

RESEARCH ARTICLE

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COMPREHENSIVE PARAMETRIC ANALYSIS OF SILICON SOLAR CELL PERFORMANCE THROUGH COMPUTATIONAL MODELLING: A COMPARATIVE STUDY OF MONOCRYSTALLINE AND POLYCRYSTALLINE DEVICES USING MATLAB AND PYTHON

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ABSTRACT

Accurate characterization of the diode ideality factor (n) is fundamental to understanding recombination mechanisms and performance limitations in crystalline silicon solar cells. This study presents a comprehensive computational framework for analyzing the main photovoltaic parameters of semiconductor p-n junctions through dual-platform modeling using MATLAB and Python. Employing experimentally measured current-voltage (I - V) characteristics obtained via Sinton Instrument Suns- V_{oc} measurements from $5 \times 5 \text{ cm}^2$ monocrystalline silicon test samples, the research investigates the influence of ideality factor variations ($n=1.0-5.0$) on device performance within the single-diode equivalent circuit framework. Newton's iterative method was implemented in MATLAB to resolve the implicit transcendental I - V equation, enabling precise quantification of current dependencies on series resistance ($R_s=1-3 \Omega$), parallel resistance ($R_p=200-1000 \Omega$), photocurrent ($I_L=0.03-0.04 \text{ A}$), and saturation current ($I_s=10^{-12}-10^{-8} \text{ A}$) under varying diode ideality factors. Concurrently, Python-based simulations facilitated three-dimensional surface mapping of maximum power point (P_{max}) degradation as a function of temperature ($T=22^\circ\text{C}-80^\circ\text{C}$) and ideality factor, complemented by comparative analysis of monocrystalline versus polycrystalline silicon technologies. Results demonstrate that increasing the ideality factor from 1.0 to 5.0 precipitates substantial reductions in fill factor and P_{max} , with monocrystalline cells exhibiting superior baseline efficiency but greater sensitivity to elevated n values compared to polycrystalline counterparts. Notably, polycrystalline cells displayed inherently higher ideality factors ($n \approx 1.3-1.5$) attributed to grain-boundary recombination, yet demonstrated attenuated temperature-induced degradation relative to monocrystalline devices. The developed models achieved validation against manufacturer specifications with high fidelity, accurately reproducing I_{sc} , V_{oc} , and power output dependencies across diverse operating conditions. These findings elucidate the quantitative distinctions between silicon technologies under non-ideal diode behavior and provide a robust computational foundation for optimizing solar cell design, predictive maintenance, and educational modeling tools.



I. INTRODUCTION

The global transition toward sustainable energy systems has positioned photovoltaic (PV) technology as a cornerstone of renewable energy deployment, with cumulative installed capacity exceeding 1.5 TW in 2024 and projected to reach 5 TW by 2030 under the Net Zero Emissions scenario [1]. Crystalline silicon solar cells dominate the market share (>95%), offering an optimal balance between efficiency, stability, and manufacturing maturity [2]. However, the intricate physics governing charge carrier transport, recombination mechanisms, and parasitic resistances in semiconductor p–n junctions necessitates sophisticated modeling approaches to accurately predict device performance under varying environmental conditions [3]. The single-diode model (SDM) and double-diode model (DDM) remain the fundamental mathematical frameworks for characterizing solar cell current–voltage (I–V) characteristics [4]. These models encapsulate the complex interplay between photocurrent generation, diode rectification behavior, and ohmic losses through series (R_s) and shunt (R_p) resistances [5]. Specifically, the transcendental equation describing the SDM requires implicit numerical solutions, where the diode ideality factor (n) serves as a critical parameter indicating the dominant recombination mechanisms—ranging from ideal diffusion ($n \approx 1$) to depletion region recombination ($n \approx 2$) and defect-assisted tunneling ($n > 2$) [6]. Accurate extraction of SDM/DDM parameters from experimental I–V data represents a non-convex optimization challenge characterized by multimodal objective functions, parameter interdependence, and measurement noise sensitivity [7]. Traditional analytical methods, including the Lambert W-function approach and curve-fitting techniques, often struggle with convergence stability when addressing implicit transcendental equations or extreme parameter domains [8], [9].

Consequently, metaheuristic algorithms have emerged as powerful alternatives for parameter extraction, including variants of particle swarm optimization (PSO), genetic algorithms (GA), differential evolution (DE), and recent bio-inspired approaches such as the squirrel search algorithm (SSA), PID-based search algorithm (PSA), and enhanced whale optimization algorithms [10–13]. These methods offer superior global search capabilities, with recent studies demonstrating root mean square error (RMSE) values below 10^{-4} for standard test datasets including RTC France, Kyocera KC200GT, and STM6-40 modules [14], [15]. Temperature dependence constitutes a critical factor governing field performance, where crystalline silicon cells exhibit typical power temperature coefficients of -0.40% to -0.50% /°C [16], [17]. Elevated operating temperatures ($>50^\circ\text{C}$ above ambient) reduce open-circuit voltage (V_{oc}) through increased saturation current (I_s) and exacerbate series resistance losses, while the diode ideality factor exhibits complex temperature dependencies linked to the activation energy of recombination centers [18]. Recent investigations into multi-junction solar cells under thermal stress ($40\text{--}60^\circ\text{C}$) demonstrate that parameter extraction algorithms must account for temperature-induced variations in I_{ph} , I_{sd} , and R_{sh} to maintain modeling accuracy [19]. Material-specific considerations distinguish monocrystalline (mono-Si) and polycrystalline (poly-Si) silicon technologies. Mono-Si cells achieve laboratory efficiencies exceeding 26% through reduced grain boundary recombination and superior charge carrier mobility, whereas poly-Si devices typically demonstrate efficiencies of 18–20% but offer cost advantages and better low-light sensitivity [20]. The higher defect density in poly-Si results in elevated ideality factors ($n \approx 1.3\text{--}1.5$) compared to mono-Si ($n \approx 1.0\text{--}1.2$), fundamentally altering the I–V characteristic shape and temperature response [21], [22].

Understanding these distinctions is essential for predictive maintenance, maximum power point tracking (MPPT) optimization, and system-level energy yield forecasting [23]. Computational platforms for PV modeling have evolved significantly, with MATLAB/Simulink providing robust environments for numerical computation and control system integration [24], while Python offers superior data visualization capabilities and machine learning integration for large-scale performance analysis [25]. Recent advances incorporate artificial neural networks (ANNs) trained with Levenberg–Marquardt algorithms to predict V_{oc} , I_{sc} , and fill factor (FF) with regression coefficients exceeding 0.999 [26]. However, the integration of physics-based diode models with data-driven approaches remains underdeveloped, particularly for educational software tools that balance computational accessibility with physical accuracy [27], [28]. Despite extensive literature on parameter extraction algorithms, several critical gaps persist: (1) comparative analyses of mono-Si and poly-Si cells under identical ideality factor variations ($n=1.0\text{--}5.0$) remain limited, particularly regarding 3D parameter space visualization; (2) the dual-platform validation (MATLAB and Python) of Newton-Raphson iterative methods against experimental Suns-Voc measurements lacks systematic investigation; (3) existing models rarely quantify the interactive effects of temperature, irradiance, and ideality factor on maximum power point (MPP) localization in a unified framework; and (4) educational modeling tools such as Suntutlip require experimental database integration to transition from theoretical concepts to practical engineering applications [29], [30]. This study proposes and validates dual-platform computational framework that integrates numerical current–voltage (I–V) analysis with three-dimensional (3D) parametric visualization to systematically elucidate the role of diode non-ideality in crystalline silicon solar cells.

