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Optimized parameter extraction techniques for enhanced performance evaluation of organic solar cells

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ABSTRACT

The global energy landscape is in the midst of a transformative shift, compelled by the urgent need to reduce our reliance on fossil fuels and embrace eco-friendly alternatives. Organic photovoltaics (OPVs) have emerged as a promising alternative, offering the distinct advantage of performing well in low-light conditions, including indoor environments. Extensive research and development efforts are dedicated to realizing the full potential of OPVs as adaptable, cost-effective, and environmentally friendly solar energy solutions. This paper conducts a thorough examination of the intricate characterization of organic solar cells, with a specific emphasis on crucial parameters like power conversion efficiency, open-circuit voltage, and fill factor. The study utilizes a single diode model to simulate these cells' behavior, employing a meticulous process for parameter extraction. This method leverages Origin software and Python programming, incorporating open-source packages to ensure robust validation. This systematic and rigorous approach significantly enhances our comprehension of OPVs and plays a substantial role in optimizing their performance. In essence, this research represents a significant step forward in advancing sustainable energy technologies, laying a foundation for a greener and more environmentally conscious future.

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NOMECLATURE

G	: Solar irradiance (W/m^2)	P_{max}	: Maximum electrical power
I	: Output current	R_L	: Electrical load
I_L	: Photocurrent	R_S	: Series resistance
I_{MPP}	: Current at maximum power point	R_{SH}	: Shunt current through R_{SH}
I_{SC}	: Short circuit current	T	: Temperature
I_0	: Reverse saturation current of diode	I_{01}	: Reverse saturation current of diode D_1
n	: Ideality factor of diode D_1	I_{02}	: Reverse saturation current of diode D_2
n_1	: Ideality factor of diode D_2	V	: Voltage generated
n_2	: Ideality factor of diode	V_{MPP}	: Voltage at the maximum power point
V_{TT}	: Thermal voltage	V_{OC}	: Open circuit voltage

N_S	: Number of cells	D_1 & D_2	: Diode
e	: Charge of electron	q	: Charge
V_D	: Diode voltage	k	: Boltzmann constant
V_{PV}	: Output voltage	I_s	: Reverse-bias saturation current
CSV	: Comma separated values		

1. INTRODUCTION

The global energy scenario is experiencing a significant transformation, driven by the need for sustainable practices and environmental responsibility. While fossil fuels have historically dominated the energy mix, there is a growing shift towards cleaner alternatives such as renewable energy sources. This transition is supported by advancements in technology, declining costs, and favorable policies. Efforts to improve energy efficiency, electrify various sectors, and promote decentralized energy systems are gaining momentum. Furthermore, addressing energy access and equity remains a crucial aspect of global energy initiatives. By embracing responsible energy practices, we can mitigate climate change, reduce greenhouse gas emissions, and pave the way for a greener and more sustainable future [1]. Solar photovoltaics (PV) have a crucial role in the global energy scenario, contributing to the transition towards cleaner and sustainable energy sources. Solar PV systems harness sunlight to generate electricity, reducing dependence on fossil fuels and mitigating greenhouse gas emissions. With falling prices and cost competitiveness, solar PV is increasingly accessible and economically viable. Its scalability, diverse applications, and integration with energy storage make it a versatile solution for decentralized energy generation, enhancing energy independence and resilience. Moreover, solar PV stimulates job creation, supports local economic development, and fosters a more sustainable and resilient energy future [2].

Organic photovoltaics (OPVs) present an alternative to conventional solar PV with distinct advantages in the global energy landscape. Their flexibility and versatility enable integration into various applications like flexible solar panels and wearable electronics. OPVs offer scalability and low-cost production using solution-based techniques, making solar energy more accessible, especially in emerging markets. They demonstrate improved performance under low light conditions, expanding their utility in indoor environments. With lower environmental impact and potential recyclability, OPVs align with sustainable practices. Although efficiency and stability are areas for ongoing improvement, OPVs hold promise as they can be seamlessly integrated into building design and complement traditional PV technologies. Ongoing research and development efforts continue to enhance OPVs' potential in the overall energy scenario as a flexible, cost-effective, and environmentally friendly solution for solar energy generation [3]. Organic solar cells, also known as OPVs, are a type of solar cell technology that utilizes organic materials, typically polymers or small molecules, to convert sunlight into electricity. Unlike traditional inorganic solar cells, which predominantly use silicon as the active material, organic solar cells rely on organic semiconductors to absorb light and generate electrical current. These organic materials can be deposited onto flexible substrates using low-cost manufacturing techniques such as printing or coating, enabling the production of lightweight, flexible, and potentially transparent solar panels. Organic solar cells offer the potential for low-cost and large-scale production, as well as unique applications in areas such as wearable electronics, building-integrated photovoltaics (BIPV), and other emerging technologies. Ongoing research and development efforts aim to improve organic solar cells' efficiency, stability, and commercial viability to enhance their role in the renewable energy landscape [3].

Characteristics parameters of organic solar cells, also known as OPVs, include power conversion efficiency (PCE), open-circuit voltage (V_{OC}), short-circuit current (I_{SC}), fill factor (FF), external quantum efficiency (EQE), stability and degradation, material absorption range, and manufacturing cost. PCE represents the ability to convert sunlight into electricity, while V_{oc} and I_{sc} indicate the maximum voltage and current output, respectively. FF quantifies charge extraction efficiency, and EQE measures the percentage of incident photons converted to charge carriers. Stability, material absorption range, and manufacturing cost are also essential considerations. Evaluating and optimizing these parameters enables the assessment of organic solar cells' performance, efficiency, stability, and cost-effectiveness, promoting their potential as a sustainable and economically viable solution for renewable energy generation [4], [5]. Efficiency is determined by the PCE of the cell, which is expressed as a percentage. Higher PCE values indicate more efficient energy conversion. The efficiency of organic solar cells has been steadily improving over the years, with current state-of-the-art OPVs achieving PCE values exceeding 18%. This progress is attributed to advancements in organic materials, device engineering, and fabrication techniques. Researchers are continuously exploring novel materials and device architectures to enhance light absorption, charge transport, and charge extraction within organic solar cells. Efforts are also focused on reducing energy losses due to non-radiative recombination and improving the stability of organic solar cells. Increasing efficiency is crucial for making organic solar cells a competitive alternative to traditional inorganic solar cells and accelerating their commercial adoption as a sustainable and efficient renewable energy technology [6].

