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A Graphical–Analytical Framework for Single-Diode Model Identification Using Datasheet I–V Curves

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Abstract

Accurate extraction of single-diode model (SDM) parameters is essential for photovoltaic performance analysis, especially when only datasheet values or graphical I–V characteristics are available. This study presents a graphical–deterministic parameter extraction framework that combines calibrated curve digitization, local differential analysis, uncertainty-aware slope estimation, and analytical SDM closure. Unlike conventional datasheet-based analytical methods that operate directly from tabulated characteristic points, the proposed approach explicitly incorporates the graphical-to-numerical conversion stage and evaluates its impact on the estimation of the resistive parameters. The shunt and series resistances are obtained as effective local slope estimates near short-circuit and open-circuit conditions, respectively, while the photocurrent, saturation current, and ideality factor are determined from characteristic operating point equations. The ideality factor is solved through a deterministic scalar root procedure within the physically admissible interval $1 \leq n \leq 2$. The method was evaluated using four photovoltaic devices, including laboratory-scale cells and commercial modules. Normalized reconstruction errors of 0.82% and 0.88% were obtained for the RTC-France cell and the KC200GT module, respectively. The INAOE laboratory cell and the SP450M half-cut module showed higher sensitivity to graphical slope extraction and energetic closure. For the SP450M module, the use of an equivalent series cell number $N_{S,eq} = 72$ improved agreement with the digitized graphical I–V curve, although the reconstructed maximum power remained below the nominal datasheet value, revealing a graphical/datasheet consistency issue. These results show that the proposed framework is a transparent and reproducible alternative for SDM identification from graphical sources, while also defining its sensitivity limits when applied to low-resolution curves or half-cut high-power modules with complex equivalent electrical configurations.

Keywords: parameter extraction; photovoltaic; solar energy; solar cells



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1. Introduction

Photovoltaic (PV) device modeling is a key tool for evaluating performance, identifying internal loss mechanisms, and developing monitoring and control strategies. Among the

equivalent-circuit representations available in the literature, the single-diode model (SDM) and its five-parameter formulation remain widely used because they provide a practical compromise between physical fidelity and mathematical simplicity. In addition, these models require a limited set of parameters that are commonly available in manufacturers' datasheets, which facilitates their implementation in both research and engineering applications [1,2]. For this reason, the SDM has become a standard framework for reproducing current–voltage (I–V) characteristics and analyzing resistive and recombination-related losses.

The accuracy of any SDM-based simulation depends strongly on the reliability of the extracted parameters. Consequently, a wide range of parameter extraction methods have been reported. These include analytical and non-iterative formulations that derive explicit or semi-explicit parameter expressions from characteristic datasheet points [3–6], as well as approaches based on analytical reformulations of the model, including Lambert W-based solutions. More recently, datasheet-driven methods supported by optimization algorithms have also been proposed [7].

Optimization-based techniques can achieve close agreement between modeled and reference curves; however, they usually depend on solver configuration, convergence criteria, and, in many cases, stochastic search mechanisms. These factors increase computational cost and may limit strict reproducibility when implementation details are not fully specified. Even when only datasheet information is used, optimization-oriented strategies remain sensitive to algorithm settings and search heuristics [7], which may be undesirable in deterministic modeling environments.

The methodological validity of recovering XY data from published plots using calibrated digitization tools has been examined in independent studies [8–10]. These studies show that reliable graphical data recovery requires explicit axis calibration, traceable coordinate mapping, and control of the uncertainty introduced by point selection, pixel resolution, and image quality. Therefore, in the present work, the digitization stage is not treated as an error-free preprocessing step. Instead, the influence of pixel discreteness, local window selection, and repeated extraction is considered in the uncertainty analysis of the slope-derived resistive parameters.

Within this context, the present work does not modify the underlying photovoltaic physical model. Instead, it proposes a structured graphical–digital methodology for extracting SDM parameters directly from manufacturer-provided I–V images. The main contribution of the proposed approach is the integrated use of (i) controlled curve digitization with explicit scale calibration; (ii) mathematical transformation of image coordinates into electrical units; and (iii) deterministic evaluation of local slopes in characteristic regions of the I–V curve, including an explicit assessment of the uncertainty associated with pixel resolution and local window selection. In this way, the method remains consistent with established analytical SDM approaches [3–6], while avoiding stochastic search procedures and reducing dependence on iterative solvers.

Model validation is carried out through a quantitative comparison between reconstructed and simulated curves using the root mean square error (RMSE) as the main statistical indicator. Because RMSE assigns greater weight to larger deviations, it is well suited to identifying discrepancies that may arise in critical regions of the I–V characteristic, particularly near the knee and maximum power region [11]. The use of this metric provides a transparent and consistent basis for evaluating the agreement between the reconstructed and simulated curves.

The novelty of this work does not reside in modifying the SDM itself or in proposing a new closed-form photovoltaic model. Instead, the contribution lies in integrating the graphical digitization stage into the analytical parameter extraction workflow. Existing analytical SDM methods generally assume that the input quantities are already available as

numerical datasheet values or tabulated I-V points [3–7]. In contrast, the present framework starts from graphical I-V information, performs explicit axis calibration, estimates the local differential slopes from digitized curve regions, propagates the graphical uncertainty into the resistive parameters, and then closes the SDM analytically using characteristic operating point equations. This provides a traceable bridge between manufacturer-reported graphical data and deterministic SDM identification, which is particularly useful when complete numerical I-V datasets are unavailable.

2. Materials and Method

2.1. Materials

Four photovoltaic devices were selected to evaluate the proposed methodology across different photovoltaic technologies and power levels. The set includes the RTC-FRANCE silicon solar cell [12], a crystalline silicon (c-Si) solar cell fabricated at INAOE [13], and two commercial modules: the Kyocera KC200GT polycrystalline module [14] and the Sunpro SP450M monocrystalline module [15]. This selection covers both laboratory-scale devices with low current levels and commercial modules with substantially higher power ratings, allowing the methodology to be assessed under different electrical ranges and structural configurations.

The electrical parameters—short-circuit current (I_{SC}), open-circuit voltage (V_{OC}), current and voltage at maximum power point (I_m , V_m), and maximum power (P_{max})—were taken directly from manufacturer datasheets or officially reported documentation [12–14]. According to these sources, all devices were characterized under Standard Test Conditions (STC: $G = 1000 \text{ W/m}^2$, $T = 25 \text{ }^\circ\text{C}$), except for the RTC-FRANCE cell, whose reference measurements were reported at $33 \text{ }^\circ\text{C}$ [12].

Table 1 summarizes the nominal electrical characteristics of the selected devices together with their corresponding photovoltaic technologies. The KC200GT module has a rated power of 200 W, with a tolerance of $+10\%/-5\%$ [14], whereas the SP450M module is rated at 450.18 W under STC [15]. In contrast, the INAOE cell exhibits lower current and power values, consistent with its laboratory-scale fabrication and smaller active area [13]. By combining commercial modules with research-scale devices, the selected dataset provides a suitable basis for evaluating the robustness of the proposed parameter extraction procedure under heterogeneous device conditions.

Table 1. Performance Parameters of Photovoltaic Devices and Their Technology.

Name	Type	Technology	I_{SC} (A)	V_{OC} (V)	I_m (A)	V_m (V)	P_{max} (W)	N_s	T ($^\circ\text{C}$)	G (W/m^2)
RTC-FRANCE [12]	Cell	Poly-Si	0.76	0.572	0.689	0.450	0.310	1	33	1000
INAOE [13]	Cell	c-Si	28.76×10^{-3}	0.52	22.27×10^{-3}	0.32	7.126×10^{-3}	1	25	1000
KC200GT [14]	Panel	Poly-Si	8.21	32.9	7.63	26.3	200 ($+10\%/-5\%$) *	54	25	1000
SP450M [15]	Panel	mono-Si	11.56	49.8	10.98	41	450.18	144	25	1000

* For KC200GT, the rated power is 200 W, while $V_m I_m = 200.669 \text{ W}$ was used as the reference maximum power operating point.

The selected devices were not intended to constitute a statistically exhaustive database of photovoltaic technologies. Instead, they were chosen as representative test cases to evaluate the proposed graphical–analytical workflow under different electrical scales and equivalent series cell configurations. The dataset includes single-cell devices, a 54-cell commercial module, and a 144-cell half-cut commercial module represented in the SDM by an equivalent series cell number $N_{S,eq} = 72$. These devices cover power levels from the milliwatt range to hundreds of watts, allowing the method to be tested under progressively

more demanding conditions, particularly regarding the influence of the high-voltage local slope and the equivalent electrical representation of the module on energetic closure. Therefore, the validation should be interpreted as a methodological assessment of the extraction framework rather than as a universal benchmark for all photovoltaic technologies.

2.2. Graphical Method for Extracting Electrical Parameters

The electrical behavior of photovoltaic devices was described using the single-diode model (SDM), whose mathematical formulation relates the output current and voltage through five parameters: photocurrent (I_{PV}), reverse saturation current (I_0), diode ideality factor (n), series resistance (R_S), and shunt resistance (R_P) [1,2,5,6]. Among these parameters, accurate estimation of R_S and R_P is particularly important because they strongly influence the differential slope of the I–V characteristic in the regions near open-circuit and short-circuit conditions, respectively (Figure 1).