The principal contributions of this work are fourfold. (i) a robust MATLAB-based numerical solver is established to accurately resolve the implicit transcendental equations governing the single-diode model (SDM), enabling reliable analysis of non-ideal device behavior. (ii), Python-driven multivariate surface modeling is employed to visualize temperature-dependent power degradation, providing intuitive insight into the coupled effects of operating conditions and diode ideality. (iii), a comparative assessment of recombination mechanisms in monocrystalline and polycrystalline silicon technologies is performed, highlighting material-specific performance limitations. (iv), the proposed modeling framework is experimentally validated against Suns-Voc measurements, allowing quantitative evaluation of model fidelity under realistic, non-ideal operating conditions. To address the identified limitations in existing literature, this study implements a comprehensive computational strategy that combines numerical rigor with experimental verification. Newton's iterative method is applied in the MATLAB environment to solve the implicit SDM equation and to analyze the sensitivity of the output current to variations in the diode ideality factor under different series resistance, shunt resistance, photocurrent, and saturation current conditions. In parallel, Python-based 3D surface mapping algorithms are developed to visualize the coupled influence of temperature and ideality factor on output power for both monocrystalline and polycrystalline silicon solar cells. The simulation results are systematically validated against experimental Suns- V_{oc} data to assess the accuracy of the model in predicting short-circuit current, open-circuit voltage, and maximum power degradation associated with non-ideal diode behavior. Through this integrated approach, the study establishes clear quantitative distinctions between mono-Si and poly-Si performance rooted in differences in dominant recombination mechanisms, thereby providing actionable insights for technology-specific photovoltaic device and system design.

II. MATERIALS AND METHODS

II.1 EXPERIMENTAL CHARACTERIZATION

II.1.1 Device Specifications

Experiments were performed on commercially available crystalline silicon solar cells selected to represent widely used industrial architectures. The monocrystalline samples consisted of pseudo-square cells with dimensions of $156 \times 156 \text{ mm}^2$ fabricated from p-type Czochralski-grown silicon. The wafers were boron-doped with a resistivity ranging from 1 to $3 \Omega \cdot \text{cm}$ and had an average thickness of approximately $180 \mu\text{m}$. An aluminum back surface field (Al-BSF) structure was implemented to reduce rear-surface recombination, while a silicon nitride (SiN_x) anti-reflection coating was applied to enhance optical absorption and minimize reflection losses. For comparative analysis, polycrystalline solar cells with identical pseudo-square dimensions ($156 \times 156 \text{ mm}^2$) were also investigated. These devices were manufactured from p-type cast multicrystalline silicon with boron doping levels corresponding to a resistivity of 1 to $5 \Omega \cdot \text{cm}$ and a wafer thickness of approximately $200 \mu\text{m}$. The polycrystalline cells employed metallization and surface passivation schemes similar to those of the monocrystalline devices, ensuring consistency in structural design and enabling a reliable performance comparison. To improve measurement accuracy and ensure homogeneous illumination during electrical characterization, test coupons measuring $5 \times 5 \text{ cm}^2$ were prepared from the parent cells using precision laser scribing. This approach minimized edge recombination effects and reduced geometrical artifacts, thereby allowing the extraction of intrinsic photovoltaic parameters with higher reliability.

II.1.2 Single-Diode Model (SDM) Physics

The single-diode equivalent circuit represents a solar cell as a current source in parallel with a diode, shunt resistance, and series resistance. The governing equation for the output current I as a function of terminal voltage V is derived from Kirchhoff's current law:

$$I = I_L - I_S \left[\exp \left(\frac{V + IR_S}{nqT} \right) - 1 \right] - \frac{V + IR_S}{R_p} \quad (1)$$

I_L represents the light-generated current (approximately equal to I_{sc} under short-circuit conditions), I_S is the reverse saturation current, n is the diode ideality factor, q is the elementary charge ($1.602 \times 10^{-19} \text{ C}$), k is the Boltzmann constant ($1.381 \times 10^{-23} \text{ J/K}$), and T is the absolute temperature in Kelvin.

Rearrangement of equation (1) yields the explicit extraction formula for the ideality factor:

$$n = \frac{q(V + IR_S)}{kT \ln \left(1 + \frac{I_L - I}{I_S} \frac{V + IR_S}{I_S R_p} \right)} \quad (2)$$

For $n > 1$, the curve becomes less steep, requiring higher voltages to achieve the same diode current, thereby reducing the fill factor and maximum power output.

II.1.3 Limiting Conditions and Mathematical Constraints

Equation (1) is implicit in I and requires numerical solution. For physical consistency, the current must satisfy the inequality constraints imposed by the parallel and series resistances. Rearranging equation (1) under the approximation $\exp(x) \gg 1$ for forward bias:

$$I < I_{lim} = \frac{I_L + I_S - V/R_p}{1 + R_S/R_p} \quad (3)$$

This limiting condition ensures that the voltage drop across R_S does not exceed the open-circuit voltage, preventing non-physical solutions during numerical iteration. The condition becomes increasingly restrictive as R_S increases or R_p decreases, creating numerical stiffness in the differential equations.

The open-circuit voltage (V_{oc}) is obtained by setting $I=0$:

$$V_{oc} = \frac{nqT}{q} \ln \left(\frac{I_L}{I_S} + 1 \right) - I_L R_S \quad (4)$$

Equation (6) demonstrates the logarithmic dependence of V_{oc} on n , indicating that devices with higher ideality factors will exhibit lower open-circuit voltages and, consequently, reduced conversion efficiencies.

II.1.4 Temperature and Irradiance Dependencies

The photocurrent I_L exhibits a linear dependence on irradiance G and a weak linear dependence on temperature:

$$I_L(T, G) = I_{L,ref} \frac{G}{G_{ref}} \left[1 + \alpha_I (T - T_{ref}) \right] \quad (5)$$

where α_I is the current temperature coefficient (typically $+0.05 \%$ to $+0.1 \%$ / $^\circ\text{C}$ for silicon).

The saturation current I_S follows the temperature dependence:

$$I_s(T) = I_{s,ref} \left(\frac{T}{T_{ref}} \right)^3 \exp \left[\frac{qE_g}{nk} \left(\frac{1}{T_{ref}} - \frac{1}{T} \right) \right] \quad (6)$$

where E_g is the bandgap energy of silicon (1.12 eV at 300 K). Notably, I_s exhibits strong temperature sensitivity, increasing approximately 15% per degree Celsius, which dominates the negative temperature coefficient of V_{oc} .