Accurate characterization of OPV solar cells is indispensable for predicting their current-voltage (I-V) traits and extracting essential intrinsic parameters. This process is pivotal for comprehending the fundamental physics and optimizing the overall performance of these devices. Leveraging sophisticated computational methodologies and mathematical models, researchers can effectively simulate the operational behavior of OPVs across diverse conditions. This modelling framework facilitates the precise determination of critical parameters, including open-circuit voltage, short-circuit current, fill factor, and power conversion efficiency. The I-V attributes derived from modelling can be corroborated by empirical measurements, thereby enhancing the credibility and precision of the models. Ultimately, the utilization of modelling techniques for OPV solar cells constitutes an essential instrument, fostering insights into their operational characteristics, steering advancements in design, and expediting their integration into real-world applications within the renewable energy sector [7], [8]. Figure 1, the single diode model, as expounded in the preceding response, stands as a valuable mathematical asset in emulating the current-voltage (I-V) traits of OPV solar cells. This model portrays the OPV cell as an analogous electrical circuit comprising a solitary diode, encompassing the pivotal charge transport and recombination mechanisms. By assimilating parameters garnered from both modelling exercises and empirical data, the single diode model adeptly anticipates the I-V curve of the OPV cell across varied operational scenarios. This model lays the groundwork for refining crucial performance indicators such as open-circuit voltage, short-circuit current, fill factor, and power conversion efficiency. While the single diode model streamlines the intricate physics inherent in OPV cells, more advanced models are concurrently being refined to encompass supplementary phenomena. Notwithstanding, the single diode model endures as an efficient and extensively employed instrument for comprehending and enhancing the operational characteristics of OPV devices [9]–[12].

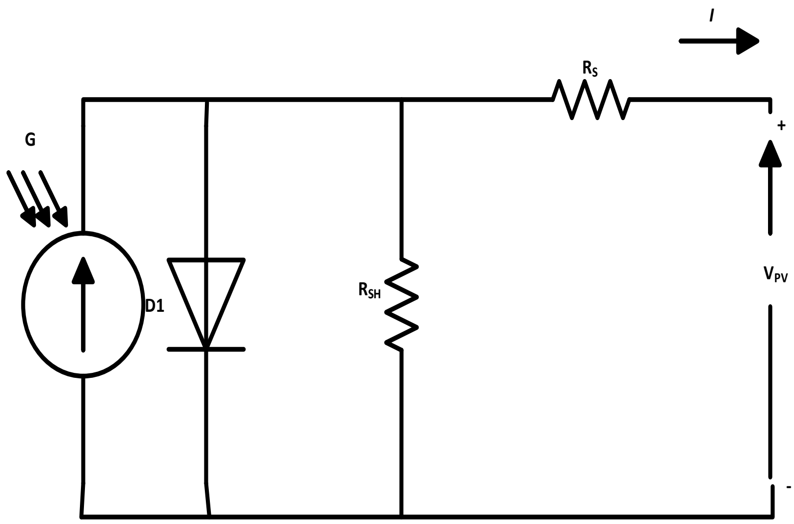

Figure 1. OPV model with one diode

$$I = I_L - I_o\left[e^{\frac{V+IR_{SH}}{nT}} - 1\right] - \frac{V+IR_S}{R_{SH}} \quad (1)$$

Figure 2, the dual diode model serves as an advanced mathematical framework employed to simulate the I-V attributes inherent to OPV solar cells. This model integrates a pair of diodes to encapsulate the intricate charge transport and recombination mechanisms within the device. One diode encapsulates bulk charge transport and recombination, while the other diode delineates charge transfer and recombination transpiring at interfaces. Through the consideration of diverse parameters and a precise portrayal of the physical dynamics of the OPV cell, the dual diode model furnishes an accurate emulation of the I-V curve. In doing so, it optimizes crucial performance metrics encompassing open-circuit voltage, short-circuit current, fill factor, and power conversion efficiency. Despite introducing augmented intricacy, this model enriches the comprehension and design of OPV devices [9]–[12].

$$I = I_L - I_{01}\left(e^{\frac{V+IR_{SH}}{N_S n1 V_T}} - 1\right) - I_{02}\left(e^{\frac{V+IR_{SH}}{N_S n2 V_T}} - 1\right) - \frac{V+IR_S}{R_{SH}} \quad (2)$$