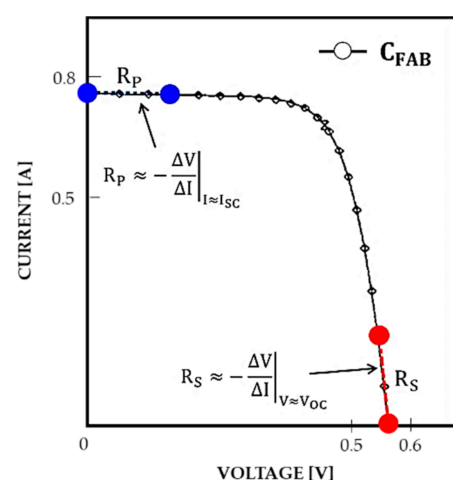


Figure 1. I–V characteristics of the photovoltaic device highlighting the local regions used for slope-based estimation of the shunt resistance (R_P) near short-circuit conditions and the series resistance (R_S) near open-circuit conditions. The resistances are approximated from the discrete local slope ($\frac{\Delta V}{\Delta I}$) of the curve in accordance with the single-diode model formulation.

From a physical perspective, the effect of series resistance becomes more pronounced in the high-voltage region approaching V_{OC} , where resistive voltage losses increasingly distort the shape of the curve. In contrast, shunt resistance mainly influences the low-voltage region near I_{SC} , altering the initial slope of the characteristic [16–18]. The contribution of series resistance to power dissipation and performance degradation in crystalline silicon devices has been quantitatively examined in recent studies, further highlighting the importance of accurate slope-based estimation in this region [1,16–18].

Manufacturers commonly provide I–V characteristics in graphical form within technical datasheets, together with the nominal electrical parameters. When numerical datasets are unavailable, parameter identification must rely on graphical reconstruction of the curve. Graphical and semi-analytical approaches have been reported previously, and several review studies have summarized analytical, non-iterative, and optimization-based techniques for SDM parameter extraction [3–7]. However, many optimization-based methods depend on iterative minimization schemes [12] or stochastic metaheuristic algorithms, including growth optimizers, generalized distribution-based search methods, and bio-inspired swarm strategies [19–22]. These approaches often increase algorithmic complexity and may reduce reproducibility when implementation settings are not fully controlled.

In the proposed methodology (Figure 2), the I–V curve image is first subjected to a calibrated preprocessing stage. This stage includes axis identification, geometric alignment,

cropping, and scale normalization. The pixel coordinates are then mapped into electrical units through an affine coordinate transformation consistent with validated graphical digitization procedures [8,9]. Explicit axis calibration ensures a direct correspondence between the image domain and the physical voltage–current coordinate system.

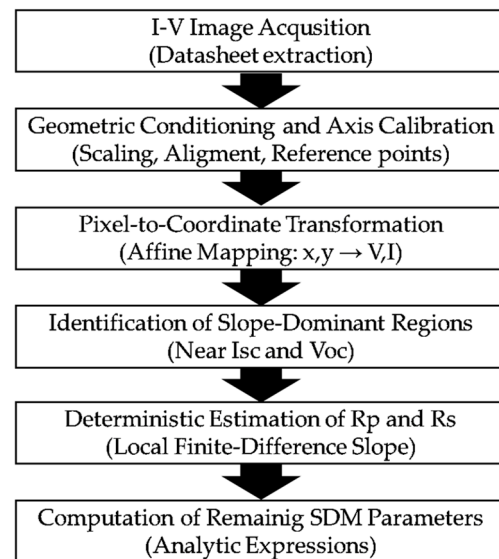


Figure 2. A block diagram of the graphical–digital SDM parameter extraction procedure, including image calibration, coordinate transformation, slope-based estimation of R_S and R_P , and analytical computation of the remaining model parameters.

Once the curve has been numerically reconstructed, the local slopes in the vicinities of I_{SC} and V_{OC} are evaluated to obtain effective slope-derived estimates of R_P and R_S , respectively. This slope-based determination is supported by the physical interpretation of the SDM and by its differential formulation [1,2]. However, these estimates are treated as local approximations rather than as fully decoupled physical parameters. In real devices, the local slope near short-circuit conditions may still contain a small contribution from R_S , whereas the local slope near open-circuit conditions may also be affected by the diode dynamic conductance and the shunt branch. Therefore, the slope-derived values are used as deterministic initial estimates for the analytical closure of the SDM, and their sensitivity to digitization noise, pixel resolution, and local interval selection is evaluated explicitly. Unlike population-based optimization methods, the proposed approach does not require stochastic search, repeated random initialization, or multi-parameter iterative fitting. Instead, it relies on deterministic analytical relationships derived from the SDM framework [1,2].

2.2.1. Deterministic Analytical Formulation for SDM Parameter Extraction

The steady-state electrical behavior of photovoltaic devices is commonly described using the single-diode model (SDM), which provides a physically consistent representation of the nonlinear current–voltage (I–V) characteristic under standard test conditions (STC) [1,2]. The implicit formulation of the SDM is given by

$$I = I_{PV} - I_0 \left[\exp \left(\frac{V + IR_S}{nN_s V_T} \right) - 1 \right] - \frac{V + IR_S}{R_P}, \quad (1)$$

where I_{PV} is the photocurrent, I_0 the reverse saturation current, n the ideality factor, R_S and R_P the series and shunt resistances, respectively, N_s the number of series-connected cells, and $V_T = kT/q$ the thermal voltage. This formulation has been extensively validated for modeling and parameter identification of crystalline silicon devices [1–3].

In the proposed method, parameter extraction is structured as a deterministic analytical procedure. The resistive parameters R_S and R_P are first estimated from the local differential behavior of the calibrated I-V curve. These values are not interpreted as perfectly decoupled physical quantities, but as effective slope-derived estimates that reduce the remaining unknowns to I_{PV} , I_0 , and n .

Implicit differentiation of Equation (1) with respect to V yields the differential slope

$$\frac{dV}{dI} = -\frac{\frac{\partial f}{\partial I}}{\frac{\partial f}{\partial V}}, \quad (2)$$

where $f(V, I)$ denotes the SDM implicit function.

For the SDM, the local differential resistance can be written in the general form

$$-rd = \frac{dV}{dI} \quad (3)$$

or, equivalently, the positive local resistance is

$$rd = -\frac{dV}{dI}. \quad (4)$$

This quantity contains the combined contribution of R_S , R_P , and the diode dynamic conductance. Therefore, the association between local slope and resistive parameters is only asymptotic. Near short-circuit conditions, the exponential contribution of the diode is small and the shunt branch dominates the low-voltage differential response. Under this limiting condition, the local resistance is approximated as

$$R_P \approx -\left.\frac{dV}{dI}\right|_{I \rightarrow I_{SC}}. \quad (5)$$

This approximation is valid when $R_P \gg R_S$ and when the diode dynamic conductance is small in the short-circuit region.

Near open-circuit conditions, the exponential contribution of the diode becomes dominant and the high-voltage local slope becomes more sensitive to series resistance. Under this limiting condition, the local resistance is approximated as

$$R_S \approx -\left.\frac{dV}{dI}\right|_{V \rightarrow V_{OC}}. \quad (6)$$

This expression should not be interpreted as an exact isolation of R_S . In real cells and modules, the shunt branch and the diode dynamic conductance may still influence the local slope near V_{OC} . Therefore, the value obtained from Equation (4) is treated as an effective high-voltage slope estimate of R_S .

In practice, the local slopes were evaluated from calibrated graphical data using finite-difference intervals:

$$R_P \approx -\left.\frac{\Delta V}{\Delta I}\right|_{I \approx I_{SC}}, \quad (7)$$

$$R_S \approx -\left.\frac{\Delta V}{\Delta I}\right|_{V \approx V_{OC}}. \quad (8)$$

To reduce the effect of digitization noise, ΔV and ΔI were not obtained from a single arbitrary pair of points. Instead, the local slope was calculated from a linear regression over a narrow window of digitized points around the corresponding operating region. The number of points and the pixel span of each local window are reported in Table 2, while the

corresponding pixel-scale sensitivity is summarized in Table 3. This procedure provides deterministic initial values for R_S and R_P , while explicitly recognizing the uncertainty introduced by pixel discreteness, local window selection, and the graphical resolution of the original I–V curve.

Table 2. Local slope extraction settings and resistive parameters obtained from calibrated I–V curves.

Device	Image Resolution (px)	L_x (px)	L_y (px)	m Near I_{SC}	Pixel Span Near I_{SC}	R_P (Ω)	m Near V_{OC}	Pixel Span Near V_{OC}	R_S (Ω)
RTC FRANCE	481×665	297	333	15	170	333.333 *	12	20–25	0.075
KC200GT	803×919	625	732	11	350–420	200	11	35–50	0.3
INAOE	1184×896	833	683	121	120	913	41	40	7.8
SP450M	1310×976	1125	780	89	88	90.909	39	38	0.68

* For the RTC-France cell, the low-voltage region near I_{SC} is close to the pixel-resolution limit because the current variation is very small in the original published graph. Therefore, the corresponding R_P value should be interpreted as an effective slope-derived estimate with comparatively higher graphical uncertainty.

Table 3. Graphical sensitivity summary associated with pixel scaling and local slope extraction.

Device	δV_{px} (V/px)	δI_{px} (A/px)	Relative Voltage Scale (%/px)	Relative Current Scale (%/px)	Most Sensitive Local Region	Main Affected Parameter
RTC-France	1.93×10^{-3}	2.28×10^{-3}	0.337	0.300	near I_{SC}	R_P
KC200GT	5.26×10^{-2}	1.12×10^{-2}	0.160	0.137	near V_{OC}	R_S
INAOE	6.24×10^{-4}	4.21×10^{-5}	0.120	0.146	near V_{OC}	R_S, n
SP450M	4.43×10^{-2}	1.48×10^{-2}	0.089	0.128	near V_{OC} and MPP	$R_S, P_{max, sim}$

2.2.2. Characteristic Operating Point Equations

Using the datasheet parameters I_{SC} , V_{OC} , I_{MPP} , V_{MPP} , and N_S , substitution into (1) yields three characteristic equations.