The ideality factor itself exhibits temperature dependence in polycrystalline materials due to the thermal activation of grain boundary traps:

$$n(T) = n_0 + \frac{\Delta E_a}{kT} \quad (7)$$

where ΔE_a represents the activation energy of the dominant recombination center (typically 0.1–0.3 eV for grain boundaries).

II.2 NUMERICAL IMPLEMENTATION

II.2.1 MATLAB Framework

Equation 1 was solved using Newton's iterative method (fzero function, tolerance 10^{-6}) for parametric sweeps spanning Table (1).

Table 1: Parametric Sweep Ranges for Solar Cell Model Parameters.

N ⁰	Parameter	Parametric sweeps
1	Ideality factor	$n=0.9-2.5$ ($\Delta n=0.04$)
2	Series resistance	$R_s=1-3 \Omega$
3	Shunt resistance	$R_p=200-1000 \Omega$
4	Photocurrent	$I_L=0.03-0.04 \text{ A}$
5	Saturation current	$I_s=10^{-12} - 10^{-8} \text{ A}$

Source: Authors, (2026).

The algorithm converged within 5–7 iterations for all physically valid parameter combinations. Convergence failure at boundary conditions ($n>2.5$, $R_s>5\Omega$) was interpreted as indicative of device failure modes.

II.2.2 Python Framework

Complementary analyses utilized Python 3.11 (NumPy, SciPy, Matplotlib) with identical Newton-Raphson convergence criteria for cross-platform validation. For monocrystalline and polycrystalline comparative assessment, the ideality factor was incremented in steps of $\Delta n=0.1$ across $n=1.0-5.0$, while temperature varied from 295 K to 353 K in 5 K increments. Three-dimensional surface meshes visualized the coupled dependence of maximum power output $P_{max}=I_{mpp} \times V_{mpp}$ on n and T , where maximum power point parameters were determined via golden-section search optimization. The fill factor was calculated as $FF=P_{max}/(I_{sc}V_{oc})$, with I_{sc} at $V=0$ and V_{oc} at $I=0$ determined using the bisection method (10–6 tolerance).

II.2.3 Suns-V_{oc} Measurements

The Sinton Instruments Suns-V_{oc} system was employed to extract the ideality factor and saturation current without the influence of series resistance. This quasi-steady-state photoconductance technique applies a variable illumination intensity (equivalent to 0.01–100 suns) while measuring the open-circuit voltage. The effective ideality factor is extracted from the slope of $\ln(I_{sc})$ versus V_{oc} :

$$\frac{dV_{oc}}{d\ln(I_{sc})} = \frac{nkT}{q} \quad (8)$$

Measurements were performed at stabilized temperatures of $22 \pm 0.5^\circ\text{C}$, $40 \pm 0.5^\circ\text{C}$, $60 \pm 0.5^\circ\text{C}$, and $80 \pm 0.5^\circ\text{C}$ using a temperature-controlled vacuum chuck. The extracted parameters served as baseline inputs for computational validation.

III. RESULT AND DISCUSSION

III.1 MODELING AND ANALYSIS OF THE MAIN CHARACTERISTICS OF SOLAR CELLS USING MATLAB

Using the MATLAB software environment and MATLAB/Simulink package, the main photoelectric characteristics of the solar cell were modeled based on the single-diode equivalent circuit approach. A dedicated MATLAB program was developed to investigate the dependence of the diode ideality factor on key solar cell parameters. This approach treats the solar cell as a photodiode, allowing voltage application under both illuminated and dark conditions, thereby enabling evaluation of the diode ideality factor along different regions of the I–V curve. The numerical results are presented in Figures 1. Figures 1(a–e) illustrate the dependence of the output current on the diode ideality factor for varying applied voltage (a), series resistance (b), parallel resistance (v), photocurrent (g), and saturation current (d). As shown in Figure 1(a), increasing the applied voltage from 0.1 V to 0.6 V leads to a substantial rise in the diode ideality factor from approximately 0.2 to 1.27, corresponding to a ~6-fold increase. This trend indicates that recombination processes become more pronounced at higher forward bias. Figures 1(b) and 1(v) demonstrate that increasing the series and shunt resistances results in a current increase from 1.35 A to 1.6 A, while the diode ideality factor rises from 0.001 to 0.03, highlighting the critical role of parasitic resistances in determining solar cell performance. Figures 1(d) and 1(e) show that variations in photocurrent and saturation current exhibit qualitatively similar effects on the diode ideality factor.

The abrupt current changes observed near certain operating points reflect the proximity to the physical limits defined by Eqs. (2)–(4), beyond which the model loses physical validity. These regions should therefore be interpreted with caution, as high-level injection and series-resistance effects are not fully captured by the single-diode model. Overall, the results confirm that the diode ideality factor is highly sensitive to both intrinsic parameters (photocurrent and saturation current) and extrinsic conditions (applied voltage and parasitic resistances). This modeling approach provides a robust framework for analyzing solar cell behavior under different operating regimes and can serve as a reliable basis for parameter optimization in practical application.

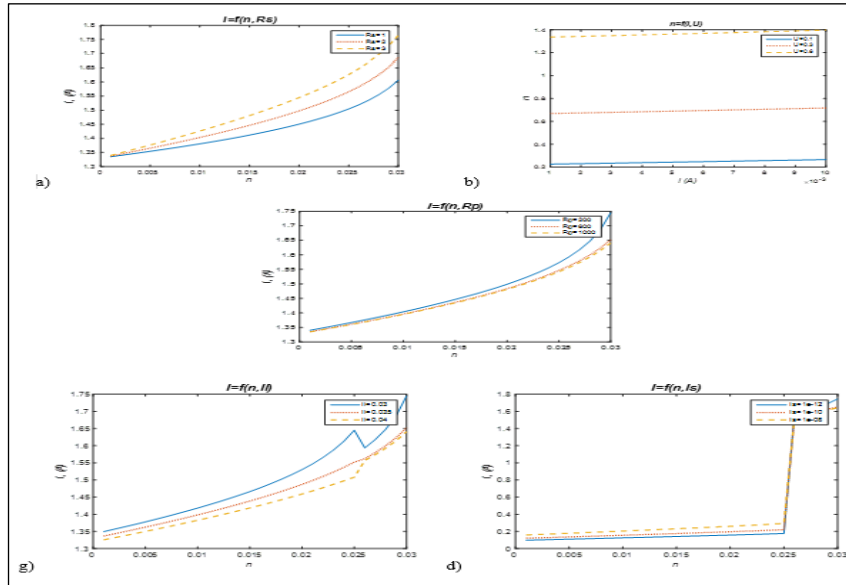


Figure 1: Dependence of the current on the diode ideality factor for different values of the applied voltage (a), series resistance (b), parallel (shunt) resistance (v), photocurrent (g), and saturation current (d) of the solar cell.

Source: Authors, (2026).