The parameter extraction process for organic solar cells is essential for accurately determining key device parameters that characterize their performance. It involves a combination of experimental measurements, electrical characterization techniques, and numerical modelling. Through I-V measurements under various illumination conditions, parameters such as V_{OC}, I_{SC}, FF, and PCE are directly determined. Numerical models, including the single diode or double diode models, complement experimental data by extracting intrinsic parameters like series resistance, shunt resistance, and ideality factor. The accurate extraction of these parameters aids in understanding device performance, guiding optimization efforts, and facilitating the design of more efficient and reliable organic solar cells [13]. In this paper, a single diode model of an organic solar cell has been utilized for the purpose of parameter extraction. The extraction process consists of two main steps: initially, the solar I-V model was employed in the Origin software to extract the parameters, followed by validation using the Brano *et al.*'s model [14], [15]. To implement this model, Python programming language was employed, and open-source packages such as *scipy.optimize.least_square* were utilized. The parameter extraction methodology involved the use of the solar I-V model in the Origin software. This model allowed for the determination of various key parameters of the organic solar cell. Once the parameters were obtained, this model was employed to validate the extracted values. This model, implemented in Python, facilitated the verification of the extracted parameters and ensured the reliability of the results. To accomplish the implementation of this model in Python, several open-source packages were utilized. One such package, *scipy.optimize.least_square*, provided optimization algorithms for minimizing the residuals between the experimental and simulated data. By employing these algorithms, the accuracy of the parameter extraction process was enhanced. Further details and explanations regarding the entire working process will be elaborated in the subsequent sections of the paper. These sections will provide a comprehensive understanding of the methodology employed, the steps taken, and the specific details related to the parameter extraction and validation process. Overall, this paper presents a detailed and systematic approach to parameter extraction in organic solar cells, utilizing a single diode model and validating the results through this model implemented in Python. The use of open-source packages and software tools ensures the reproducibility and transparency of the methodology, thereby enhancing the credibility of the obtained results.

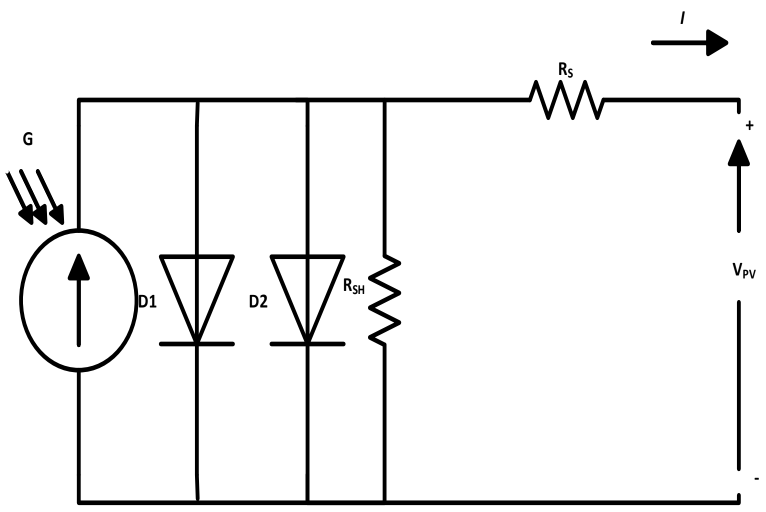

Figure 2. OPV model with double diode

The investigation pertaining to parameter derivation in organic solar cells through the utilization of the single diode model has predominantly revolved around devising precise and streamlined techniques to delineate the electrical attributes of these systems. The single diode model delineates an organic solar cell as a diode interconnected in parallel with a resistor, with its parameters ascertained by synergizing empirical measurements and mathematical simulation [16]. One commonly employed technique for parameter extraction is the fitting of I-V curves. Researchers compare the experimental I-V characteristics of the solar cell with the predictions of the single diode model to determine the values of the model parameters. This approach has been extensively utilized in numerous studies and provides valuable insights into the performance and efficiency of the device [17]. The scholarly literature on parameter extraction of organic solar cells using the single diode model highlights the diverse approaches employed to characterize the electrical properties and optimize the performance of these devices. Experimental measurements, mathematical modelling, and optimization techniques all play crucial roles in advancing the understanding and development of organic solar cell technologies. The process of parameter extraction begins with the acquisition of I-V curves, which describe the relationship between the current passing through the solar cell and the voltage applied across it. These experimental measurements serve as the basis for comparing with the predictions of the single diode model. The model represents the solar cell as a diode in parallel with a resistor, capturing the essential electrical characteristics of the device [18]. In the pursuit of parameter extraction within the context of the single diode model, investigators employ the utilization of curve fitting methodologies. Empirical I-V curves are harmonized with theoretical I-V curves produced by the model, the objective being to minimize disparities between the two datasets. This fitting procedure serves to unveil pivotal parameters, encompassing the diode ideality factor, series resistance, shunt resistance, and photocurrent. The diode ideality factor provides insight into the efficacy of charge carrier transportation across the diode junction within the solar cell. The series resistance accommodates resistive losses transpiring within the device, while the shunt resistance encapsulates inadvertent parallel pathways permitting current to circumvent the active region of the solar cell. The photocurrent parameter quantifies the magnitude of current generated by the solar cell under the influence of illumination [19]. While I-V curve fitting is a widely used approach, researchers have also explored alternative methods such as impedance spectroscopy (IS) analysis. IS analysis involves applying an alternating current (AC) signal with varying frequencies to the solar cell and measuring the resulting impedance. The impedance response provides information about the device's electrical properties, including the series resistance, shunt resistance, and capacitance. By analyzing the impedance spectra obtained from IS measurements, researchers can extract additional parameters that contribute to a more comprehensive understanding of the solar cell's behavior The series resistance represents the resistive losses within the device and affects its overall performance. The shunt resistance accounts for any parallel paths that allow current to bypass the active region, leading to reduced efficiency.