Short-circuit condition ($V = 0$):

$$I_{SC} = I_{PV} - I_0 \left[\exp \left(\frac{I_{SC} R_S}{n N_S V_T} \right) - 1 \right] - \frac{I_{SC} R_S}{R_P} \quad (9)$$

Open-circuit condition ($I = 0$):

$$0 = I_{PV} - I_0 \left[\exp \left(\frac{V_{OC}}{n N_S V_T} \right) - 1 \right] - \frac{V_{OC}}{R_P} \quad (10)$$

Maximum power point:

$$I_{MPP} = I_{PV} - I_0 \left[\exp \left(\frac{V_{MPP} + I_{MPP} R_S}{n N_S V_T} \right) - 1 \right] - \frac{V_{MPP} + I_{MPP} R_S}{R_P} \quad (11)$$

From the open-circuit equation (Equation (10)), the photocurrent can be expressed as

$$I_{PV} = I_0 \left[\exp \left(\frac{V_{OC}}{n N_S V_T} \right) - 1 \right] + \frac{V_{OC}}{R_P}. \quad (12)$$

Substituting (12) into the short-circuit equation (Equation (9)) yields

$$I_{SC} = I_0 \left[\exp \left(\frac{V_{OC}}{n N_S V_T} \right) - \exp \left(\frac{I_{SC} R_S}{n N_S V_T} \right) \right] + \frac{V_{OC} - I_{SC} R_S}{R_P}. \quad (13)$$

Solving (13) for I_0 gives an explicit expression in terms of n :

$$I_0(n) = \frac{I_{SC} - \frac{V_{OC} - I_{SC}R_S}{R_P}}{\exp\left(\frac{V_{OC}}{nN_S V_T}\right) - \exp\left(\frac{I_{SC}R_S}{nN_S V_T}\right)} \quad (14)$$

Thus, once R_S and R_P are known, I_0 becomes a single-variable function of n .

2.2.3. Automatic Determination of the Ideality Factor

To ensure global consistency of the reconstructed I–V curve, the ideality factor is determined by enforcing agreement at the maximum power point.

The maximum power point satisfies

$$\frac{dP}{dV} = 0 \Rightarrow I + V \frac{dI}{dV} = 0, \quad (15)$$

as established in analytical SDM studies [5,6].

Substituting $I_0(n)$ and $I_{PV}(n)$ into (1), the reconstructed curve depends only on n . Defining the scalar residual

$$F(n; R_S; R_P; T; G) = P_{\max, \text{sim}}(n) - P_{\max, \text{fab}}, \quad (16)$$

the ideality factor is obtained by solving

$$F(n) = 0. \quad (17)$$

This formulation reduces the multi-parameter identification problem to a one-dimensional nonlinear equation. For each device, the scalar residual $F(n)$ was evaluated within the admissible interval $1 \leq n \leq 2$ to verify whether the analytical closure produced an internal or boundary solution. This procedure was used to confirm the existence of a physically admissible ideality factor for each parameter set.

The scalar equation $F(n) = 0$ was solved in MATLAB using a deterministic one-dimensional root-finding procedure within the admissible interval $1 \leq n \leq 2$. The numerical solution was stopped when both $|F(n)| < 10^{-10}$ and $|n_{k+1} - n_k| < 10^{-8}$ were satisfied. The values of n reported in the tables were rounded for presentation, whereas the full numerical precision was retained for the reconstruction of the I–V curves and for the RMSE calculation. This clarification is important because the proposed framework is deterministic and does not involve stochastic search or multi-parameter optimization; however, the final estimation of n still requires the numerical solution of a scalar equation. Therefore, this stage is more accurately described as a deterministic scalar root solution rather than as a purely non-iterative evaluation. This treatment is consistent with analytical SDM formulations in which the remaining model parameters are constrained through characteristic operating point equations [3–6].

Importantly, this establishes the implicit dependence

$$n = n(R_S; R_P; T; G), \quad (18)$$

which reflects the intrinsic coupling of SDM parameters. If resistive or environmental parameters are perturbed during sensitivity analysis, the ideality factor can be recalculated by resolving (17), ensuring physical consistency of the reconstructed I–V curve.

Once n is obtained, I_0 and I_{PV} are calculated from Equations (14) and (12), respectively.

2.2.4. Axis Identification and Reference Points

For each photovoltaic device, the I–V curve image obtained from the manufacturer datasheet or from the corresponding experimental source was imported using its original available resolution. This criterion was adopted to avoid interpolation artifacts or geometric distortions that could affect the subsequent axis calibration and coordinate transformation. For traceability, both the image resolution and the pixel length of the calibrated voltage and current axes were recorded for each device, following recommended practices for graphical data extraction [8,9].

Three reference points were identified for axis calibration, as illustrated in Figure 3: the origin (x_0, y_0) , the open-circuit voltage intercept $(x_{V_{OC}}, y_0)$, and the short-circuit current intercept $(x_0, y_{I_{SC}})$. These points define the graphical correspondence between pixel coordinates and the physical electrical quantities used in the subsequent affine transformation.

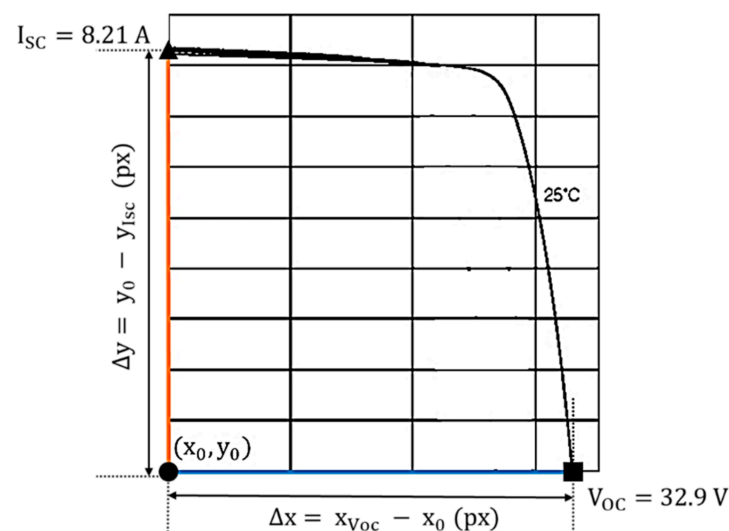


Figure 3. Axis calibration and affine mapping of pixel coordinates into electrical quantities using reference intercept points extracted from the KC200GT datasheet.

The corresponding electrical values V_{OC} and I_{SC} were taken directly from Table 1. Pixel coordinates were converted into electrical values using a linear affine transformation [9]. This procedure was restricted to Cartesian I–V plots with linear voltage and current axes. Graphs with logarithmic, nonlinear, or distorted axes were not included in the present analysis because they require a different calibration model.

Voltage mapping:

$$V = a_x(x - x_0) \quad (19)$$

where:

$$a_x = \frac{V_{OC}}{x_{V_{OC}} - x_0} \quad (20)$$

Current mapping:

$$I = a_y(y_0 - y) \quad (21)$$

where:

$$a_y = \frac{I_{SC}}{y_0 - y_{I_{SC}}} \quad (22)$$

The uncertainty introduced by pixel discreteness was estimated by assuming ± 1 pixel uncertainty in the manual selection of each point. Therefore, the voltage and current uncertainty associated with a two-point interval were propagated into the local slope estimate.

Assuming ± 1 pixel selection uncertainty:

$$\Delta V = a_x, \Delta I = a_y$$

First-order slope uncertainty:

$$\Delta\left(\frac{dV}{dI}\right) \approx \frac{\Delta V}{\Delta I} \quad (23)$$

Regression reduces uncertainty according to (22):

$$\sigma_{\text{slope}} \propto \frac{1}{\sqrt{m}} \quad (24)$$

Linear regression over m points was used to reduce the influence of point-to-point digitization noise. For each device, two local windows were selected: one near I_{SC} for the shunt-dominated slope and one near V_{OC} for the series-dominated slope. The number of points and the pixel span of each local window are reported in Table 2, while the corresponding pixel-scale sensitivity is summarized in Table 3.

Graphical preprocessing and manual pixel coordinate extraction were performed using Adobe Photoshop 2024 (v25.12.4). This step included graph cropping, axis alignment, image resolution verification, and manual identification of the pixel coordinates associated with the reference points and the I–V curve. The extraction was performed in manual mode using linear X–Y axes. The extracted pixel coordinates were then converted into voltage–current values through the affine calibration procedure described in Section 2.2.4. No smoothing, interpolation, or filtering was applied before slope estimation. The calibrated voltage–current coordinates were processed in MATLAB (MathWorks, R2025b) for local regression, uncertainty propagation, scalar root solution, RMSE calculation, and I–V reconstruction. The proposed methodology is not software-dependent; any equivalent workflow capable of image preprocessing, axis calibration, local regression, and scalar root solving may be used.

2.2.5. Sensitivity Analysis of Graphical Extraction

To evaluate the effect of graphical uncertainty on the extracted parameters, a sensitivity analysis was performed considering three main sources of error: pixel discreteness, axis calibration uncertainty, and local window selection. First, the calibrated reference points were perturbed by ± 1 pixel in the horizontal and vertical directions to quantify the effect of axis calibration on the voltage and current scaling factors. Second, the local regression windows used to estimate the short-circuit and open-circuit slopes were varied by changing the number of selected points around each operating region. The procedure was used to identify the main sources of graphical uncertainty; however, a full inter-operator repeatability analysis is left for future work.