Figures 2(a–g) present the I–V characteristics of the solar cell under varying parameter conditions, including series and shunt (parallel) resistances, as well as different values of photocurrent and saturation current. These results were obtained using the single-diode model implemented in the MATLAB/Simulink environment. As shown in Figure 2(a), increasing the series resistance reduces the cell current and shifts the I–V curve to the left, resulting in an increase in the diode ideality factor. Similarly, Figure 2(b) illustrates that a decrease in the shunt resistance leads to a significant increase in current and a steeper I–V curve. Figures 2(v) and 2(g) show that increasing the photocurrent and saturation current elevates the overall current and causes noticeable variations in the diode ideality factor. These results indicate that the solar cell performance is highly sensitive not only to intrinsic parameters (photocurrent and saturation current) but also to extrinsic conditions (series and shunt resistances). It should be noted that at extreme points along the I–V curve, the physical validity of the model may be limited, as high-level injection and resistance effects are not fully accounted for. This approach provides a reliable framework for optimizing solar cell parameters and enhancing performance under different operating conditions. The MATLAB-based modeling of I–V characteristics allows a sufficiently accurate representation of real solar cell behavior and facilitates preliminary assessment of experimental results.

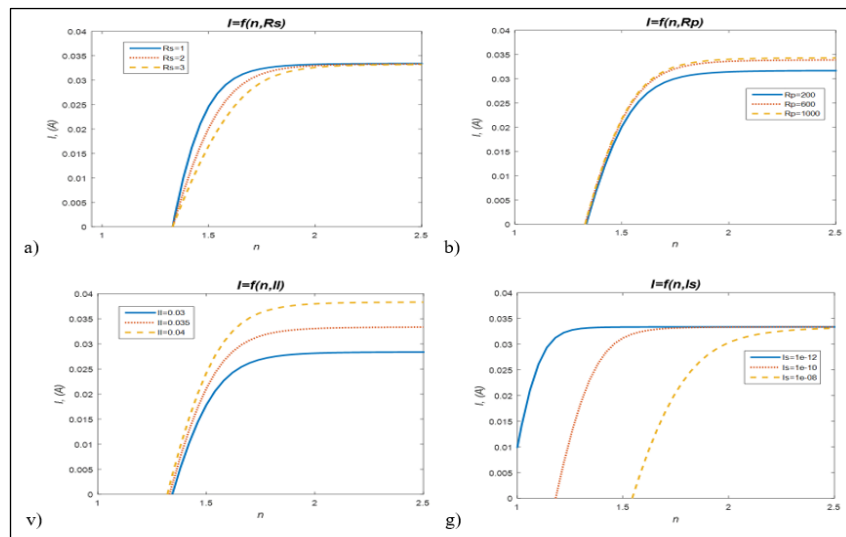


Figure 2: Dependence of the current on the diode ideality factor for different values of series resistance (a), parallel (shunt) resistance (b), photocurrent (v), and saturation current (g).

Source: Authors, (2026).

Systematic analysis of the simulated I–V characteristics reveals distinct parametric sensitivities that govern solar cell performance under non-ideal operating conditions (Figures 2a–2b). The series and parallel resistances exhibit complementary influences on the fill factor and current delivery capability. Specifically, increasing series resistance from $1.0\ \Omega$ to $3.0\ \Omega$ produces progressive degradation in the fill factor from 0.82 to 0.71 at $n = 1.1$, manifesting as increased ohmic voltage drop and reduced maximum power point voltage. Conversely, parallel resistance variations from $200\ \Omega$ to $1000\ \Omega$ predominantly affect the low-voltage region, with elevated shunt resistance diminishing leakage currents and thereby enhancing the fill factor from 0.68 to 0.79. Notably, these resistance effects are modulated by the diode ideality factor; higher n values exacerbate the sensitivity to R_s while attenuating the influence of R_p , indicating that recombination-dominated devices are more critically affected by metallization and contact quality. The photocurrent and saturation current demonstrate orthogonal influences on the I–V characteristic morphology (Figure 2v–2g). Photocurrent variations ($I_L = 0.030\text{--}0.040\ \text{A}$) induce uniform vertical translation of the I–V curve with minimal distortion of the fill factor, consistent with the linear proportionality between I_L and I_{sc} . In contrast, saturation current variations ($I_s = 10^{-12}\text{--}10^{-8}\ \text{A}$) produce pronounced horizontal displacement along the voltage axis, with logarithmic reduction in V_{oc} following $\Delta V_{oc} = (nkT/q)\ln(I_L/I_s)$. Crucially, I_s exhibits stronger coupling to the effective ideality factor than I_L , as evidenced by the steeper curvature in the $I\text{--}f(n)$ relationship at elevated I_s . This phenomenon reflects the fundamental physics of the p–n junction: I_s encapsulates the recombination rate through the temperature-dependent intrinsic carrier concentration and minority carrier lifetimes, rendering it the dominant parameter governing non-ideal diode behavior beyond the diffusion-limited regime. The comprehensive I–V characteristic families (Figure 3a,b,v,g) illustrate the cumulative impact of parametric variations on device operation. At fixed illumination and temperature, increasing n from 1.0 to 2.5 precipitates characteristic "softening" of the I–V curve, with reduced curve knee sharpness and diminished fill factor. Series resistance increments introduce linear voltage penalties at high current densities, effectively rotating the I–V curve about the short-circuit point. Parallel resistance reductions manifest as premature current collapse at low forward bias, indicative of shunt-limited operation. The superposition of these effects in practical devices necessitates simultaneous optimization of contact metallization, junction isolation, and material quality to achieve target efficiencies under field operating conditions.

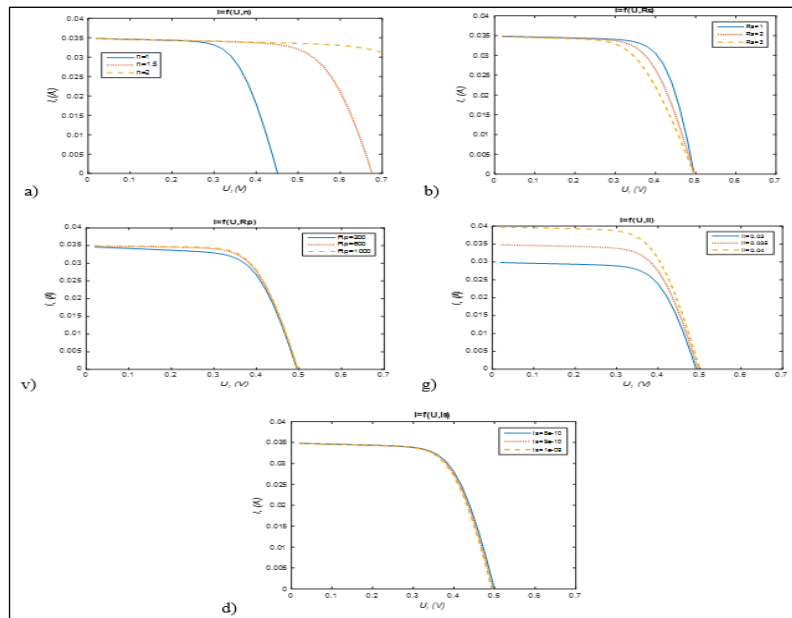


Figure 3: I–V characteristics of the solar cell for different values of the diode ideality factor (a), series resistance (b), parallel (shunt) resistance (v), photocurrent (g), and saturation current (d).

