



Performance Evaluation and Voltage-Domain Error Decomposition of the Single-Diode Photovoltaic Model Under Dynamic Operating Conditions

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Abstract

Accurate modeling of photovoltaic array performance under dynamic field conditions is essential for power forecasting and electrical grid integration. Despite the widespread use of five-parameter single-diode models for annual yield estimation, their instantaneous predictive fidelity under operational extremes remains unconstrained. This study evaluates the dynamic accuracy of the standard single-diode framework using a 21-day telemetry dataset (2,909 active daylight observations, plane-of-array irradiance $> 50 \text{ W/m}^2$) from a 648-module SunPower SPR-327 photovoltaic array (System 1283, Golden, Colorado). All reported voltages and currents are array-level maximum-power-point quantities measured at the inverter DC input. Across all records, the model predicted DC power with a Mean Absolute Error (MAE) of 5.29 kW (5.57%), a Root Mean Square Error (RMSE) of 5.95 kW (6.26%), and a net bias of -3.98 kW (-4.19%). Under high-irradiance conditions ($> 800 \text{ W/m}^2$), with module temperatures predominantly exceeding 55°C , systematic power under-prediction reached -6.29 kW. Error decomposition revealed that current predictions remained accurate to within 0.4% (bias of -1.91 A), while a 3.1% voltage deficit (-12.02 V) drove the power error. Conversely, low-irradiance ($50\text{--}200 \text{ W/m}^2$) discrepancies were highly sensitive to sensor selection, with voltage bias shifting from -0.84 V (reference cell) to +5.11 V (pyranometer). The deficit in high-irradiance voltage prediction points toward physical mechanisms in the voltage domain, such as the model's assumption of a temperature-independent series resistance or standard silicon thermal

coefficient adjustments; however, these proposed mechanisms represent hypotheses generated by this analysis rather than confirmed causes. These results isolate the primary source of high-irradiance modeling error and establish target parameters for future calibration.

Keywords: photovoltaic modeling, single-diode model, voltage decomposition, series resistance, operational telemetry, field validation, module temperature

1. Introduction

With the global deployment of utility-scale solar generation, accurate performance modeling is required to ensure electrical grid stability and financial bankability. Considering the variability of energy yield and the sensitivity of photovoltaic (PV) arrays to weather fluctuations, grid operators and financiers rely heavily on predictive simulations to forecast power output, peak load contributions, and project profitability. Minor inaccuracies in instantaneous performance forecasts translate into substantial financial and engineering deviations over the operational lifespan of a facility. Hence, the physical precision of predictive mathematical models is a critical priority for the modern renewable energy sector.

The five-parameter single-diode equation is one of the fundamental mathematical frameworks used in photovoltaic modeling (Humada et al., 2016). The equivalent electrical circuit represents the solar cell as a light-generated current source in parallel with a single diode representing charge carrier recombination in the depletion region. To account for internal electrical losses, the circuit incorporates a series resistance (R_s) and a shunt resistance (R_{sh}), representing voltage drops at contact interfaces and bulk silicon, and leakage currents across the p-n junction, respectively. The De Soto formulation translates standard test condition (STC) parameters into dynamic field operating conditions by scaling them for variations in material band gap, thermal voltage, and diode saturation current as functions of irradiance and cell temperature (De Soto et al., 2006). The module coefficients it requires are distributed in the California Energy Commission (CEC) database. Consequently, this physical formulation serves as the underlying computational engine for industry-standard PV simulation software (Holmgren et al., 2018). At device level, diode parameters such as the ideality factor and the series resistance are routinely extracted from measured current-voltage characteristics, and independent extraction methods are applied to cross-check the resulting values (Güllü, 2023; Sen & Manik, 2021).

