curve alongside the full I-V curve. The metrics for evaluation, RMSE and NRMSE, were calculated as per expressions by Tina and Ventura [34]:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (I_{S,i} - I_{M,i})^2} \quad (10)$$

$$NRMSE = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^n (I_{S,i} - I_{M,i})^2}}{\sqrt{\frac{1}{n} \sum_{i=1}^n I_{M,i}^2}} \quad (11)$$

where $I_{S,i}$ represents the current of the simulated model, $I_{M,i}$ is the current of the reference curve, and n is the number of points from the measured curve. The modeled current at each reference voltage point is captured exactly using the Newton-Raphson method, thereby avoiding the approximation error that arises when the measured current is

substituted directly into the implicit equation that Časlan et.al. analyzed [35].

Table 1 shows the input parameters derived from the curves that were used as input parameters for the methods, as well as RMSE and NRMSE values for the whole curve. The proposed SDM DE method achieves lower error than Villalva on all 11 curves, but the difference is not uniform. For some curves, both methods produce similar results, while for others, SDM DE performs much better. This variability is informative, since the input operating points are nearly identical across all panels; the difference in improvement stems not from discrepancies in the datasheet values themselves, but from how well the assumption of a fixed n (which the Villalva method maintains throughout the process) matches the actual shape of the specific curve. For panels where this assumption is closer to reality, both methods converge on similar results.

Table 1. Input and error metrics for every curve

ID	I_{sc} (short-circuit current) (A)	V_{oc} (open-circuit voltage) (V)	I_{mp} (current at MPP) (A)	V_{mp} (voltage at MPP) (V)	RMSE (A)		NRMSE (%)	
					Villalva method	SDM DE	Villalva method	SDM DE
4846	9.6168	50.9420	9.0342	42.4840	0.0813	0.0733	0.8957	0.8076
4847	9.6354	50.8080	9.0815	42.4530	0.0765	0.0519	0.8396	0.5696
4848	9.6089	50.8520	9.0681	42.5340	0.0653	0.0614	0.7174	0.6741
4849	9.5913	50.8950	9.0607	42.3500	0.0684	0.0483	0.7531	0.5320
4850	9.6071	50.7740	9.1090	42.2600	0.0743	0.0694	0.8171	0.7626
4851	9.6314	50.8760	9.0970	42.4690	0.0722	0.0628	0.7925	0.6889
4854	9.6162	50.8640	9.1076	42.3630	0.0634	0.0517	0.6964	0.5670
4855	9.6261	51.0230	9.1013	42.4220	0.0721	0.0649	0.7931	0.7133
4856	9.6191	50.8550	9.0823	42.3630	0.0749	0.0624	0.8235	0.6859
4857	9.6061	50.9040	9.0730	42.5190	0.0737	0.0643	0.8105	0.7071
4896	9.6303	51.0420	9.0984	42.6400	0.0740	0.0645	0.8123	0.7082

Across the 11 curves, the SDM DE determined ideality factor in ranges from approximately 1.14 to 1.28, consistently below the value of 1.3 fixed by the Villalva method, confirming that the panels in this dataset are, to varying degrees, better represented by a somewhat lower ideality factor. However, since R_s and R_{sh} are optimized jointly with n rather than fixed, the magnitude of improvement for a given curve depends on the combined adjustment of all three parameters, not on the deviation of n alone. This joint compensation is why the accuracy gap does not simply scale with how far the fitted n departs from 1.3, but instead reflects the overall electrical characteristic of each panel. Notably, this variability is observed among modules of identical nameplate power and from the same manufacturer, indicating unit-to-unit differences that a single fixed

ideality factor cannot capture, which is precisely the practical advantage of determining n as part of the optimization rather than assuming it in advance.

Overall, the SDM DE method shows lower error values than the Villalva method for all metrics and, without exception, for the set of 11 curves. Table 2 shows the mean metric results for all 11 curves.

Table 2. Mean error metrics for compared methods

Method	Mean RMSE	Mean NRMSE
Villalva method	0.0724	0.796
SDM DE	0.0613	0.674

Figs. 5, 6 and 7 show the I-V and P-V curves of the three tested PV modules. Graphical comparison confirms that both tested methods follow the measured I-V curve well across the whole length of

the curve, including the area around the short-circuit conditions, the knee of the curve around the maximum power point, as well as near open-circuit conditions. Since the Villalva and SDM DE methods are calibrated to the same three reference points, their modeled curves almost overlap at this display scale, and the quantitative differences in accuracy shown in Tables 1 and 2, while consistently present,

remain visually subtle. The images therefore primarily confirm that both methods yield physically consistent results, without visible artefacts or deviations in the curve shape, whereas the difference in performance between the methods becomes apparent only through numerical comparison and by closely zooming in to the graphs.