The capacitance parameter reflects the energy storage capability of the solar cell [20]. Furthermore, researchers have turned to advanced optimization algorithms to improve the efficiency and accuracy of parameter extraction. Genetic algorithms and particle swarm optimization are two examples of optimization techniques employed in this context. These algorithms search for the best-fit values of the parameters by iteratively modifying them and evaluating the resulting simulated I-V curves or impedance spectra against the experimental data [21], [22]. In [23] genetic algorithms mimic the process of natural selection, where a population of potential solutions evolves over generations. The fittest solutions, which exhibit the closest match to the experimental data, are more likely to be selected for subsequent iterations [24]. Particle swarm optimization, on the other hand, simulates the movement of particles within a multidimensional parameter space. Each particle represents a potential solution, and their collective behavior leads to the identification of optimal parameter values. By employing these optimization algorithms, researchers aim to overcome the challenges associated with manual or exhaustive search methods. These techniques facilitate a more efficient exploration of the parameter space and help identify optimal solutions that may not be immediately apparent through traditional approaches.

In the realm of parameter extraction for organic solar cells through the utilization of the single diode model, a diverse array of techniques is embraced with the intention of achieving precise and streamlined characterization of the electrical attributes of these devices. The amalgamation of strategies such as I-V curve fitting, impedance spectroscopy analysis, and optimization algorithms collectively propels the progression of our comprehension and the evolution of technologies relating to organic solar cells. These methodologies collectively empower researchers to deduce critical model parameters' values, enhance the efficacy of organic solar cells, and ultimately catalyze the widespread integration of this sustainable energy technology.

2. METHOD

Numerical techniques, also known as numerical methods, refer to mathematical algorithms and procedures used to solve problems and perform calculations using numerical approximations. These techniques are employed when analytical solutions are difficult or impossible to obtain, or when dealing with complex systems or large amounts of data. Numerical techniques involve translating mathematical models or problems into a computational form, where numerical approximations and algorithms are applied to obtain solutions or results. These methods rely on iterative processes, where calculations are repeated and refined to converge towards an accurate solution. Numerical techniques play a crucial role in the study and optimization of organic solar cells. These techniques are employed to model, simulate, and analyze the behavior of organic solar cells, as well as to optimize their performance. Here are some ways in which numerical techniques are used for organic solar cells.

Device modelling and simulation: Numerical techniques allow researchers to develop mathematical models that describe the behavior of organic solar cells. These models take into account various physical and electrical phenomena, such as charge generation, transport, recombination, and light absorption. By solving the mathematical equations representing these phenomena using numerical methods, researchers can simulate the performance of organic solar cells under different operating conditions, material properties, and device architectures. This helps in understanding the underlying physics and optimizing the design of organic solar cells.

Parameter extraction: Numerical techniques are utilized to extract the parameters of the mathematical models used to describe organic solar cells. Experimental data, such as I-V characteristics, are fitted to the mathematical models using optimization algorithms. Numerical methods, such as least squares fitting, are employed to minimize the differences between the experimental data and the simulated results, thereby determining the values of key parameters that characterize the organic solar cell.

2.1. Shockley diode equation using curve fit module

In study [25], the Shockley diode equation is a mathematical model that describes the behavior of a diode under forward bias. It relates the current flowing through a diode (I) to the voltage across the diode (V). The equation is given as (3), (4):

$$I = I_s\left(e^{\frac{V}{nV_T}} - 1\right) \tag{3}$$

$$I = I_L - I_0\left[e\ \left(\frac{qV_D}{nkT}\right) - 1\right] - \frac{V_D}{R_{SH}} \tag{4}$$

where $V_D = V_{PV} + R_s I$. The Shockley diode equation helps us understand how the I-V characteristics of a diode change with varying voltage and other factors.

2.2. Curve fit module in python

The curve fit module is a part of the *scipy.optimize* library in Python. It provides a method for fitting a mathematical model to a set of data points using a least-squares optimization algorithm. In simpler terms, it allows us to find the best-fitting parameters for a given equation to match a given set of data.

2.3. Fitting the I-V data of a diode

Certainly, when fitting current-voltage (I-V) data of a diode using a curve fit module, several steps are involved to ensure accurate modeling. Initially, the data is prepared, often involving normalization and cleaning to remove any outliers or inconsistencies. Then, selecting an appropriate mathematical model such as the Shockley diode equation is crucial. Finally, the curve fitting process involves adjusting parameters within the chosen model to best align with the experimental data points, typically through iterative optimization techniques, resulting in a fitted curve that represents the behavior of the diode.

2.4. Model of Brano, based on single diode model

In the domain of solar cell research, a noteworthy contribution emerges from Brano in reference [14]. Brano introduces a pioneering technique designed to meticulously ascertain solar cell parameters. What distinguishes Brano's methodology is its resolute dedication to circumventing any oversimplifications or presumptions during the course of extracting the quintet of parameters delineated in (2). This innovative approach marks a departure by exclusively leaning upon routine technical data amassed under standard test conditions (STC), aligned with the constructs of a single-diode model. The crux of Brano's method lies in the formulation of five distinct mathematical equations. These equations have been carefully designed to calculate the correct values of the five parameters required for the single-diode model. Through the concurrent solution of these equations, Brano's method enables the extraction of the previously unknown parameters, providing a robust and accurate characterization of the solar cell's behavior. The formulation of these mathematical equations within Brano's method underscores the meticulousness and attention to detail of this innovative approach. Each equation takes into account specific aspects of the solar cell's electrical behavior, including current-voltage relationships, resistive losses, and the impact of temperature and irradiance variations. By simultaneously considering these multiple factors, Brano's method offers a comprehensive understanding of the solar cell's behavior and facilitates the determination of precise parameter values. The precise parameter values obtained through Brano's method allow for a deeper understanding of the underlying mechanisms governing solar cell operation. Consequently, researchers and engineers can optimize solar cell designs, develop more efficient manufacturing processes, and enhance the overall performance and integration of solar energy conversion technologies. In conclusion, Brano's method represents a significant advancement in solar cell research. By eliminating simplifications and assumptions, this innovative approach enables the extraction of the five critical parameters required for the single-diode model, based solely on the normal technical data collected under STC. Concurrently solving the formulated mathematical equations ensures the accuracy and reliability of the extracted parameter values. This breakthrough not only enhances our understanding of solar cell behavior but also holds immense potential for optimizing solar energy conversion technologies [15].