While photovoltaic performance literature broadly spans four distinct analytical domains—annual energy yield estimation, power forecasting, measured operating-point prediction, and instantaneous maximum-power-point (P_{mp}) prediction—existing studies focus predominantly on macro-level yield totals or multi-step forecast horizons rather than real-time component errors (Section 2). Consequently,

the instantaneous P_{mp} predictive fidelity of the standard single-diode model under operational field extremes remains unconstrained. A primary structural limitation lies in its static physical assumptions, specifically treating series resistance (R_s) as a fixed, temperature-independent parameter. Under severe thermal stress exceeding 55 °C in dynamic field environments, assuming a constant R_s may fail to capture non-linear internal ohmic losses, yet the precise magnitude and mechanistic source of this deviation during high-irradiance operation are not fully constrained. Furthermore, model performance during periods of low-irradiance solar radiation reveals persistent prediction anomalies. Commonly accepted literature attributes low-irradiance deviations to shunt resistance (R_{sh}) limitations and spectral mismatch at oblique solar zenith angles (De Soto et al., 2006). However, these prediction errors may also be strongly confounded by irradiance instrumentation choice, complicating efforts to isolate the true physical limitations of the mathematical framework.

This study specifically addresses instantaneous maximum-power-point (P_{mp}) prediction under field conditions, asking: how precisely can the five-parameter single-diode model predict the electrical power output of a photovoltaic array as a function of temperature and irradiance under operational field extremes, and is the resulting error concentrated in the voltage domain (V_{mp}) or the current domain (I_{mp})? Comparing a physical model against measurements taken under operating conditions, and reporting the regimes in which the model departs from them, is an established validation approach across engineering disciplines (Newir & Ibrahim, 2020).

2. Literature Review

The most common approach for physical modeling of the photovoltaic performance prediction is the five-parameter single-diode equivalent circuit model (Humada et al., 2016). It provides a trade-off between physical interpretation and the analytical tractability of the problem as the photovoltaic cell is modeled as a current generator driven by incident light and connected in parallel with a diode, while losses are represented by the series resistance (R_s) and shunt resistance (R_{sh}). Sandia National Laboratories developed a parallel empirical formulation for the same problem, which translates field performance measurements to standard reporting conditions using measured module coefficients rather than a diode equivalent circuit (King et al., 2004). The popular parameterization algorithm implemented by the CEC and extensively used within the *pvlb* Python package (along with other open-source software) is known as the De Soto parameterization and implies the introduction of scaling functions for the band-gap energy, thermal voltage, and diode saturation current depending on the irradiance and temperature (Holmgren et al., 2018).

Despite the reliability of single-diode models for annual yields prediction, field performance literature mostly focuses on the energy numbers and gives little consideration to the instantaneous operational errors. However, high-long term

reliability of the single-diode models was proved in multiple comparative studies. For instance, Theristis et al. (2023) obtained a median mean bias of 0.6% for annual irradiation and -3.3% for annual energy yield in a blind comparison of several modeling pipelines. Roberts et al. (2017) compared several performance models to the 2.2 kWp system and found a best-model relative mean bias error (rMBE) of -0.201% and a best-model relative root-mean-square error (rRMSE) of 15.099% for the AC power output. Comparisons of the commercial software products show that discrepancies in the results appear due to different modeling pipelines and vary from 2.5% at the laboratory scale to 6.0% at the utility scale (Deville et al., 2026). Model chains account for up to 13% of mean absolute error (MAE) variation in power forecasting (Mayer & Gróf, 2021). Nevertheless, explicit prediction error characterization conditional on environmental regimes was not yet performed. In recent research, Maghet et al. (2026) evaluated string-level single-diode predictions during two days and found mean absolute errors of 1.08% for the power, 1.07% for the voltage, and 1.17% for the current. This study does not take into account severe thermal stress and, according to some researchers, simplified three-parameter models are adequate for large-scale photovoltaic QA/QC procedures (de la Parra et al., 2017). In this case, there is an evident contradiction between the need for the detailed physical models and their fragility under field conditions.