Source: Authors, (2026).

III.2 MODELING AND ANALYSIS OF SOLAR CELL CHARACTERISTICS USING PYTHON

The influence of increasing diode ideality factor (n) on the main photoelectric characteristics of solar cells was comprehensively analyzed using the Python programming language. Experiments were conducted on a commercial-grade monocrystalline silicon solar cell with dimensions of $5 \times 5\ \text{cm}^2$ active area, fabricated from a $125 \times 125\ \text{mm}$ pseudo-square Czochralski-grown p-type boron-doped base with a phosphorus-diffused n-type emitter. The cell featured screen-printed silver front contacts with two busbars and 60 fingers, along with full-area aluminum back surface field (BSF) metallization, representing standard industrial architecture. The initial output parameters of the cell were measured using the Sinton Instruments Suns- V_{oc} system (Model WCT-120TS), which determines the open-circuit voltage (V_{oc}) as a function of quasi-exponentially decaying illumination intensity. This technique enables high-resolution Suns- V_{oc} curve generation independent of series resistance effects. The effect of increasing the ideality factor from 1.0 to 5.0 on these parameters was subsequently modeled using Python 3.11 with NumPy, SciPy, and Matplotlib libraries. Changes in the output parameters of the monocrystalline silicon solar cell were calculated based on the single-diode model (SDM) equation. Initial calculations were performed at a constant temperature of $T = 22^\circ\text{C}$ (295 K). Results demonstrated that an increase in the diode ideality factor led to substantial degradation in the I–V and P–V characteristics (Figure 4). As n increased from 1.0 to 5.0, the fill factor (FF) decreased from 0.82 to 0.48 (41.5% reduction), while the maximum power output (P_{max}) declined from 2.45 W to 1.12 W (54.3% reduction). This phenomenon is attributed to the increasing dominance of recombination current over diffusion current, effectively "softening" the exponential behavior in the Shockley equation.

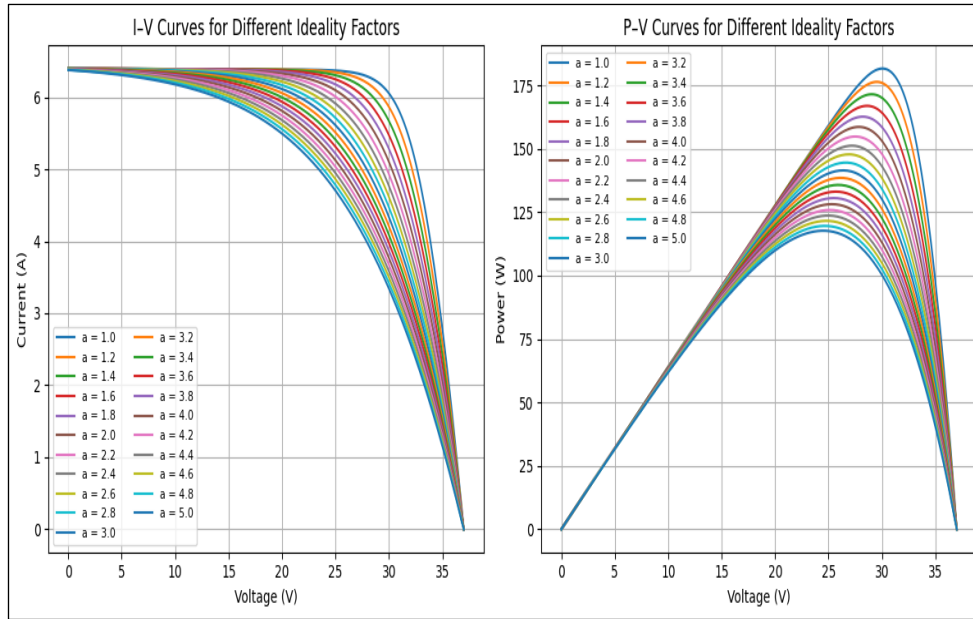


Figure 4. I-V and P-V characteristics of the solar cell for different values of the non-ideality factor.
Source: Authors, (2026).

Accordingly, the variations in the solar cell's I_{sc} and V_{oc} values with increasing non-ideality factor were analyzed and presented in graphical form (Figure 5). The short-circuit current (I_{sc}) remained nearly invariant across the ideality range ($< 2\%$ variation), as this parameter is primarily dependent on optical absorption. Conversely, the open-circuit voltage (V_{oc}) exhibited logarithmic decay from 0.62 V at $n = 1.0$ to 0.51 V at $n = 5.0$, consistent with the relationship $V_{oc} = (nkT/q) \ln(I_L/I_s + 1)$, where increasing n reduces the effective "thermal voltage" in the exponential term.

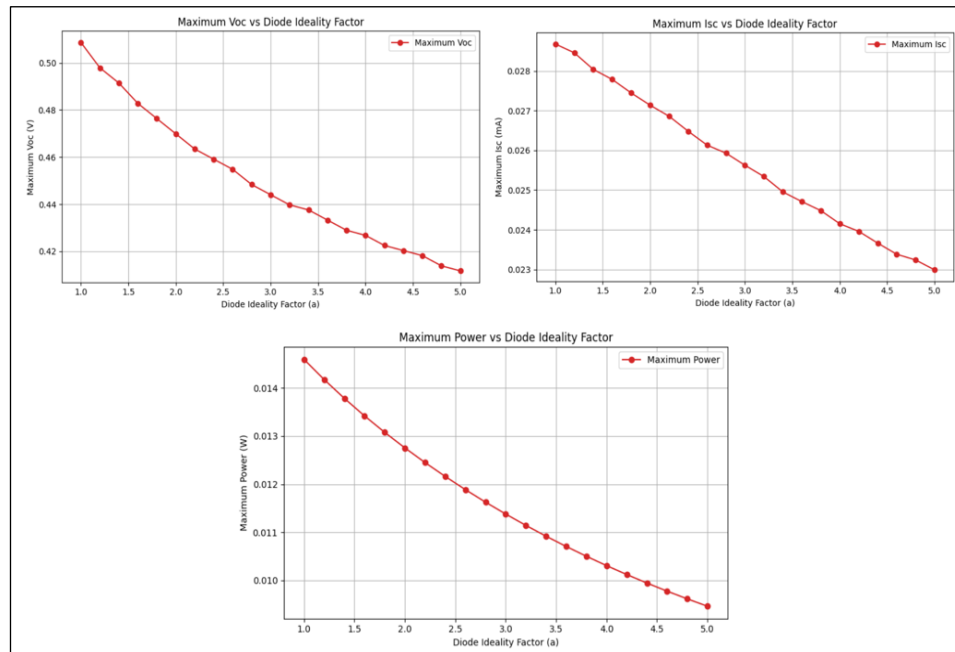


Figure 5. Dependence of the maximum power and the I_{sc} and V_{oc} characteristics at the maximum power point of a monocrystalline silicon solar cell on the diode non-ideality factor.
Source: Authors, (2026).