For each perturbation, R_S , R_P , n , I_0 , I_{PV} , $P_{\max}$, RMSE, and NRMSE were recalculated. The relative sensitivity of a parameter x was evaluated as follows:

$$S_x = \left(\frac{x_{\text{perturbed}} - x_{\text{reference}}}{x_{\text{reference}}} \right) \times 100\% \quad (25)$$

In this expression, $x_{\text{reference}}$ corresponds to the value obtained using the original calibrated image and selected local regression window, whereas $x_{\text{perturbed}}$ corresponds to the value obtained after applying a controlled graphical perturbation. Positive values of S_x indicate an increase in the extracted parameter with respect to the reference case, while negative values indicate a decrease.

The pixel contribution to the voltage and current scaling was estimated from the calibrated axis lengths. If L_x and L_y are the horizontal and vertical axis lengths in pixels, respectively, the electrical increments associated with one pixel are given by the following:

$$\delta V_{px} = \frac{V_{OC}}{L_x} \quad (26)$$

and

$$\delta I_{px} = \frac{I_{SC}}{L_y} \quad (27)$$

Thus, the local slope uncertainty associated with pixel discreteness was propagated into the differential resistance estimate. For a local resistance calculated as ($r_d = -\Delta V / \Delta I$), the first-order relative uncertainty was estimated as follows:

$$\frac{u(r_d)}{r_d} = \sqrt{\left(\frac{u(\Delta V)}{\Delta V}\right)^2 + \left(\frac{u(\Delta I)}{\Delta I}\right)^2} \quad (28)$$

When the local slope was obtained by linear regression, the standard error of the fitted slope was also included. If the local regression is expressed as

$$I = \beta_0 + \beta_1 V, \quad (29)$$

the local differential resistance is

$$r_d = -\frac{1}{\beta_1}. \quad (30)$$

Therefore, the regression-related uncertainty in r_d can be propagated as follows:

$$u(r_d) = \frac{u(\beta_1)}{\beta_1^2} \quad (31)$$

The combined uncertainty of the slope-derived resistance was then estimated by considering the pixel contribution, the regression uncertainty, and the variation associated with local window selection:

$$u_c(r_d) = u_{px}^2(r_d) + u_{reg}^2(r_d) + u_{win}^2(r_d) \quad (32)$$

This procedure makes it possible to distinguish between deviations caused by the SDM analytical closure and deviations introduced by the graphical extraction stage. The analysis is particularly relevant for high-voltage modules, where small errors in the local slope near V_{OC} can be amplified in the maximum power region.

3. Validation and Discussion of the Proposed Method

The graphical–deterministic procedure described in Section 2 enabled the extraction of the complete set of single-diode model (SDM) parameters for each photovoltaic device analyzed in this study. The methodology was implemented in two clearly differentiated stages. First, the resistive parameters R_s and R_p , were estimated as effective local slope values from the calibrated I–V curve (Figure 4). These estimates were not treated as perfectly decoupled quantities, but as physically motivated initial values whose uncertainty depends on pixel resolution, local window selection, and graphical quality. Second, the analytical closure of the model was completed by calculating I_{PV} , I_0 , and n from the characteristic equations associated with short-circuit, open-circuit, and maximum power conditions, following established SDM formulations [1–6].

It should be noted that the validation sources are heterogeneous. The RTC-France cell is a widely used benchmark case, the KC200GT and SP450M correspond to commercial datasheet-based modules, and the INAOE cell provides an experimental laboratory-scale reference. Therefore, the validation combines benchmark, datasheet, and experimental graphical sources. Although this does not replace a broad experimental campaign under

controlled irradiance and temperature, it allows the proposed workflow to be assessed under different levels of graphical and electrical complexity.

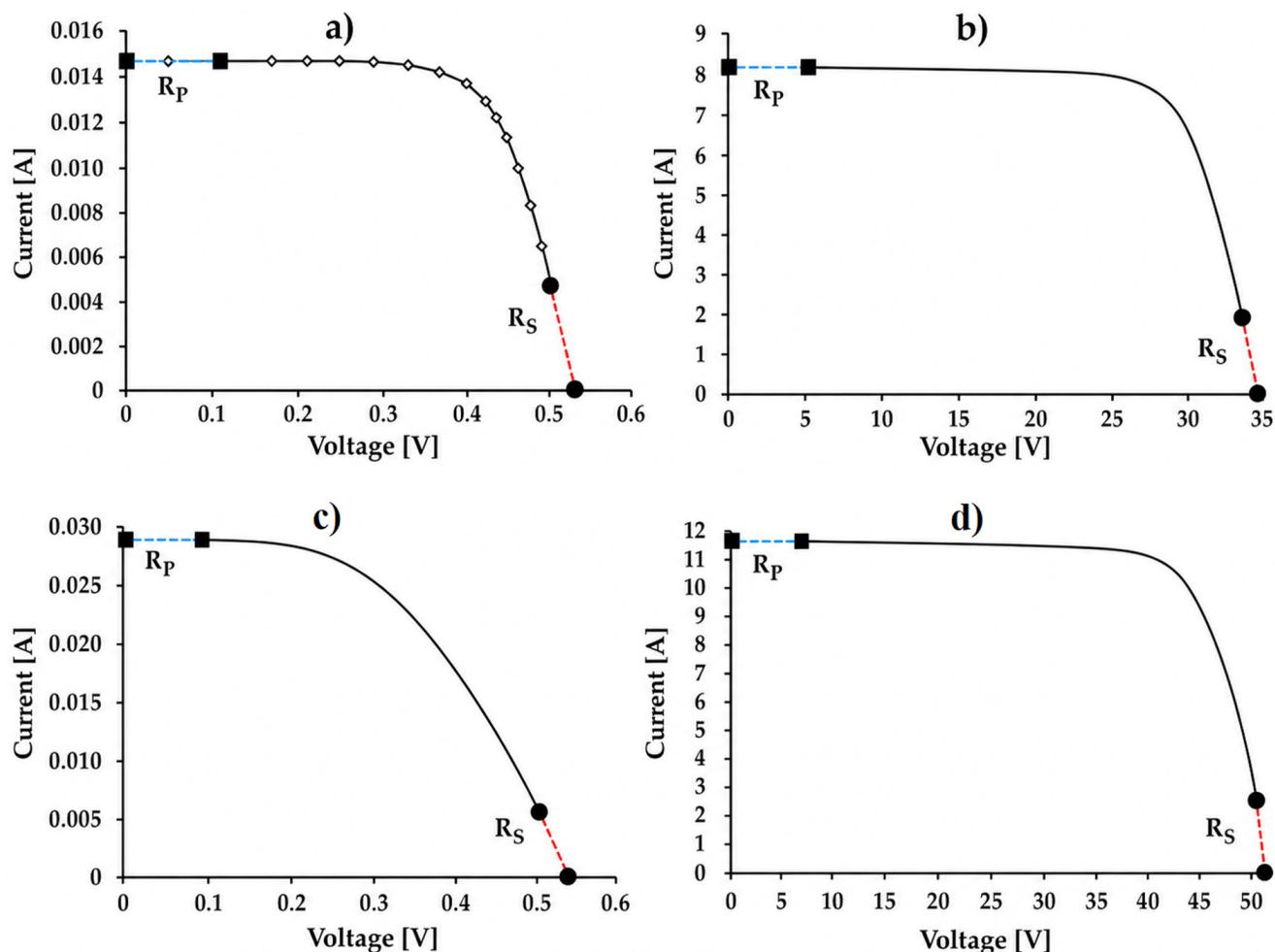


Figure 4. Local slope extraction for estimating (R_S) and (R_P): (a) RTC-France, (b) KC200GT, (c) INAOE, and (d) SP450M. Zoomed regions for RTC-France illustrate the digitized points and local regressions near (I_{SC}) and (V_{OC}); the corresponding point number and pixel span are reported in Table 2.

The diode ideality factor was determined automatically by restricting the solution to the interval $1 \leq n \leq 2$, which is commonly adopted for crystalline silicon devices in SDM-based studies, and selecting the value that minimized the deviation between the simulated maximum power and the value reported by the manufacturer.

Table 2 summarizes the graphical calibration parameters, local regression settings, and slope-derived resistive parameters obtained from the calibrated I–V curves. The image resolution, calibrated axis lengths, number of digitized points, and pixel span of the local fitting windows are reported to make the graphical extraction procedure traceable. For each device, the voltage and current scaling factors were obtained from the calibrated axis lengths and the nominal V_{OC} and I_{SC} values listed in Table 1. The local resistance near I_{SC} was associated with the shunt-dominated region and used to estimate R_P , whereas the local resistance near V_{OC} was associated with the series-dominated region and used to estimate R_S . In continuous curves without visible discrete markers, m corresponds to the number of sampled digitized points used in the local linear regression. The estimated R_S and R_P values are physically interpretable as effective local slope parameters and are consistent with the order of magnitude expected for crystalline silicon cells and modules [1–3]. In particular, the relatively large R_S value obtained for the laboratory-fabricated INAOE device is consistent

with the presence of contact resistance and non-optimized metallization pathways, which are frequently observed in experimental photovoltaic structures [3,5]. In addition, the use of localized slope analysis provides a physically motivated way to reduce the initial coupling between resistive and exponential contributions, a difficulty widely recognized in analytical and parameter identification studies based on the SDM [6,21].