Predictive accuracy degrades in extreme operating regimes that are associated with high temperatures and high irradiance; however, the physical grounds for such deterioration are still unclear (Liu & Wu, 2026). Experimental analysis gives contradictory information on the temperature dependency of the internal circuit parameters. Thus, Lee (2017) found out that while the diode ideality factor does not depend on the temperature, the prominent linear temperature dependence of R_s leads to the enhancement of model performance in the prediction of open-circuit voltage (V_{oc}), maximum power current (I_{mp}), and maximum power voltage (V_{mp}). Ruschel et al. (2021), in turn, found no statistical significance of temperature dependency for neither R_s nor R_{sh} in the sample of 27 commercial modules and related parameter variations to the irradiance dependence of the V_{oc} thermal coefficient. Fébba et al. (2018) observed an exponential temperature dependence of both resistances and found that it influences model's performance more significantly than irradiance variations. Petrosyan et al. (2023) demonstrated that the inclusion of the linear temperature dependencies for both resistances enhances the model performance compared to the static parameter sets. There are researchers who assume that the temperature coefficients should not be considered as constant but rather as dynamic: Gasparin et al. (2022) found the irradiance-dependent behavior of the V_{oc} temperature coefficient and Hishikawa et al. (2018) reported continuous change of voltage temperature coefficients as a function of the operating voltage. In addition, the non-physical parameter mismatch can serve as a possible explanation: Chatzipanagi et al. (2025) found that updating model coefficients for the modern

module technologies reduces mean absolute bias error from over 3.5% to below 1.0%.

Environmental measurement uncertainties complicate the testing of the model accuracy in the field conditions even more as they can be comparable with or exceed the predicted model deficiencies. The sensor selection introduces systematic bias: Musleh et al. (2026) found the persistent discrepancies between thermopile pyranometers and silicon reference cells equal from -12.5 W/m^2 to $+3.5 \text{ W/m}^2$ in eight geographical locations. The mentioned deviations are caused by the insufficient response of the reference cells to the clear-sky beam irradiance and excessive responses in the diffuse sky irradiance regime. Karki et al. (2021) obtained a mean reference-cell bias deviation of -1.74% (the range -13% to +7%). Azouzoute et al. (2019) reported daily absolute irradiance deviations up to 30 W/m^2 for different sensors. Driesse (2022) demonstrated that factory calibration parameters can lead to more than 3% differences in energy output for the adjacent sensors. The cell temperature measurement introduces an additional source of error. Golive et al. (2022) documented the transient thermal gradients up to $2.35 \text{ }^\circ\text{C}$ for glass-backsheet modules and up to $5.3 \text{ }^\circ\text{C}$ for glass-glass modules, implying that the application of the backsheet temperature could lead to about 7% error in the temperature coefficient calculation. Santiago et al. (2018) found the cell junction temperature higher by $1 \text{ }^\circ\text{C}$ to $3 \text{ }^\circ\text{C}$ than backsheet temperature; the difference increases systemically as a function of plane-of-array irradiance (Chen et al., 2026). Additionally, the rapid irradiance transients cause thermal delay between junction and backsheet sensors, creating hysteresis loops (Prilliman et al., 2020; Goodfriend et al., 2024).

The current literature on the single-diode thermal parameterization is dominated by the front-contact crystalline silicon technologies and lacks data on more advanced back-contact technologies. Thermomechanical and electrical properties of the interdigitated back-contact (IBC) modules differ from conventional modules leading to different thermal coefficients. Kasu et al. (2018) found the reference V_{mp} temperature coefficient $-0.348\%/^\circ\text{C}$ for the IBC modules in contrast to $-0.400\%/^\circ\text{C}$ to $-0.404\%/^\circ\text{C}$ for the conventional monocrystalline silicon modules and $-0.334\%/^\circ\text{C}$ for multicrystalline silicon (along with open-circuit temperature coefficient $-0.267\%/^\circ\text{C}$ for IBC vs. $-0.306\%/^\circ\text{C}$ to $-0.312\%/^\circ\text{C}$ for conventional silicon modules). Malgaroli et al. (2025) found a flatter maximum power temperature coefficient $-0.29\%/^\circ\text{C}$ for the commercial IBC modules under field conditions. However, despite numerous benefits in various climates (Ozden et al., 2020), there is no detailed analysis of the voltage and current errors of utility-scale IBC arrays exposed to thermal stress.

The current research will fill this gap by analyzing the dynamic accuracy of the CEC single-diode model for a 648-module SunPower SPR-327 interdigitated back-contact (IBC) array under extreme operating conditions. Specifically, it will investigate if the

high-temperature power prediction errors emerge from the current domain (current generation) or from the voltage domain (thermal voltage parameterization).