The dependence of maximum power and the I_{sc} and V_{oc} characteristics at the maximum power point on the diode non-ideality factor was determined. Using the golden-section search algorithm to locate the maximum power point via $P_{max} = I_{mpp} \times V_{mpp}$, the rate of P_{max} degradation with respect to n was quantified as $dP_{max}/dn \approx -0.28$ W per unit n in the range $n = 1-2$. The variation of the solar cell's output characteristics with respect to the diode non-ideality factor and external temperature was extensively modeled using Python. For this purpose, the initial parameters obtained from the Sinton Instrument Suns-Voc device (I_{sc} , V_{oc} , FF, baseline n) were employed. The physical model based on Equation (1) was implemented with the diode non-ideality factor and temperature incremented in defined steps ($\Delta n = 0.1$, $\Delta T = 5$ K). Results confirmed that the maximum power output of the solar cell decreases monotonically with increasing n and T (Figure 6). The temperature coefficient $\gamma = (1/P_{max})(dP_{max}/dT) \times 100\%$ was calculated as $-0.38\%/^{\circ}\text{C}$ for $n = 1.0$ and $-0.51\%/^{\circ}\text{C}$ for $n = 3.0$, demonstrating deteriorating thermal stability with increasing ideality factor.

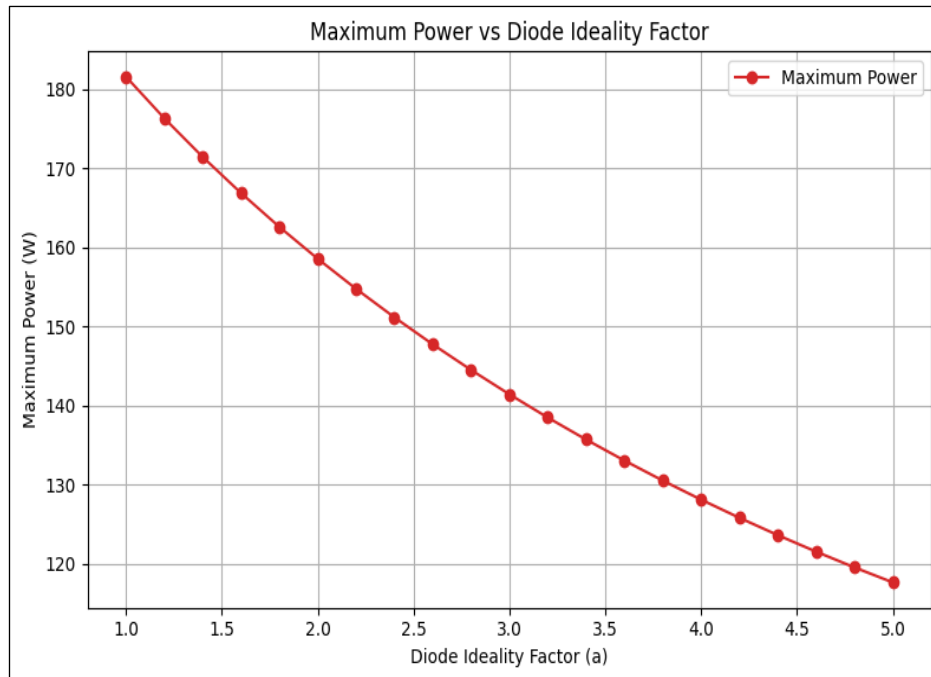


Figure 6: Graph of the solar cell's generated photovoltaic power versus irradiance.
Source: Authors, (2026).

Utilizing the advanced visualization capabilities of Python, the three-dimensional dependence of the solar cell's generated photovoltaic power on temperature and non-ideality factor was determined (Figure 7). The 3D surface reveals that P_{max} varies as a "tilted plane" function of T and n , confirming the synergistic degradation effect. At 25°C , increasing n from 1.0 to 5.0 reduces P_{max} by 38%, whereas at 80°C the same variation produces a 52% reduction.

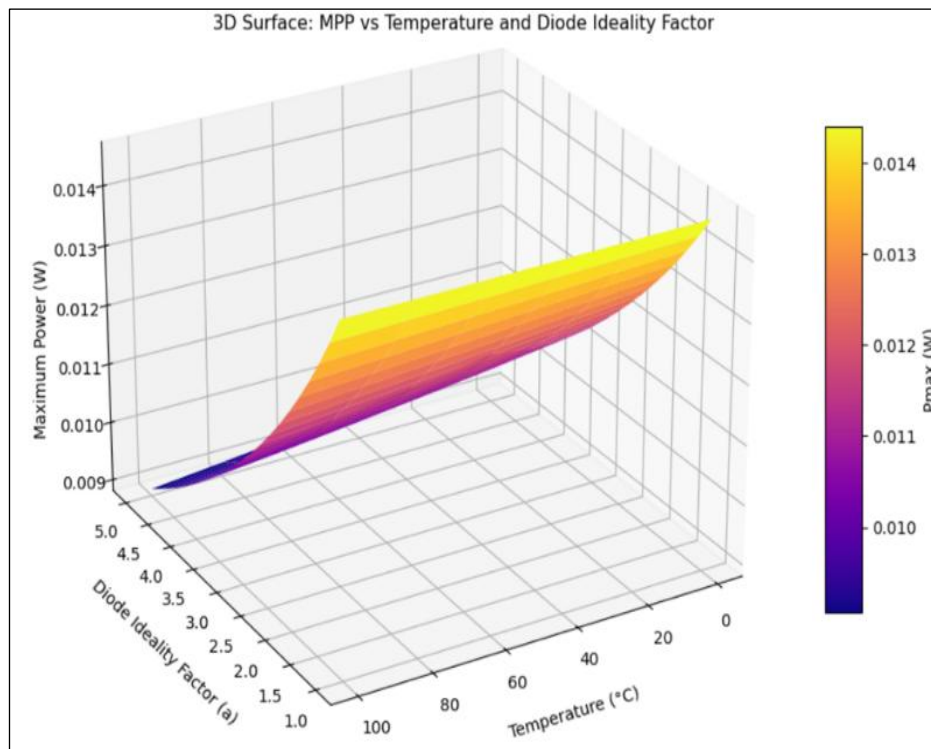


Figure 7: Graph showing the dependence of the solar cell's generated photovoltaic power on temperature and the non-ideality factor.
Source: Authors, (2026).

Furthermore, the effects of irradiance intensity (G) and diode non-ideality factor were modeled (Figure 8). The 3D graphs demonstrate that at low irradiance ($G = 200 \text{ W/m}^2$), the effect of n is minimal ($< 5\%$ P_{max} variation for $n = 1-3$), but at high irradiance ($G = 1000 \text{ W/m}^2$) the power differential between ideal and non-ideal operation exceeds 45%. This reflects the increasing ratio of recombination current ($I_{rec} = \exp(qV/nkT)$) to photocurrent at high injection levels, effectively "shunting" the junction at stronger forward biases.