The foundational equation can be derived by utilizing the I_{SC} values. The premise rests on the assumption that the voltage equates to zero at the juncture of short-circuit current. Through the act of substituting these designated values into (1), the intended result shall be realized:

$$f_{n1}: \ I_L + \left[1 - e^{\left(\frac{I_{SC}R_S}{nT}\right)}\right] I_0 - \frac{I_{SC}R_S}{R_{SH}} - I_{SC} = 0 \tag{5}$$

The subsequent equation can be derived by employing the V_{OC} values. This derivation similarly rests on the presumption that the current corresponds to zero at the juncture of open-circuit voltage. Through the process of substituting these specified values into (1), the intended outcome will be achieved:

$$f_{n2}: \ I_L + \left[1 - e^{\left(\frac{V_{OC}}{nT}\right)}\right] I_0 - \frac{V_{OC}}{R_{SH}} = 0 \tag{6}$$

The third equation can be derived using the data from the maximum power point (MPP), where V represents V_{MPP} and I represent I_{MPP}. By substituting these values into (1), the desired outcome will be obtained:

$$f_{n3}: \ I_L + \left[1 - e^{\left(\frac{I_{MPP}R_S + V_{MPP}}{nT}\right)}\right] I_0 - \frac{I_{SC}R_S + V_{MPP}}{R_{SH}} - I_{MPP} = 0 \tag{7}$$

Subsequently, the fourth equation can be obtained by expressing equation in terms of V, where V represents V_{MPP} and I represents I_{MPP}:

$$f_{n4}: \frac{-nT - \left[e^{\left(\frac{I_{MPP}R_S + V_{MPP}}{nT}\right)}\right] I_0 R_{SH}}{nT(R_S + R_{SH}) + \left[e^{\left(\frac{I_{MPP}R_S + V_{MPP}}{nT}\right)}\right] I_0 R_{SH} R_S} + \frac{I_{MPP}}{V_{MPP}} = 0 \tag{8}$$

Lastly, the fifth equation of the model can be obtained by expressing. In this case, V represents V_{MPP} and I represents I_{MPP}:

$$f_{n5}: \frac{V_{MPP}nT\left[I_0 R_{SH} + I_L R_{SH} - 2V_{MPP} + \left[e^{\left(\frac{I_{MPP}V_{MPP}R_S + V^2{}_{MPP}}{V_{MPP}nT}\right)} I_0 R_{SH}\right] I_{MPP}V_{MPP}R_S - V_{MPP}(nT + V_{MPP})\right]}{V_{MPP}\left\{I_0 R_S R_{SH}\left[e^{\left(\frac{I_{MPP}V_{MPP}R_S + V^2{}_{MPP}}{V_{MPP}nT}\right)}\right] + nT(R_{SH} + R_S)\right\}} = 0 \tag{9}$$

3. RESULTS AND DISCUSSION
3.1. Extraction of data points from the graph

The graph image was prepared for analysis by removing irrelevant elements, such as labels or annotations that obstructed the curve. The pre-processed image was typically converted into a jpeg format to simplify the analysis. Then algorithm identifies the curve within the image by detecting its edges or contours. Edge detection algorithms, Canny edge detection, was employed to locate the boundaries of the curve accurately. Once the curve was detected, a tracing algorithm was used to follow its path and extract its points. This involved boundary following techniques to track the curve's trajectory. The traced curve was sampled at regular intervals or based on certain criteria to obtain a set of discrete points. The points represent the curve's coordinates in the digital space and can be stored as (x, y) pairs. The extracted points underwent additional processing steps, such as filtering or smoothing, to remove noise or irregularities introduced during the extraction process [26]–[28].

3.2. Fitting of I-V data using origin lab software

Data was imported the data into Origin Lab software by loading a file. After that a fitting function 'SolarIV' represented the mathematical model. After that, adjusting fitting parameters: Once the fitting function is selected, you need to adjust the initial values of the parameters. These parameters control the shape, position, and other characteristics of the curve. You can manually set initial values or let the software estimate them automatically. Origin Lab software was used for optimization algorithms to minimize the difference between the fitted curve and the actual data. It adjusts the parameters of the fitting function to find the best fit. You can choose different algorithms and customize fitting options based on your requirements. After that a fitting process, Origin Lab provides statistical measures to evaluate the quality of the fit, such as the coefficient of determination (R-squared), and root-mean-square error (RMSE) statistic. These measures help assess how well the fitted curve represents the data. Origin Lab generates a plot showing the original data points and the fitted curve. This allows you to visually assess the fit and make any necessary adjustments to the model or parameters. You can extract the fitted parameters, their uncertainties, and other relevant information for further analysis shown in Figures 3, 4 and 5.

3.3. Extraction of V_{MPP} and J_{MPP} from python

First, you need to import the I-V curve data into Python. This can be done using various libraries, such as NumPy or Pandas, from CSV files, Excel sheets, or directly through data arrays. Plot the I-V curve using a suitable plotting library like Matplotlib. This helps to visualize the characteristics of the PV device and locate the MPP on the graph. Identify the MPP on the I-V curve. The MPP corresponds to the point where the power output is maximized. You can use various peak detection algorithms available in Python to find this point. Once the MPP was detected, you can extract the corresponding voltage (V_{MPP}) and current (J_{MPP}) values from the I-V curve data. In Figures 6, 7 and 8, can present the extracted V_{MPP} and J_{MPP} values.