The results show that the graphical stability of the local slope extraction depends strongly on the operating region and on the shape of the curve. For the KC200GT and SP450M modules, the high-voltage region near V_{OC} was sufficiently steep to provide stable estimates of R_S . In the SP450M case, the estimated value ($R_S = 0.681 \Omega$) is consistent with the apparent high-voltage resistance obtained from the nominal datasheet operating points, supporting the order of magnitude of the slope-derived series resistance. In contrast, the low-voltage region of the RTC-France curve is nearly horizontal, and the current variation associated with R_P is close to the pixel-resolution limit. Therefore, the corresponding R_P value carries higher graphical uncertainty. For the INAOE cell, the local slope near V_{OC} led to a relatively high R_S value, which is consistent with the expected influence of contact resistance and non-optimized metallization in laboratory-scale photovoltaic devices.

To complement the local slope extraction results, a graphical sensitivity summary was obtained from the calibrated voltage and current scales. For each device, the electrical value associated with one pixel was calculated from the calibrated axis lengths as $\delta V_{px} = V_{OC}/L_x$ and $\delta I_{px} = I_{SC}/L_y$. These quantities provide a direct estimate of the minimum voltage and current increments imposed by the graphical resolution of each image. The most sensitive local region and the main affected parameter were identified from the local fitting windows used near I_{SC} and V_{OC} . The resulting graphical sensitivity summary is presented in Table 3.

The results in Table 3 show that the graphical sensitivity depends not only on the global image resolution, but also on the local shape of the I–V curve in the region used for slope estimation. For the RTC-France cell, the low-voltage region near I_{SC} is nearly horizontal; therefore, small current variations approach the pixel-resolution limit and increase the uncertainty of the shunt-related slope used to estimate R_P . The KC200GT module shows lower relative pixel sensitivity and well-defined local fitting windows, which is consistent with its low normalized reconstruction error. For the INAOE laboratory cell, the high-voltage region near V_{OC} is more sensitive because the extracted R_S is relatively large, contributing to the lower-bound solution obtained for n . In the SP450M module, the relative pixel scale is fine; however, the energetic closure remains sensitive to the high-voltage local slope and to the equivalent series cell representation $N_{S,eq} = 72$. Therefore, the SP450M discrepancy is not only associated with image resolution, but also with the consistency among the digitized graphical curve, the nominal maximum power point, and the equivalent electrical configuration used in the SDM.

Once the slope-derived values of R_S and R_P were obtained, the remaining SDM parameters were calculated through the analytical closure described in Section 2. The ideality factor n was obtained by solving the scalar residual $F(n) = 0$ within the admissible interval $1 \leq n \leq 2$. The resulting values of I_0 , I_{PV} and n were then used to reconstruct the I–V curve and to calculate the simulated maximum power, $P_{max,sim}$. The energetic validation was performed by comparing $P_{max,sim}$ with the reference maximum power $P_{max,ref}$, which corresponds to the manufacturer-reported or experimentally reported maximum power value used for each device. The resulting SDM parameters and energetic validation are summarized in Table 4.

Table 4. SDM parameters and energetic validation obtained after analytical closure.

Device	N _S Used in SDM	n	I ₀ (A)	I _{PV} (A)	P _{max,sim} (W)	P _{max,ref} (W)	Error (%)
RTC-France	1	1.116	2.79×10^{-9}	0.76017	0.310099	0.31005	+0.02
KC200GT	54	1.076	2.18×10^{-9}	8.2223	200.669	200.669	~0
INAOE	1	1.00 *	4.61×10^{-11}	29.006×10^{-3}	6.862×10^{-3}	7.126×10^{-3}	−3.70
SP450M	72 **	1.037	5.87×10^{-11}	11.6485	391.04	450.18	−13.14

* The solution converged to the lower bound of the admissible interval ($n = 1$), indicating a constraint-limited analytical closure. ** For the SP450M module, the manufacturer reports a 144-cell half-cut architecture. For SDM implementation, $N_{S,eq} = 72$ was used as the equivalent number of series-connected cells.

The results in Table 4 show that the analytical closure remains stable for the RTC-France cell and the KC200GT module. For RTC-France, the reconstructed maximum power was 0.310099 W, in close agreement with the reference value of 0.31005 W. This corresponds to a relative deviation of approximately +0.02%, which is sufficiently small considering that the extraction was performed from the original published graphical curve. Similarly, for the KC200GT module, the reconstructed maximum power was 200.669 W, which coincides with the reference value calculated from the nominal maximum power operating point $V_m I_m = 26.3 \times 7.63$. The resulting deviation was approximately 0%, indicating strong energetic consistency between the local slope estimates and the analytical SDM closure.

The INAOE laboratory-fabricated cell showed a higher sensitivity to the slope-derived resistive parameters. Using $R_S = 7.8 \Omega$ and $R_P = 913 \Omega$, the scalar closure converged to the lower bound of the admissible interval, $n = 1$. The reconstructed maximum power was 6.862×10^{-3} W, compared with a reference value of 7.126×10^{-3} W, corresponding to a relative deviation of approximately −3.70%. This behavior is consistent with the expected influence of contact resistance, non-optimized metallization pathways, and graphical slope uncertainty in laboratory-scale photovoltaic devices. Therefore, the INAOE case is interpreted as a sensitivity case rather than as a perfect energetic closure case.

For the SP450M module, the analytical closure was recalculated using an equivalent series cell number $N_S = 72$, consistent with the electrical interpretation of the 144-cell half-cut module architecture. With the slope-derived values $R_S = 0.68 \Omega$ and $R_P = 90.909 \Omega$, the scalar solution yielded $n = 1.037$, $I_0 = 5.87 \times 10^{-11}$ A and $I_{PV} = 11.6485$ A. Under these conditions, the reconstructed maximum power was 391.04 W. This value is consistent with the maximum power region observed in the digitized graphical curve, but it remains below the nominal manufacturer value of 450.18 W, corresponding to a deviation of approximately −13.14%.

This result indicates that the SP450M case should not be interpreted simply as a failure of the SDM analytical closure. Instead, it reveals a combined sensitivity associated with graphical consistency, local high-voltage slope extraction, and the equivalent number of series-connected cells used in the model. The manufacturer reports the module as a 144-cell device; however, because this corresponds to a half-cut architecture, the electrical series configuration is more consistently represented in the SDM using $N_{S,eq} = 72$. Even under this correction, the nominal maximum power point of 450.18 W remains higher than the maximum power suggested by the digitized graphical curve. Therefore, the SP450M module is treated as a graphical/datasheet consistency case and as a limit condition for the proposed extraction framework.

Overall, the energetic validation confirms that the proposed graphical–analytical method can provide consistent SDM parameters when the graphical curve, the characteristic operating points, and the equivalent series cell number are mutually compatible. The RTC-France and KC200GT cases demonstrate stable reconstruction with low relative deviations. In contrast, the INAOE and SP450M cases illustrate the sensitivity of the method to graphical slope extraction and device-specific structural features. These results support

the usefulness of the proposed framework as a transparent parameter extraction procedure, while also defining the conditions under which additional experimental information, higher-resolution curves, or multi-irradiance validation may be required.

To further clarify the determination of the ideality factor, the scalar residual $F(n)$ was evaluated within the admissible interval $1 \leq n \leq 2$. Table 5 summarizes the numerical behavior of the closure for each device. Internal solutions indicate that the residual equation produced an admissible value of n inside the selected interval, whereas boundary solutions indicate that the closure converged to one of the limits of the admissible range. This verification is important because the proposed method is deterministic, but the final value of n is still obtained from a one-dimensional scalar root solution.

Table 5. Numerical verification of the ideality factor closure through the scalar residual $F(n)$.

Device	Search Interval	n Obtained	Root Behavior	Interpretation
RTC-France	$1 \leq n \leq 2$	1.116	Internal solution	Stable analytical closure
KC200GT	$1 \leq n \leq 2$	1.076	Internal solution	Stable analytical closure
INAOE	$1 \leq n \leq 2$	1.000	Lower-bound solution	Constraint-limited closure
SP450M	$1 \leq n \leq 2$	1.037	Internal solution	Graphical/datasheet consistency-sensitive closure

The RTC-France and KC200GT cases produced internal solutions within the admissible interval, confirming stable analytical closure for these devices. The INAOE cell converged to the lower bound, $n = 1.00$, which is consistent with the increased sensitivity observed when the updated slope-derived values $R_S = 7.8 \, \Omega$ and $R_P = 913 \, \Omega$ were used. In contrast, the SP450M module produced an internal solution, $n = 1.037$, after representing the half-cut architecture with $N_{S,eq} = 72$. Although this solution is mathematically admissible, the reconstructed maximum power remains below the nominal datasheet value, confirming that the SP450M case is mainly limited by graphical/datasheet consistency and equivalent-series cell-number sensitivity rather than by the absence of a valid scalar solution.

For the RTC-France cell and the KC200GT module, the reconstructed curves showed good agreement with the three characteristic operating points: short-circuit current (I_{SC}), open-circuit voltage (V_{OC}), and maximum power (P_{max}) (Figure 5). The resulting closed-form expression for the output current as a function of voltage is given by

$$I(V) = \frac{R_P}{R_S + R_P} (I_{PV} + I_0) - \frac{V}{R_S + R_P} - \frac{nN_S V_T}{R_S} W \left(\frac{R_S R_P I_0}{nN_S V_T (R_S + R_P)} \exp \left(\frac{R_P (V + R_S (I_{PV} + I_0))}{nN_S V_T (R_S + R_P)} \right) \right), \quad (33)$$

where W denotes the principal branch of the Lambert W function.