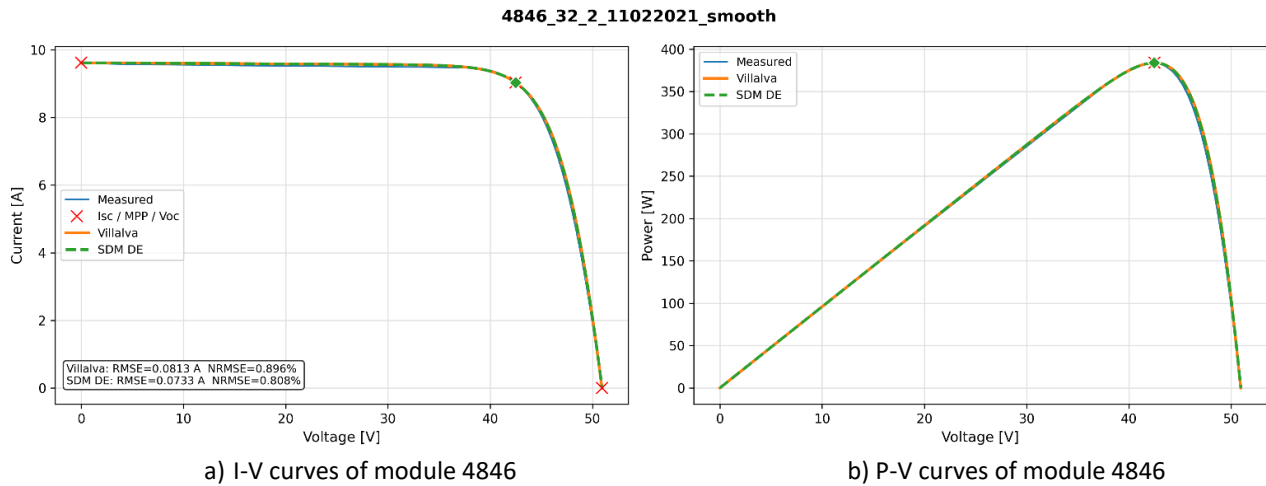


Fig. 5. I-V and P-V curves for panel 4846

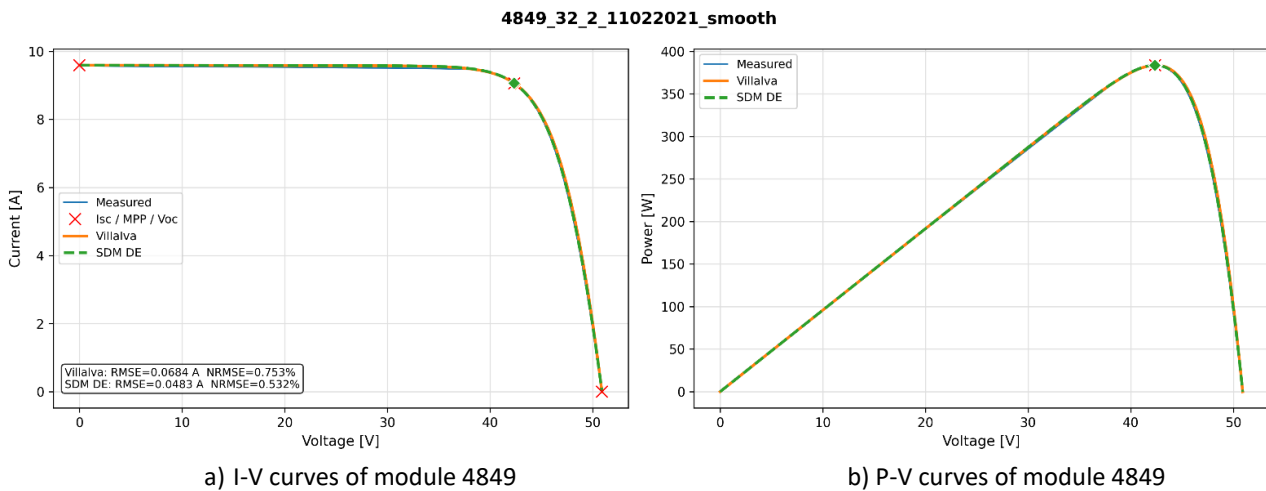


Fig. 6. I-V and P-V curves for panel 4849

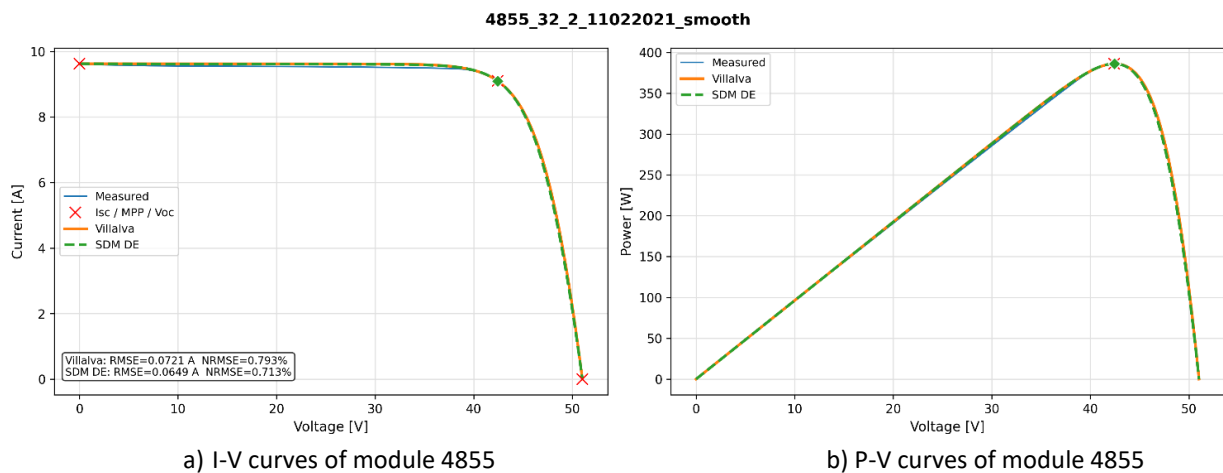


Fig. 7. I-V and P-V curves for panel 4855

Another important clarification concerns time management. Villalva's method executes all 11 curves in 1.672 s (average of 0.152 s/curve), while the proposed SDM DE method takes 24.817 s (2.2561 seconds). SDM DE execution time can be substantially reduced by replacing the general Newton-Raphson root-finding with a reduced Newton-Raphson 2x2 formulation of the implicit I-V equations, an approach that can provide significant improvement in execution time.

6. CONCLUSION

This paper compared the SDM DE method for single-diode model parameter extraction with Villalva's analytical approach using measured I-V curves from the publicly available Sandia dataset. The results show that the SDM DE method achieves lower RMSE and NRMSE values than the Villalva et al. method [8] for every curve used.

Analysis of the results on an individual-curve basis also pointed to the likely source of this advantage. Since the Villalva method fixes the diode ideality factor, whereas the SDM DE determines it as part of the DE search, alongside R_s and R_{sh} , the discrepancy between the methods increases for panels where the curve shape deviates from the fixed value. This suggests that the flexibility in determining the ideality factor is the key contributor to the accuracy of the SDM DE approach.

A graphical comparison of modeled and measured curves confirms that both methods yield a physically consistent, well-fitted model, whereas the actual performance becomes apparent only through numerical comparison and by closely zooming in to the graphs, although the quantitative advantage of the SDM DE is consistent and measurable across the entire processed dataset.

This improved accuracy, however, comes at a computational cost. The SDM DE method is considerably slower than Villalva's approach, reflecting the inherent trade-off between the flexibility of metaheuristic optimization and the speed of closed-form analytical solutions. As shown in Section 4, this gap can be narrowed by replacing the general-purpose Newton-Raphson solver with a reduced 2x2 formulation of the implicit I-V equations. Once this speedup is realized, the proposed method would be well suited to practical applications requiring both accuracy and computational efficiency, such as large-scale performance monitoring and

diagnostic tools for deployed PV systems, where fast and reliable parameter extraction from field-measured curves is essential.

The relatively small and homogeneous dataset used in this study, 11 curves from panels of a single power class and manufacturer, limits the generalizability of the observed magnitude of improvement, and results on modules of different technologies, power rating, or degradation state are needed. Future research could encompass a broader, more heterogeneous set of modules from the dataset as well as testing additional parameter-extraction methods for a more comprehensive comparison.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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