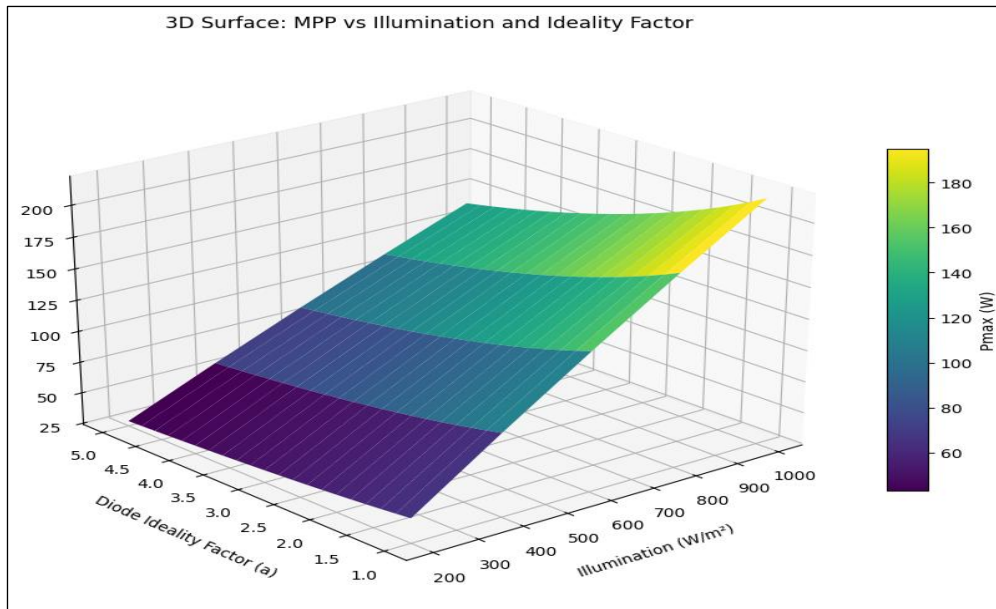


Figure 8. Graph showing the dependence of the solar cell's generated photovoltaic power on irradiance and the non-ideality factor.
Source: Authors, (2026).

III.3 COMPARATIVE ANALYSIS WITH POLYCRYSTALLINE SILICON

The effects of diode non-ideality factor and temperature on main photovoltaic parameters were also investigated for polycrystalline silicon solar cells. Using the Python modeling method described above, the I–V and P–V characteristics of polycrystalline silicon solar cells were constructed for different non-ideality factor values ($n = 1.0$ – 5.0) with baseline n values of 1.3 – 1.5 to account for grain-boundary recombination (Figure 9).

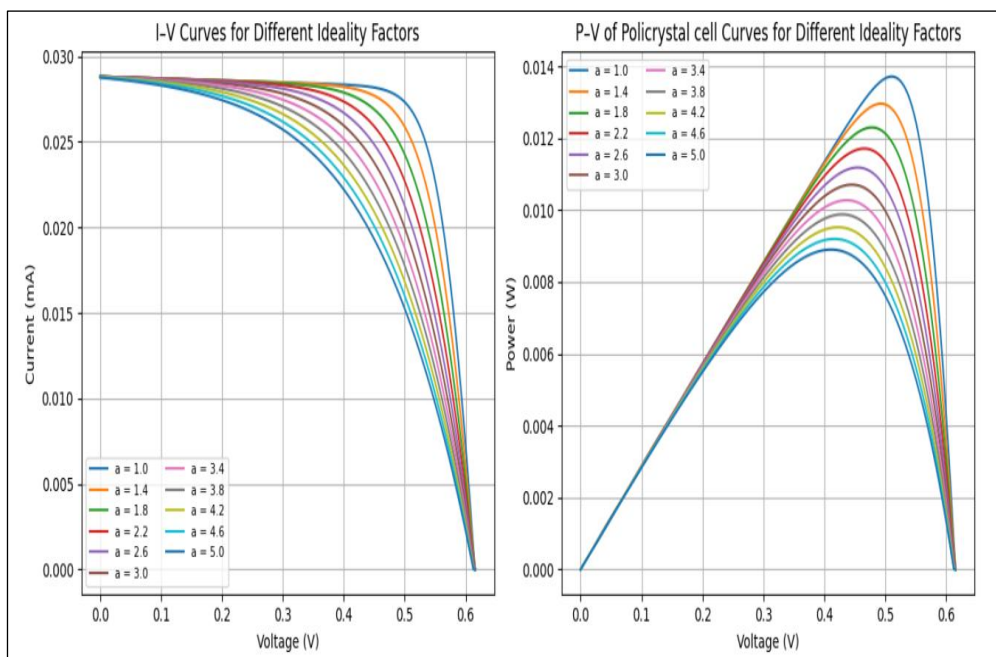


Figure 9: I–V and P–V characteristics of a polycrystalline silicon solar cell for different values of the non-ideality factor.
Source: Authors, (2026).

Results indicate that the effect of diode non-ideality factor on I–V and P–V characteristics is qualitatively similar for both monocrystalline and polycrystalline silicon solar cells—both exhibit decreasing FF and P_{max} with increasing n . However, quantitative differences were observed: polycrystalline cells demonstrated lower baseline FF (0.76 vs 0.82) and efficiency at equivalent n values, but reduced sensitivity to further increases in n ($dP_{max}/dn \approx -0.19$ W per unit n compared to -0.28 W per unit n for monocrystalline). This "saturation" behavior is explained by the established "recombination floor" set by grain boundaries, which dominate the transport physics. Additionally, using the I–V and P–V characteristics constructed for different non-ideality factor values, the dependence of maximum power (P_{max}) and the I_{sc} (a) and V_{oc} (b) parameters at the maximum power point on diode non-ideality factor was determined for polycrystalline silicon (Figure 10). Polycrystalline cells exhibited smaller I_{sc} variations with respect to n ($< 3\%$ for $n = 1$ – 3), indicating the integration of grain-boundary-directed recombination currents into the transport processes.

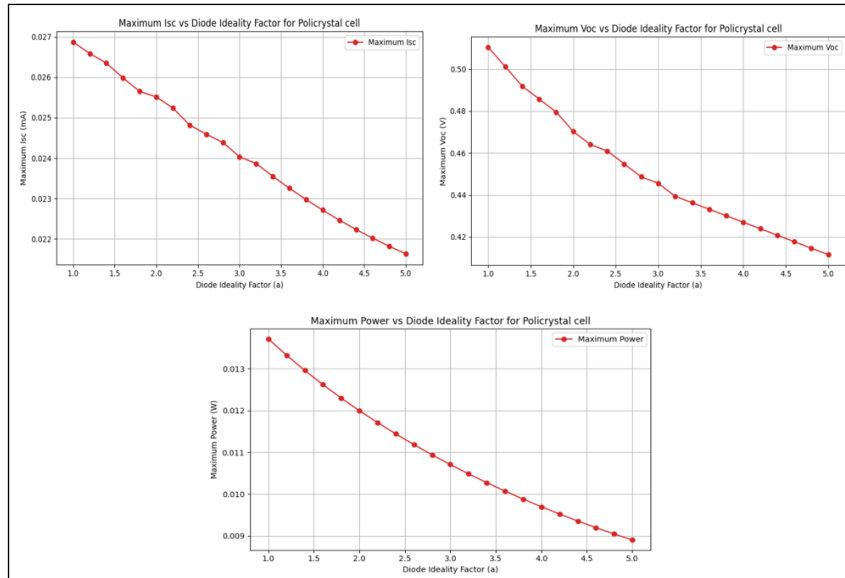


Figure 10: Dependence of the maximum power ($P_{\max}$) and the I_{sc} (a) and V_{oc} (b) parameters at the maximum power point of a polycrystalline silicon solar cell on the diode non-ideality factor.