For both devices, the simulated maximum power matched the datasheet value within numerical tolerance, indicating internal consistency among the differential slope estimation, the manufacturer-reported operating points, and the analytical structure of the SDM. This result is consistent with analytical non-iterative approaches reported in [4–6], as well as with classical SDM formulations [1,2].

For the INAOE laboratory-fabricated cell, the reconstructed I – V curve showed greater sensitivity to the slope-derived resistive parameters than the RTC-France and KC200GT cases. Using the updated local slope estimates $R_S = 7.8 \, \Omega$ and $R_P = 913 \, \Omega$, the analytical closure converged to the lower bound of the admissible ideality factor interval, $n = 1$. Under these conditions, the reconstructed maximum power was approximately $6.86 \times 10^{-3} \, \text{W}$, which is 3.70% lower than the reference value obtained from the experimental maximum power point. This deviation is consistent with the expected influence of contact resistance, non-optimized metallization, and graphical slope uncertainty in laboratory-scale photovoltaic devices. Therefore, the INAOE case should be interpreted as a sensitivity case rather than as a perfect energetic closure case (see Figure 6).

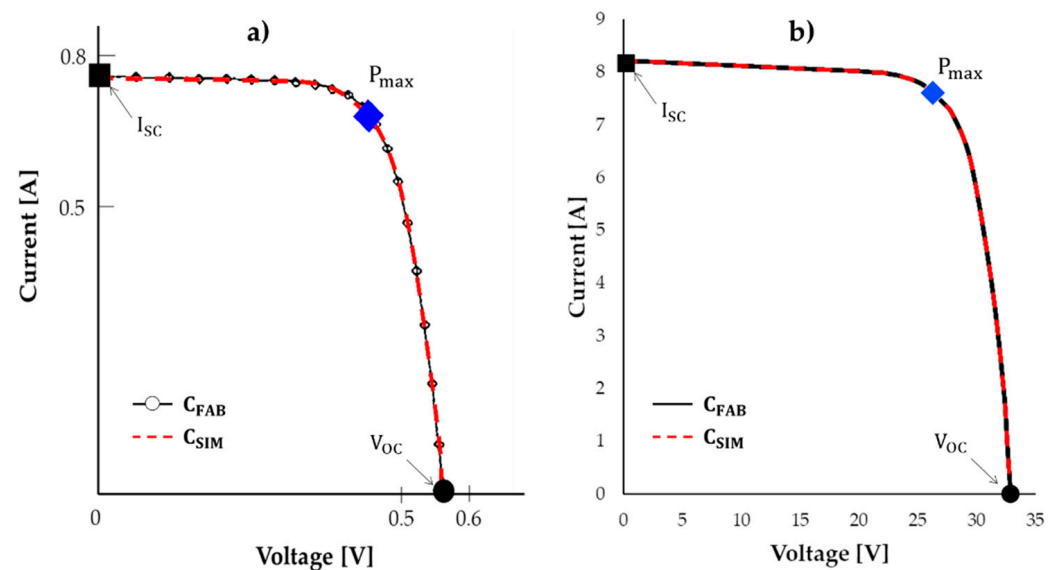


Figure 5. Reconstruction of the curve (red dashed line) based on the parameters obtained from the extraction for (a) RTC-France and (b) Kyocera KC200GT.

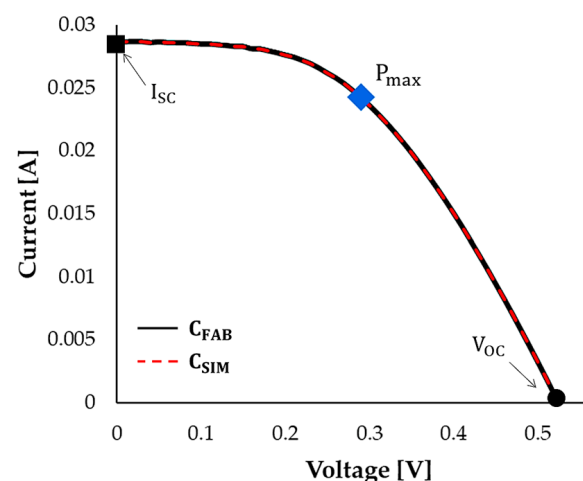


Figure 6. Comparison between the reconstructed I-V curve (red dash line) and experimental curve (black line) in INAOE solar cell.

The SP450M module represents the most demanding case for the proposed graphical slope-based procedure (Figure 7). The manufacturer reports this module as a 144-cell device; however, for the SDM implementation, an equivalent series cell number $N_{S,eq} = 72$ was used to represent the electrical configuration of the module. This interpretation is consistent with the voltage level of the device and avoids treating the 144-cell designation as 144 full-size cells electrically connected in series.

Using the slope-derived values $R_S = 0.68 \, \Omega$ and $R_P = 90.909 \, \Omega$, together with $N_S = 72$, the analytical closure of the SDM yielded $n = 1.037$, $I_0 = 5.87 \times 10^{-11} \, A$, and $I_{PV} = 11.6485 \, A$. Under these conditions, the reconstructed maximum power was $P_{max,sim} = 391.04 \, W$. This value is consistent with the maximum power region observed in the digitized graphical curve; however, it remains lower than the nominal manufacturer value of $P_{max,ref} = 450.18 \, W$. The corresponding deviation is approximately -13.14% . Therefore, the SP450M case should be interpreted as a graphical/datasheet consistency and equivalent series cell number sensitivity case, rather than as a simple failure of the SDM analytical closure.

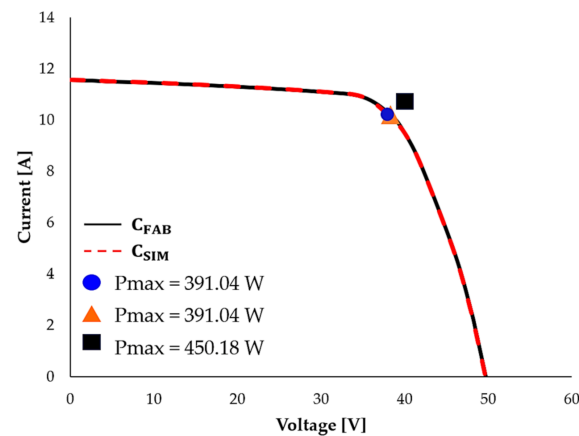


Figure 7. Reconstruction of the I–V curve for the SP450M module. The red dashed line corresponds to the SDM-reconstructed curve using $N_{S,eq} = 72$, while the black solid line corresponds to the digitized graphical reference. The reconstructed maximum power is $P_{max,sim} = 391.04$ W, whereas the nominal datasheet value is $P_{max,ref} = 450.18$ W. The discrepancy illustrates the graphical/datasheet consistency issue and the sensitivity of the SDM closure to the equivalent series cell number.

As an additional consistency check, an apparent high-voltage resistance was estimated from the nominal datasheet operating points of the SP450M module:

$$R_{app} = \frac{(V_{OC} - V_m)}{I_m} \quad (34)$$

Using $V_{OC} = 49.8$ V, $V_m = 41.0$ V, and $I_m = 10.98$ A, the apparent value is

$$R_{app} = \frac{(49.8 - 41.0)}{10.98} = 0.801 \, \Omega.$$

The apparent resistance R_{app} is of the same order of magnitude as the high-voltage slope-derived value $R_S = 0.68 \, \Omega$, indicating that the extracted resistance is not an isolated numerical artifact. Nevertheless, R_{app} should not be interpreted as the physical series resistance of the module because it also contains the nonlinear contribution of the diode and the possible influence of the shunt branch. Instead, it provides an independent high-voltage consistency check based only on nominal datasheet quantities.

Despite this agreement in the order of magnitude of the high-voltage resistance, the SP450M case remains sensitive because the graphical curve, the nominal maximum power point, and the equivalent series cell number do not lead to a single unambiguous energetic closure. The reconstructed curve agrees more closely with the maximum power region extracted from the graphical I–V curve, whereas the nominal datasheet point $V_m = 41.0$ V, $I_m = 10.98$ A corresponds to 450.18 W. This discrepancy suggests that higher-resolution I–V curves or independent measurements at different irradiance levels would be required to fully validate the extracted R_S value for this module.

From an energetic consistency perspective, the deviation observed for the SP450M module should be analyzed in terms of the agreement among the reconstructed curve, the digitized graphical reference, and the nominal datasheet maximum power point, rather than only as a direct Joule loss contribution associated with R_S . This distinction is important because the slope-derived value $R_S = 0.68 \, \Omega$ represents an effective high-voltage local resistance. Therefore, it may include not only the ohmic series contribution, but also the influence of the diode dynamic conductance and the shunt branch in the vicinity of V_{OC} .

Using $N_S = 72$, $R_S = 0.68 \, \Omega$, and $R_p = 90.909 \, \Omega$, the analytical closure yielded $P_{max,sim} = 391.04$ W. Compared with the nominal datasheet value $P_{max,ref} = 450.18$ W, the difference is

$$\Delta P = P_{\max,\text{sim}} - P_{\max,\text{ref}} = 391.04 - 450.18 = -59.14 \text{ W}, \quad (35)$$

which corresponds to a relative deviation of

$$\varepsilon_P = \frac{(P_{\max,\text{sim}} - P_{\max,\text{ref}}) \times P_{\max,\text{ref}}}{100} = \frac{(391.04 - 450.18) \times 450.18}{100} = -13.14\%. \quad (36)$$

This deviation indicates that the reconstructed curve is closer to the maximum power region extracted from the digitized graphical I–V curve than to the nominal manufacturer-reported maximum power point. Therefore, the SP450M result should be interpreted as a graphical/datasheet consistency issue combined with sensitivity to the equivalent series cell number used in the SDM representation. It does not invalidate the SDM formulation, but it shows that, for half-cut high-power modules, the graphical I–V curve, the nominal datasheet operating point, and the equivalent electrical series configuration must be mutually consistent to obtain an unambiguous energetic closure.