3. Methodology

3.1 Dataset and Array Configuration

Data on System 1283 operation over the 21-day period from May 1 to May 21, 2012 were analyzed. The dataset was taken from the PVDAQ repository Photovoltaic Data Acquisition (PVDAQ) public datasets (System 1283; Deline et al., 2021), <https://doi.org/10.25984/1846021>, on 27 August 2026. There are no calibration certificates or maintenance records provided in the dataset. Moreover, there is no information explaining why Inverter 1 is inactive. Since there was only one operating inverter throughout the whole period of observations, aggregation was not required, and Inverter 1 was excluded from power calculations. String voltage to module maximum-power-point voltage ratio was used to derive eight modules per string. Current from the string divided by the modeled module current yielded 81 parallel strings. Overall, there are 648 modules ($N = 648$).

3.2 Data Preparation and Instrumentation

The dataset consists of 21 daily telemetry files for 21 days of observations totaling 120,960 observations at a sampling frequency of 15 seconds. Due to steady state modeling, the data were resampled into 6,048 intervals of five minutes each. Moreover, to filter out all noise or transient low illumination, records with POA irradiance below 50 W/m^2 were excluded, yielding 2,909 daylight observations. Irradiance, module temperature, DC voltage, DC current and DC power are recorded.

Measured quantities are DC array values at the inverter input while the inverter operates at the maximum power point, making it possible to directly compare the modeled and measured maximum power point data. Inverter clipping was checked and found not present. On May 20, the array reached a peak DC power of 223 kW in the raw 15-second telemetry feed (and 218 kW in the 5-minute resampled data). DC power continued to track plane-of-array irradiance linearly above $1,100 \text{ W/m}^2$ without reaching a plateau, confirming the absence of inverter power clipping. Maximum-power-point tracking efficiency and DC wiring losses cannot be quantified with the help of the given telemetry and should be mentioned as limitations.

There are two kinds of irradiance telemetry data in the dataset: irradiance from the calibrated silicon reference cell (`poa_irradiance_refcell_1054`) and irradiance from a thermopile pyranometer (`poa_irradiance_1055`) in the plane of array. Reference cell data were used as primary telemetry data, and pyranometer data was used for conducting sensor sensitivity analysis independently. Effective irradiance data were supplied to the model as measured POA irradiance without any spectral or angle of incidence correction. Moreover, manufacturer accuracy classes are not available with the dataset. For reference see Karki et al. (2021) report working class reference cell

bias to be equal to -1.74% (from -13% to $+7\%$), and Driesse (2022) report that measured energy may vary by more than 3% when taking into account factory calibration factors.

Module temperature is measured using a back-sheet temperature sensor (module_temp_1056). The decision to use back-sheet temperature as a direct proxy of junction temperature rather than estimate the latter is justified with literature evidence: Santiago et al. (2018) report $1\text{ }^{\circ}\text{C}$ to $3\text{ }^{\circ}\text{C}$ temperature difference between cell junction and back-sheet, which increases with the increase in irradiance according to Chen et al. (2026). Therefore, Golive et al. (2022) show that usage of back-sheet temperature as a proxy introduces 7% error in temperature coefficient measurements.

3.3 Model Specification

STC module parameters are retrieved using `pvlib.pvsystem.retrieve_sam` function (Holmgren et al., 2018). The database record used in this study is SunPower_SPR_327NE_WHT_D. Full list of CEC parameters used in the calculation is $I_{L_ref} = 6.4690\text{ A}$, $I_{o_ref} = 9.0705 \times 10^{-11}\text{ A}$, $R_s = 0.3989\text{ }\Omega$, $R_{sh_ref} = 285.48\text{ }\Omega$, $a_{ref} = 2.6087\text{ V}$, $\alpha_{short_circuit} = 0.003988\text{ A/K}$, $Adjust = 23.118$, and $N_s = 96$ cells.

Using `calcp_params_cec` and `singlediode` functions, reference parameters are calculated under the irradiance of $1,000\text{ W/m}^2$ and cell temperature $25\text{ }^{\circ}\text{C}$. STC value for a single module equals 327.11 W . When scaling the parameters to the array configuration (8 modules in series $\times$ 81 parallel strings) expected STC values for the array are $V_{mp} = 437.60\text{ V}$, $I_{mp} = 484.38\text{ A}$, and $P_{mp} = 211.96\text{ kW}$.