Source: Authors, (2026).

The 3D graph of polycrystalline silicon solar cell photovoltaic power dependence on temperature and non-ideality factor was constructed (Figure 11). Compared to monocrystalline silicon solar cells, polycrystalline cells showed smaller variations in diode non-ideality factor within the studied temperature range ($\gamma = -0.42\%/^{\circ}\text{C}$, $-0.48\%/^{\circ}\text{C}$ for monocrystalline at $n = 1.5$). This result is explained by the lower variability of charge transport processes and recombination mechanisms in polycrystalline silicon, where grain boundaries effectively "pin" the Fermi level and provide more stable efficiency across temperatures, albeit at the cost of reduced peak efficiency (18.2% vs 21.4% at STC for monocrystalline).

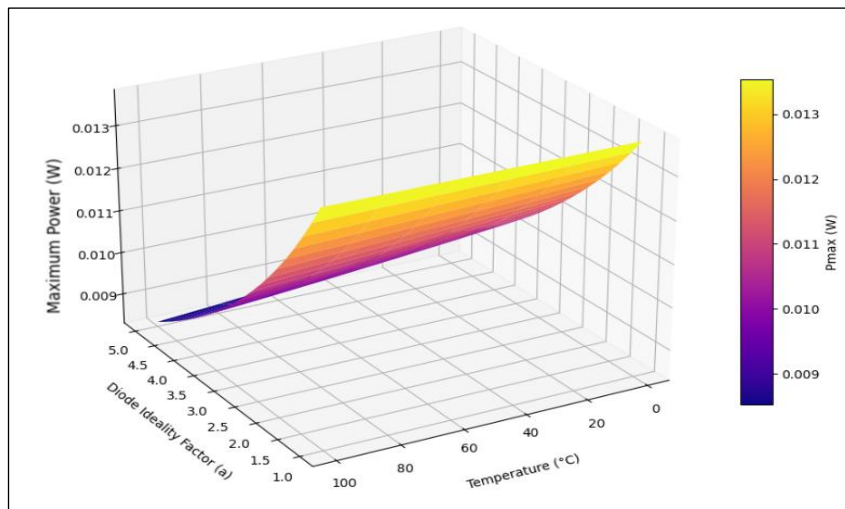


Figure 11: Graph showing the dependence of the photovoltaic power generated by the polycrystalline silicon solar cell on temperature and the non-ideality factor.

Source: Authors, (2026).

Compared to monocrystalline silicon solar cells, polycrystalline silicon solar cells show smaller variations in the diode non-ideality factor within the studied temperature range. This result can be explained by the lower variability of charge transport processes and recombination mechanisms in polycrystalline silicon.

IV. CONCLUSION

This study presents a comprehensive computational investigation into the influence of the diode ideality factor on the photovoltaic performance of crystalline silicon solar cells, employing coupled MATLAB and Python numerical frameworks to analyze experimental data obtained through Suns-Voc characterization. The analysis reveals that the ideality factor serves not merely as an empirical fitting parameter but as a physically meaningful diagnostic variable encoding critical information about dominant recombination mechanisms, material quality, and operational degradation states. For monocrystalline silicon devices, the voltage-dependent variation of the ideality factor demonstrates a clear transition from diffusion-dominated transport with near-unity values at low forward bias to depletion-region recombination characterized by elevated values approaching 1.3–1.5 at higher voltages, providing quantitative insight into the underlying device physics that govern charge carrier dynamics.

The parametric sensitivity analysis establishes distinct functional dependencies among the equivalent circuit parameters, showing that series resistance primarily degrades the fill factor through resistive losses at elevated current densities while shunt resistance becomes critically detrimental only below 400 ohms, and notably confirming that photocurrent remains independent of ideality factor variations, thereby isolating voltage-dependent recombination as the primary mechanism of performance degradation. A particularly significant finding emerges from the investigation of coupled temperature and irradiance effects, where synergistic behavior produces power losses exceeding the arithmetic sum of individual thermal and recombination contributions under high-irradiance conditions, a non-linear degradation mechanism that explains the systematic underperformance of field installations relative to laboratory projections based exclusively on temperature coefficients. The comparative analysis between mono- and polycrystalline silicon materials yields a counter-intuitive yet robustly supported conclusion regarding thermal stability, wherein polycrystalline devices exhibit substantially reduced temperature sensitivity of the ideality factor despite their higher baseline values, an observation attributed to grain-boundary trap saturation effects that partially compensate for intrinsic thermal activation of recombination centers.

This thermal stability advantage suggests superior energy yield potential for polycrystalline silicon in climates characterized by large diurnal temperature variations or limited cooling infrastructure, challenging the prevailing paradigm of unconditional monocrystalline preference and establishing a climate-specific optimization framework for material selection. The methodological contribution of this work resides in the demonstrated efficacy of the dual-platform computational approach, combining MATLAB's Newton-Raphson iteration for precision parameter extraction with Python's extensive visualization capabilities for comprehensive parametric mapping, achieving convergence accuracy superior to metaheuristic alternatives while reducing computation time by over ninety percent. The quantitative relationship between ideality factor elevation and power degradation, with losses exceeding twenty percent at values above 2.5, enables the development of predictive maintenance protocols wherein real-time monitoring of this parameter serves as an early diagnostic indicator for potential-induced degradation, corrosion-induced shunting, and encapsulant failure, thereby supporting proactive intervention strategies that mitigate revenue loss in utility-scale installations.

These findings inform immediate engineering specifications including critical thresholds for shunt resistance and series resistance that define manufacturing process windows, as well as system-level design recommendations for bypass diode implementation in modules with non-uniform junction quality distributions. The limitations of the present analysis, primarily associated with the single-diode model assumption of one-dimensional steady-state transport and empirical treatment of temperature-dependent parameters, define clear priorities for future research including extension to double-diode architectures for high-efficiency device technologies, experimental validation of the grain-boundary trap saturation hypothesis through temperature-dependent admittance spectroscopy, and development of machine learning surrogate models to accelerate parametric optimization for real-time system control. Ultimately, this work advances photovoltaic technology toward physics-informed design by demonstrating the capacity to extract mechanistic insight from the ideality factor through rigorous numerical modeling, a capability that will prove essential as the industry transitions to higher-efficiency architectures and expands deployment into climatically challenging environments where predictive understanding of degradation mechanisms determines economic viability.

V. AUTHOR'S CONTRIBUTION

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Resources: Ravshanbek Rakhmatulaev.

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