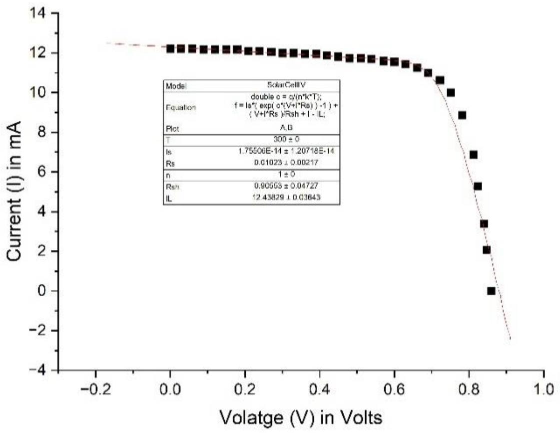

Figure 3. I-V characteristic of OSC [26]

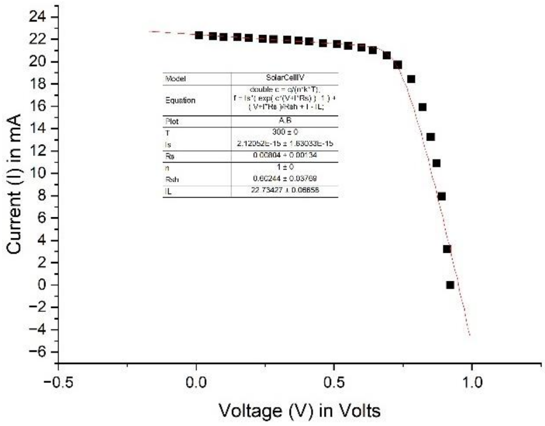

Figure 4. I-V characteristic of OSC [27]

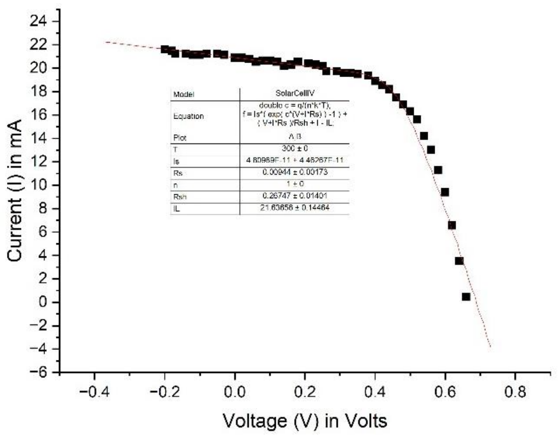

Figure 5. I-V characteristic of OSC [28]

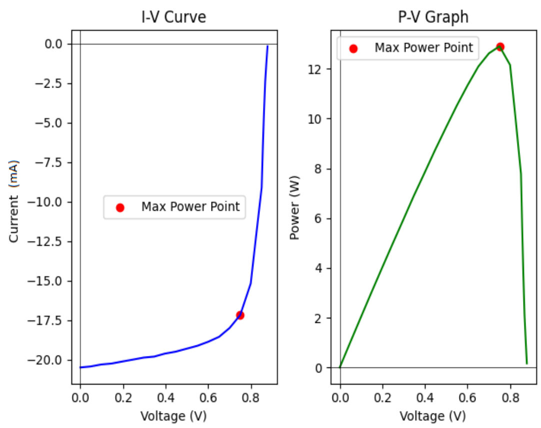

Figure 6. V_{mpp} and J_{mpp} of OSC [26]

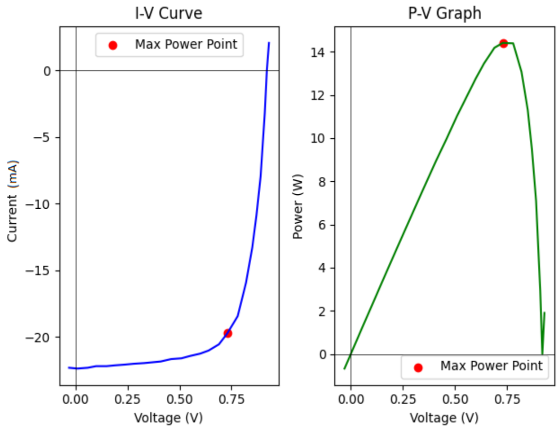

Figure 7. V_{mpp} and J_{mpp} of OSC [27]

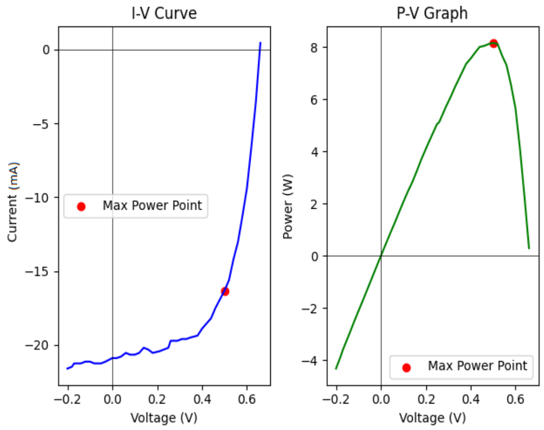

Figure 8. V_{mpp} and J_{mpp} of OSC [28]

3.4. Analysis of I-V data: fitting with Origin Lab, V_{MPP} and J_{MPP} extraction in python using least squares method

The least squares method is a mathematical technique utilized to determine the optimal solution for an over-determined linear equation system. In cases where the number of equations surpasses the count of unknown variables, an exact solution is often unattainable. The method's objective is to minimize the discord between the left-hand side (LHS) and right-hand side (RHS) of the equations. The LHS amalgamates variables and their coefficients, while the RHS accounts for constant terms. The distinction between LHS and RHS is termed the residual, gauging the error within each equation. Residual computation involves measuring the gap between the actual LHS value and the corresponding RHS value. Functioning through the minimization of the sum of squared residuals across all equations, the least squares method identifies variable values. This is accomplished by squaring the residuals and summing them, prioritizing substantial errors while penalizing smaller ones, culminating in an overall optimal fit. The mathematical pursuit revolves around minimizing the sum of squared differences (LHS-RHS) for all equations. Calculus techniques are harnessed to determine partial derivatives of the sum of squares concerning each variable, subsequently setting these derivatives to zero. Solving the resultant equation system generally involves matrix algebra, yielding the best-fit solution, as detailed in Table 1.