The different approaches reported in the literature vary not only in their mathematical strategy, whether analytical, iterative, or metaheuristic, but also in the fitting criteria adopted, including RMSE minimization, multi-point residual adjustment, or strict matching at the maximum power point (MPP) [3,6,11,20–22]. As a result, the parameter sets obtained are not strictly unique, even when the reconstructed I–V curves exhibit high macroscopic similarity.

The comparison presented in Table 6 should not be interpreted as a direct numerical ranking of methods because the input information is not identical in all cases. Several reference methods reported in the literature use tabulated experimental I–V datasets, such as the classical RTC-France dataset, whereas the present work focuses on the extraction of parameters from graphical information. Therefore, Table 6 is used as a structural comparison of parameter magnitudes, physical plausibility, and energetic consistency, rather than as a strict RMSE-based competition under identical input-data quality. Because comparable literature parameter sets are mainly available for RTC-France and KC200GT, Table 6 focuses on these two devices for structural comparison, whereas the full four-device reconstruction error is summarized in Table 7.

Table 6. Structural comparison of SDM parameters reported by different extraction methods.

Device	Method	Author	I_O (A)	I_{PV} (A)	n	R_S (Ω)	R_P (Ω)
RTC-FRANCE	NMA	Easwarakhanthan (1986) [12]	3.22×10^{-7}	0.760	1.483	0.036	53.763
	ACPSBOP	Cubas (2017) [23]	2.92×10^{-6}	0.760	1.74	0.045	246.785
	GO	Ben Aribia (2023) [19]	3.23×10^{-7}	0.760	1.481	0.036	53.718
	m_YDSE	Alqadi (2025) [21]	1.95×10^{-6}	0.763	1.69	0.024	31.504
	Proposed	Proposed (2026)	2.79×10^{-9}	0.760	1.116	0.075	333.333
KC200GT	NR	Villalva (2009) [2]	9.82×10^{-8}	8.210	1.300	0.221	415.405
	GO	Ben Aribia (2023) [19]	4.31×10^{-8}	8.192	1.248	0.004	15.103
	m_YDSE	Alqadi (2025) [21]	1×10^{-9}	8.079	1.046	0.256	2124.42
	Proposed	Proposed (2026)	2.18×10^{-9}	8.2223	1.076	0.3	200

Table 7. Comparative RMSE evaluation of reconstructed I–V curves.

Device	Method	RMSE (A)	NRMSE (%)
RTC-France	Proposed	6.2×10^{-3}	0.82
KC200GT	Proposed	72×10^{-3}	0.88
INAOE	Proposed	0.41×10^{-3}	1.42
SP450M	Proposed	1.74×10^{-1}	1.50

For the RTC-France case, the proposed method used a digitized I-V curve as the graphical reference. The curve was not reconstructed only from the three characteristic points I_{SC} , V_{OC} , and P_{max} . These points were used as operating constraints for the analytical closure of the SDM, whereas the RMSE was evaluated against the digitized I-V curve. This distinction is important because a curve artificially redrawn from only three points would not provide a valid basis for comparison with methods fitted to multi-point datasets.

As summarized in Table 6, one of the earliest studies on parameter extraction for the RTC-France solar cell was reported by Easwarakhanthan et al. (1986) [12], who used a nonlinear minimization approach. Because of its historical relevance and its broad influence on subsequent studies, this work is frequently considered a reference point for later analytical and optimization-based methods. More recent metaheuristic approaches, such as the growth optimizer (GO) introduced by Ben Aribia et al. [19], converge toward similar electrical behavior for this benchmark device, although the individual parameter values may differ.

Cubas et al. [4,5] proposed analytical formulations derived from the characteristic operating points of the device. When applied to the RTC-France cell, their method produced parameter combinations that differ in magnitude from those obtained through minimization-based approaches, while still yielding comparable I-V reconstructions. This variability is consistent with the well-documented non-uniqueness of the SDM parameter space, in which different combinations of R_S , R_P , n , and I_0 can reproduce very similar electrical characteristics [3,6,21].

Optimization-based techniques reported in [20–22] have shown reliable convergence for laboratory-scale cells such as RTC-France. However, when extended to commercial modules, including the KC200GT, a larger dispersion in the extracted resistive parameters becomes apparent. For example, the value of $R_P \approx 15 \Omega$ reported in [19] for the KC200GT implies relatively high leakage currents and recombination-related losses, which are not commonly associated with well-manufactured crystalline silicon modules operating under STC [1,16,17]. This does not invalidate the optimization framework itself, but it does highlight the sensitivity of SDM parameter estimation to the selected objective function and weighting strategy.

Recent stochastic methods, such as enhanced generalized normal distribution optimization [20] and bio-dynamics grasshopper optimization [22], continue to use reference devices such as RTC-France and KC200GT for validation. This practice reflects a broader limitation in the field: the limited availability of complete experimental I-V datasets from manufacturers, which restricts independent validation beyond the information contained in datasheets.

Ghetas and Elshourbagy [20] reported parameter sets for RTC-France that follow trends similar to those found in earlier studies, reinforcing the apparent robustness of global-search strategies for single-cell devices. Likewise, Jabari et al. [22] applied bio-dynamic optimization to both cells and modules. Although satisfactory agreement was obtained for solar cells, the extension to multi-cell modules led to greater dispersion in R_P and I_0 , illustrating the stronger parameter coupling introduced by series-connected configurations.

For the KC200GT module, Villalva et al. [2] employed the Newton–Raphson method. Although iterative approaches can provide stable solutions under suitable initialization, convergence remains strongly dependent on the initial parameter estimates and on operating conditions such as N_S , T , and G , as discussed in subsequent analytical comparisons [3,6]. This sensitivity may reduce robustness when the method is generalized across different devices.

Alqadi et al. (2025) [21] introduced a hybrid metaheuristic inspired by Young’s double-slit experiment and combined it with differential evolution for parameter estimation. For the RTC-France cell, the reported parameters include comparatively low values of R_S and R_P , with deviations approaching 50% relative to several earlier analytical studies. Under

this configuration, the ideality factor tends toward values similar to those reported by Cubas et al. [5], suggesting that the optimization process compensates for reduced resistive losses through adjustment of the exponential term.

For the KC200GT module, the results reported by Alqadi et al. [21] indicate a photocurrent approximately 130 mA lower than the datasheet short-circuit current, together with a very high R_p in the kilo-ohm range. Mathematically, this combination can improve curvature fitting while maintaining convergence; physically, however, it implies near-ideal insulation behavior that may not be fully consistent with practical interconnection losses in a 54-cell module [16–18]. In contrast, the values of R_s and n reported in [21] remain close to those obtained with the proposed graphical–deterministic method.

3.1. Comparative Structural Analysis

The comparative evaluation of the proposed graphical–deterministic method was carried out using four benchmark devices widely reported in the photovoltaic modeling literature: the RTC-France silicon cell, the KC200GT module, the INAOE laboratory-fabricated c-Si cell, and the SP450M commercial module. These devices have been repeatedly used for validation in both analytical and optimization-based parameter extraction studies [2–6,12,19–23], which makes them suitable for structural comparison under consistent operating conditions.

Unlike purely optimization-based approaches, which usually minimize a global error metric such as RMSE over the full I–V curve [3,19–22], the present method separates the extraction process into two clearly differentiated stages: (i) local differential estimation of R_s and R_p , and (ii) analytical closure of the single-diode model (SDM) through the automatic determination of I_0 , I_{PV} , and n , subject to the physical constraint $1 \leq n \leq 2$, as commonly adopted in SDM-based studies for crystalline silicon devices [1,2,16,17]. This structural decoupling helps reduce the coupling between resistive and exponential terms during the parameter initialization stage.

3.1.1. Quantitative Error Comparison

To ensure an objective comparison, the reconstructed curves were quantitatively evaluated against the digitized reference curves obtained from manufacturer datasheets or reported experimental plots [8,9,12–14]. The root mean square error (RMSE) was calculated as

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (I_{\text{sim},i} - I_{\text{ref},i})^2}, \quad (37)$$

and the normalized RMSE was obtained with respect to the short-circuit current:

$$\text{NRMSE} = \frac{\text{RMSE}}{I_{\text{SC}}} \times 100\% \quad (38)$$

Because the proposed method uses graphical data, the RMSE values include not only the deviation associated with the SDM reconstruction but also the uncertainty introduced during digitization. Therefore, the reported RMSE and NRMSE values should be interpreted as reconstruction errors relative to the digitized graphical reference, not necessarily as errors relative to the original raw experimental dataset.

The consolidated results are summarized in Table 7.

For the RTC-France cell, the normalized reconstruction error remained below 1%, with $\text{RMSE} = 6.2 \times 10^{-3}$ A and $\text{NRMSE} = 0.82\%$, indicating good agreement with the digitized graphical reference. However, because several methods reported in the literature use the classical tabulated RTC-France dataset, this result should be interpreted as the reconstruction error of the proposed graphical workflow rather than as a direct one-to-one comparison with approaches operating on original numerical datasets [3,5,6,12,21,23]. The reconstructed

curve reproduces the quasi-linear low-voltage region influenced by R_p , the exponential knee governed by n , and the curvature near V_{OC} , where the effect of R_s becomes more relevant. The agreement across these operating regions supports the internal consistency between the local differential slope estimation and the analytical closure of the SDM.