Table 1. Tabulation of the results

Parameters	Method I (Origin Lab Software)			Method II (Bruno *et al.*'s Model [14], [15])		
	Cell 1	Cell 2	Cell 3	Cell 1	Cell 2	Cell 3
I_S	$1.7551*10^{-14}$	$2.1205*10^{-15}$	$4.8099*10^{-11}$	$1.6541*10^{-14}$	$2.1004*10^{-15}$	$4.6089*10^{-11}$
R_S	0.0103	0.00841	0.0094	0.0113	0.0082	0.0095
n	1	1	1	1	1	1
R_{SH}	0.9055	0.6024	0.2675	0.9433	0.6039	0.2547
I_L	12.4383	22.7347	21.6366	12.4692	22.5065	21.5933

3.5. Discussion

We have employed a methodology encompassing the single diode model to deduce circuit parameters for organic solar cells, leveraging measurements of short-circuit current relative to thin active layers and an optical model. The resultant dataset is systematically organized in the table provided below. Employing this dataset, our coupled optoelectronic simulation yields an established lower threshold for efficiency, valuing at 12%. Our numerical analysis, upon integration of the measured current-voltage curve, effectively confirms circuit parameters aligning with the previously estimated 12% efficiency.

Our study delves into the electrical transport dynamics within an organic bulk-heterojunction solar cell, encompassing diverse experiments utilizing the single diode model and a consistent set of parameters. Notably, we observe accurate reproduction of steady-state effects within the current-voltage characteristics, alongside precise emulation of the transient photo-current response time dynamics. This accuracy is achieved through a simplified drift-diffusion model employing constant mobilities. We emphasize that intricate phenomena such as charge trapping, electric field-dependent mobilities, or CT-excitons are deemed nonessential to describe the solar cell scrutinized in this study. To optimize parameter extraction while minimizing the number of unknown variables, we advocate employing the simplest model, resorting to more complex models only if the initial approach proves inadequate. Advanced models, when warranted, can supplement the analysis by revealing additional parameters accessible through complementary experiments.

4. CONCLUSION

The future scope of the presented research involves several promising directions. The methodology for deriving model parameters, which reduces parameter correlation through a correlation matrix, opens avenues for monitoring aging trends in organic solar cells. Additionally, the research aims to explore the influence of layer attributes, morphology, and material variances on model parameters, contributing to the optimization of designs. To enhance the reliability of the technique, the plan is to include additional experiments in the analysis repertoire. Overall, the commitment is to advance precision and applicability in organic solar cell research, with a focus on sustainable and efficient energy solutions.

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REFERENCES

[1] K. Fukuda, K. Yu, and T. Someya, “The future of flexible organic solar cells,” *Advanced Energy Materials*, vol. 10, no. 25, Jul. 2020, doi: 10.1002/aenm.202000765.
[2] W. Hou, Y. Xiao, G. Han, and J.-Y. Lin, “The applications of polymers in solar cells: A review,” *Polymers*, vol. 11, no. 1, Jan. 2019, doi: 10.3390/polym11010143.
[3] J. Qin *et al.*, “Recent progress in flexible and stretchable organic solar cells,” *Advanced Functional Materials*, vol. 30, no. 36, Sep. 2020, doi: 10.1002/adfm.202002529.
[4] A. Wagenpfahl, D. Rauh, M. Binder, C. Deibel, and V. Dyakonov, “S-shaped current-voltage characteristics of organic solar devices,” *Physical Review B*, vol. 82, no. 11, Sep. 2010, doi: 10.1103/PhysRevB.82.115306.
[5] D. S. H. Chan and J. C. H. Phang, “Analytical methods for the extraction of solar-cell single- and double-diode model parameters from I-V characteristics,” *IEEE Transactions on Electron Devices*, vol. 34, no. 2, pp. 286–293, Feb. 1987, doi: 10.1109/T-ED.1987.22920.
[6] C. Li *et al.*, “Non-fullerene acceptors with branched side chains and improved molecular packing to exceed 18% efficiency in organic solar cells,” *Nature Energy*, vol. 6, no. 6, pp. 605–613, May 2021, doi: 10.1038/s41560-021-00820-x.
[7] M. N. Zidan, N. Everitt, T. Ismail, and I. S. Fahim, “Organic solar cells parameters extraction and characterization techniques,” *Polymers*, vol. 13, no. 19, Sep. 2021, doi: 10.3390/polym13193224.
[8] B. Mazhari, “An improved solar cell circuit model for organic solar cells,” *Solar Energy Materials and Solar Cells*, vol. 90, no. 7–8, pp. 1021–1033, May 2006, doi: 10.1016/j.solmat.2005.05.017.
[9] M. Hejri, H. Mokhtari, M. R. Azizian, and L. Söder, “An analytical-numerical approach for parameter determination of a five-parameter single-diode model of photovoltaic cells and modules,” *International Journal of Sustainable Energy*, vol. 35, no. 4, pp. 396–410, Apr. 2016, doi: 10.1080/14786451.2013.863886.
[10] F. Ghani, G. Rosengarten, M. Duke, and J. K. Carson, “The numerical calculation of single-diode solar-cell modelling parameters,” *Renewable Energy*, vol. 72, pp. 105–112, Dec. 2014, doi: 10.1016/j.renene.2014.06.035.
[11] S. B. Dongue, D. Njomo, and L. Ebengai, “An improved nonlinear five-point model for photovoltaic modules,” *International Journal of Photoenergy*, vol. 2013, pp. 1–11, 2013, doi: 10.1155/2013/680213.
[12] M. Uvais, A. J. Ansari, and M. Asim, “Modeling and analysis of organic solar cells using multiple diodes,” in *2022 2nd International Conference on Emerging Frontiers in Electrical and Electronic Technologies (ICEFEET)*, Jun. 2022, pp. 1–5, doi: 10.1109/ICEFEET51821.2022.9848028.
[13] K. Chennoufi, M. Ferfra, and M. Mokhlis, “An accurate modelling of photovoltaic modules based on two-diode model,” *Renewable Energy*, vol. 167, pp. 294–305, Apr. 2021, doi: 10.1016/j.renene.2020.11.085.
[14] V. Lo Brano and G. Ciulla, “An efficient analytical approach for obtaining a five parameters model of photovoltaic modules using only reference data,” *Applied Energy*, vol. 111, pp. 894–903, Nov. 2013, doi: 10.1016/j.apenergy.2013.06.046.
[15] V. Lo Brano, A. Orioli, G. Ciulla, and A. Di Gangi, “An improved five-parameter model for photovoltaic modules,” *Solar Energy Materials and Solar Cells*, vol. 94, no. 8, pp. 1358–1370, Aug. 2010, doi: 10.1016/j.solmat.2010.04.003.
[16] C. Zhang, J. Zhang, Y. Hao, Z. Lin, and C. Zhu, “A simple and efficient solar cell parameter extraction method from a single current-voltage curve,” *Journal of Applied Physics*, vol. 110, no. 6, Sep. 2011, doi: 10.1063/1.3632971.
[17] H. K. Mehta, H. Warke, K. Kukadiya, and A. K. Panchal, “Accurate expressions for single-diode-model solar cell parameterization,” *IEEE Journal of Photovoltaics*, vol. 9, no. 3, pp. 803–810, May 2019, doi: 10.1109/JPHOTOV.2019.2896264.
[18] M. Asim, A. Sarwar, M. Shahabuddin, and M. S. Manzar, “Development of solar photovoltaic model for wide range of operating conditions,” *International Journal of Power Electronics and Drive Systems (IJPEDS)*, vol. 12, no. 4, Dec. 2021, doi: 10.11591/ijpeds.v12.i4.pp2483-2491.
[19] L. Sandrolini, M. Artioli, and U. Reggiani, “Numerical method for the extraction of photovoltaic module double-diode model parameters through cluster analysis,” *Applied Energy*, vol. 87, no. 2, pp. 442–451, Feb. 2010, doi: 10.1016/j.apenergy.2009.07.022.
[20] G. Sulyok and J. Summhammer, “Extraction of a photovoltaic cell’s double-diode model parameters from data sheet values,” *Energy Science & Engineering*, vol. 6, no. 5, pp. 424–436, Oct. 2018, doi: 10.1002/ese3.216.
[21] D. Wei, M. Wei, H. Cai, X. Zhang, and L. Chen, “Parameters extraction method of PV model based on key points of I-V curve,” *Energy Conversion and Management*, vol. 209, Apr. 2020, doi: 10.1016/j.enconman.2020.112656.

[22] T. R. Ayodele, A. S. O. Ogunjuyigbe, and E. E. Ekoh, “Evaluation of numerical algorithms used in extracting the parameters of a single-diode photovoltaic model,” *Sustainable Energy Technologies and Assessments*, vol. 13, pp. 51–59, Feb. 2016, doi: 10.1016/j.seta.2015.11.003.

[23] Y. Chen, Y. Sun, and Z. Meng, “An improved explicit double-diode model of solar cells: Fitness verification and parameter extraction,” *Energy Conversion and Management*, vol. 169, pp. 345–358, Aug. 2018, doi: 10.1016/j.enconman.2018.05.035.

[24] J. A. Jervase, H. Bourdoucen, and A. Al-Lawati, “Solar cell parameter extraction using genetic algorithms,” *Measurement Science and Technology*, vol. 12, no. 11, pp. 1922–1925, Nov. 2001, doi: 10.1088/0957-0233/12/11/322.

[25] M. Diantoro, T. Suprayogi, A. Hidayat, A. Taufiq, A. Fuad, and R. Suryana, “Shockley’s equation fit analyses for solar cell parameters from I-V curves,” *International Journal of Photoenergy*, vol. 2018, pp. 1–7, 2018, doi: 10.1155/2018/9214820.

[26] W. Zhao *et al.*, “Fullerene-free polymer solar cells with over 11% efficiency and excellent thermal stabilit,” *Advanced Materials*, vol. 28, no. 23, pp. 4734–4739, Jun. 2016, doi: 10.1002/adma.201600281.

[27] Y. Ma *et al.*, “Efficient organic solar cells from molecular orientation control of M-series acceptors,” *Joule*, vol. 5, no. 1, pp. 197–209, Jan. 2021, doi: 10.1016/j.joule.2020.11.006.

[28] X. Shi *et al.*, “An electron acceptor with broad visible–NIR absorption and unique solid state packing for as-cast high performance binary organic solar cells,” *Advanced Functional Materials*, vol. 28, no. 33, Aug. 2018, doi: 10.1002/adfm.201802324.

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