A similar level of agreement was obtained for the KC200GT module, with $RMSE = 72 \times 10^{-3}$ A and $NRMSE = 0.88\%$. This result is relevant because the KC200GT module contains 54 series-connected cells, which increases the sensitivity of the exponential term $nN_s V_T T$ in the SDM formulation [1,2]. Despite this amplification, the proposed graphical-deterministic extraction remained stable without stochastic optimization or multi-parameter iterative fitting. This behavior is consistent with analytical and non-iterative SDM formulations based on characteristic operating points [3–6,23].

The INAOE laboratory-fabricated cell exhibited a higher normalized error, with $RMSE = 0.41 \times 10^{-3}$ A and $NRMSE = 1.42\%$. Unlike the RTC-France and KC200GT cases, the analytical closure converged to the lower bound of the admissible ideality factor interval, $n = 1.00$, when the updated slope-derived values $R_s = 7.8 \Omega$ and $R_p = 913 \Omega$ were used. The reconstructed maximum power was approximately 3.70% lower than the experimental reference value. This deviation is consistent with the expected influence of contact resistance, non-optimized metallization pathways, and graphical slope uncertainty in laboratory-scale photovoltaic devices [3,16,17,24]. Therefore, the INAOE cell should be interpreted as a sensitivity case rather than as a perfect energetic closure case.

The SP450M module required a specific interpretation because of its half-cut architecture. The manufacturer reports this module as a 144-cell device [15]; however, for the SDM implementation, the electrical configuration was represented using an equivalent series cell number $N_{s,eq} = 72$. This avoids interpreting the 144-half-cell designation as 144 full-size cells electrically connected in series. Under this configuration, and using the slope-derived values $R_s = 0.68 \Omega$ and $R_p = 90.909 \Omega$, the reconstructed curve yielded $RMSE = 1.74 \times 10^{-1}$ A and $NRMSE = 1.50\%$ with respect to the digitized graphical I–V curve. The reconstructed maximum power was $P_{max,sim} = 391.04$ W, which agrees with the maximum power region observed in the digitized graphical curve. Nevertheless, this value remains below the nominal datasheet value of 450.18 W, corresponding to an energetic deviation of approximately -13.14% . Therefore, the SP450M case should be interpreted as a combined graphical/datasheet consistency and equivalent series cell number sensitivity case, rather than as a simple failure of the SDM formulation.

3.1.2. Structural Interpretation Across Methods

Parameter sets reported in the literature for the same photovoltaic devices often differ substantially, even when the reconstructed I–V curves show close visual agreement [3,19,20,23]. This non-uniqueness arises from the intrinsic coupling among R_s , R_p , n , and I_0 within the exponential structure of the SDM [5,6,21]. As a result, optimization-based methods may converge to different parameter combinations depending on the objective function, initialization strategy, and constraint-handling scheme.

In contrast, the proposed graphical-deterministic procedure first estimates the resistive contributions from local differential information before resolving the exponential parameters. This approach reduces the dimensionality of the closure problem, but it does not imply that R_s and R_p are mathematically isolated from the rest of the SDM. The slope-derived values should be understood as effective estimates whose accuracy depends on the graphical quality of the I–V curve and on the selected local regression window. This reduces the nonlinear closure problem to a single scalar equation in n , which is solved within the physically admissible interval $1 \leq n \leq 2$ [16,17]. Under this framework, the resulting parameter sets remain physically interpretable, particularly for crystalline silicon devices.

The comparative RMSE results therefore suggest that, for single cells and moderate series cell configurations, the proposed method can achieve low normalized reconstruction errors without stochastic optimization. For the SP450M module, represented in the SDM using $N_{S,eq} = 72$, the reconstructed curve also showed improved agreement with the digitized graphical reference, with NRMSE = 1.50%. Nevertheless, the remaining deviation from the nominal datasheet maximum power indicates that half-cut high-power modules are particularly sensitive to the consistency among the graphical I–V curve, the nominal operating points, and the equivalent series cell representation. More broadly, the structural decoupling strategy helps reduce parameter cross-dependence during initialization while preserving physical plausibility.

These findings support the analytical robustness of the proposed approach and, at the same time, clarify its sensitivity limits in large-scale module configurations.

3.1.3. The Positioning of the Proposed Method Within the Literature

The graphical–deterministic procedure developed in this work can be positioned as a complementary approach between two established families of SDM parameter extraction techniques: analytical formulations based on characteristic operating point equations [4–7,23] and global optimization frameworks based on stochastic or metaheuristic search strategies [20–22].

Its main distinction is that it explicitly incorporates the graphical digitization stage into the extraction chain. Therefore, the method is not proposed as a replacement for analytical closed-form or optimization-based approaches, but as a traceable workflow for cases in which the available information is graphical rather than tabulated.

Unlike metaheuristic algorithms, the proposed method does not depend on multi-parameter stochastic exploration or iterative convergence toward a global optimum. Instead, the solution is obtained through a structured two-stage process in which the resistive parameters are first estimated from local differential information extracted from the calibrated I–V curve, followed by analytical closure of the exponential terms under physically admissible constraints.

At the same time, the method differs from purely algebraic approaches because it explicitly incorporates local slope information taken from the curve itself. This feature enables a direct relationship to be established between the geometric behavior of the curve in specific operating regions, particularly near I_{SC} and V_{OC} and the resistive elements of the model, thereby helping to reduce the degree of compensation among R_S , R_P , and n . Such cross-compensation effects have been widely documented in comparative reviews of SDM extraction techniques, where multiple parameter combinations can reproduce similar macroscopic electrical behavior [3,6,21].

The structural comparison presented in Section 3.1 indicates that the proposed procedure provides resistive parameters within physically plausible ranges for crystalline silicon devices [1,2,16–18], ideality factor values constrained to the interval $1 \leq n \leq 2$, consistent with commonly adopted assumptions for silicon-based SDM studies [1,2,16,17], energetic consistency at the maximum power point without additional iterative refinement, and reduced parameter interdependence during the initial estimation stage.

These characteristics do not imply superiority over optimization-based methods. Rather, they show that a deterministic, slope-informed analytical strategy can achieve comparable reconstruction accuracy while preserving parameter interpretability. Accordingly, the proposed approach should be understood as a complementary alternative within the broader landscape of SDM identification methodologies, particularly in scenarios where transparency, physical consistency, and reduced algorithmic complexity are desirable.

4. Conclusions

This work presented a graphical–deterministic procedure for single-diode model (SDM) parameter extraction based on calibrated I–V curve digitization, local differential analysis, and analytical closure under physically admissible constraints. The proposed approach does not modify the SDM itself; rather, it integrates the graphical-to-numerical conversion stage into a parameter extraction workflow. In this sense, the main contribution of the method is the traceable connection between manufacturer-reported or published graphical I–V curves and deterministic SDM parameter identification.

The resistive parameters were obtained as effective local slope estimates rather than as fully decoupled physical quantities. This distinction is important because, in real photovoltaic devices, the local slopes near I_{SC} and V_{OC} may still contain coupled contributions from the resistive branches and the diode dynamic conductance. By explicitly treating R_S and R_P as slope-derived estimates, the method provides a physically interpretable starting point for the analytical closure of the remaining SDM parameters.

The RTC-France cell and the KC200GT module showed stable analytical closure, with reconstructed maximum power values close to the corresponding reference values. These results indicate that the proposed workflow can provide accurate curve reconstruction when the local slope regions are sufficiently resolved in the graphical source. In particular, the KC200GT module maintained strong energetic consistency despite its 54-cell series configuration, supporting the applicability of the method to commercial photovoltaic modules under suitable graphical conditions.

The INAOE laboratory-fabricated cell and the SP450M module revealed the sensitivity limits of the graphical slope-based procedure. For the INAOE cell, the updated slope-derived resistive values led to a reconstructed maximum power approximately 3.70% lower than the reference value. This behavior is consistent with the expected influence of contact resistance, non-optimized metallization, and graphical slope uncertainty in laboratory-scale photovoltaic devices. For the SP450M module, the use of an equivalent series cell number $N_{s,eq} = 72$ improved consistency with the digitized graphical curve, yielding $P_{max,sim} = 391.04$ W. However, this value remains below the nominal datasheet value of 450.18 W, revealing a graphical/datasheet consistency issue and the sensitivity of the method to the equivalent electrical representation of half-cut modules.

These findings show that the proposed method should not be interpreted as a replacement for optimization-based or full experimental parameter extraction techniques. Instead, it provides a complementary framework for cases in which complete numerical I–V datasets are unavailable and the available information is primarily graphical. Its main advantages are methodological transparency, reduced dependence on stochastic search, and explicit traceability of the graphical calibration and local slope estimation stages.

The main limitation of the method is its dependence on the graphical quality of the source curve. Low-resolution images, thick curve traces, compressed datasheet figures, poorly defined axes, and subjective local window selection can increase the uncertainty of the extracted resistive parameters. This effect is especially relevant for nearly horizontal regions near I_{SC} , where current variation may approach the pixel-resolution limit, and for high power modules with half-cut equivalent electrical configurations, where small slope deviations near V_{OC} can be amplified in the maximum power region.

Future work should focus on expanding the validation database, incorporating experimentally measured I–V curves under controlled irradiance and temperature, evaluating multi-irradiance extraction strategies for R_S , and extending the uncertainty propagation analysis to different image resolutions, digitization operators, and photovoltaic technologies. These steps would allow the robustness and applicability range of the graphical–deterministic framework to be assessed beyond the representative devices considered in this study.

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