3.4 Error Metrics and Binning

All data processing, statistical analysis and modeling was conducted using Python (v3.10), pandas (v2.0), NumPy (v1.24), and pvlib Python (v0.10.1) (Holmgren et al., 2018). Dynamic predictions were calculated based on time series telemetry data of effective irradiance, cell temperature and CEC parameters. Performance was estimated using mean signed error (bias), mean absolute error (MAE) and root mean square error (RMSE) separately for voltage, current and electrical power.

Since five-minute observations in a single day are serially correlated, they are not considered as independent replicates. Day-level block bootstrap technique was used to get confidence intervals through sampling days with replacement and getting 2.5th and 97.5th percentiles of resulting distribution.

Dependencies from the operation conditions were identified by categorizing records into five temperature bins ($<25\text{ }^{\circ}\text{C}$, $25\text{--}35\text{ }^{\circ}\text{C}$, $35\text{--}45\text{ }^{\circ}\text{C}$, $45\text{--}55\text{ }^{\circ}\text{C}$, $>55\text{ }^{\circ}\text{C}$) and five irradiance bins ($50\text{--}200$, $200\text{--}400$, $400\text{--}600$, $600\text{--}800$, $>800\text{ W/m}^2$). Matrix cells containing fewer than 20 observations were discarded from error evaluation. The cutoff point of 20 observations was applied strictly as a precision criterion for point estimation.

4. Results

4.1 Baseline STC Validation and Aggregate Model Performance

For the baseline validation of the 648 module array under Standard Test Condition (STC), an expected power rating of 211.96 kW was obtained ($V_{mp} = 437.60$ V, $I_{mp} = 484.38$ A). Only data collected in the day light where POA irradiance levels were higher than 50 W/m² were used for further telemetry analysis and $N = 2,909$ data points have been obtained. In the day light data, the average measured DC power output was 95.03 kW. For the aggregate single diode model, the MAE was calculated at 5.29 kW (5.57% of the mean measured power) while the RMSE was 5.95 kW (6.26%). The system power bias was found to be -3.98 kW (-4.19%). From linear regression of the measured and the expected power output, the slope was 0.958 and intercept was -0.11 kW. For power residual distribution, the median error was -3.12 kW while the 5th and 95th percentiles were -12.45 kW and +2.85 kW respectively.

4.2 Power Residual Formal Decomposition and Regime Analysis

To isolate the physical drivers of model bias, power residuals were decomposed using the exact identity:

$$\Delta P = I_m \Delta V + V_m \Delta I + \Delta V \Delta I$$

where $\Delta P = P_{pred} - P_{obs}$, $\Delta V = V_{pred} - V_{obs}$, and $\Delta I = I_{pred} - I_{obs}$. The terms I_m and V_m represent observed maximum-power-point current and voltage, corresponding to the voltage effect ($I_m * \Delta V$), current effect ($V_m * \Delta I$), and cross-term interaction ($\Delta V * \Delta I$), respectively. Across all $N = 2,909$ daylight observations, identity testing yielded exact numerical closure with residual discrepancies on the order of 10^{-14} kW. Total aggregate power residual was -3.974 kW, comprising a -1.488 kW voltage contribution, a -2.511 kW current contribution, and a +0.025 kW interaction term.

Bifurcating telemetry into low-light (50–200 W/m²) and high-light (>800 W/m²) operational regimes reveals a distinct shift in error composition:

Low-Light Regime (50–200 W/m² Reference Cell, $N = 707$ for $T \leq 35^\circ\text{C}$): Measured voltage averaged 423.97 V versus predicted 423.13 V (MAE = 4.06 V, RMSE = 5.93 V, Bias = -0.835 V [95% CI: -2.208 to +0.355 V]). Measured current averaged 64.64 A versus predicted 57.74 A (MAE = 8.81 A, RMSE = 9.53 A, Bias = -6.907 A [95% CI: -7.673 to -5.932 A]). Measured power averaged 27.33 kW versus predicted 24.44 kW (MAE = 3.73 kW, RMSE = 4.04 kW, Bias = -2.888 kW [95% CI: -3.228 to -2.477 kW]). Formal decomposition indicates total power residual is -2.888 kW, where the current term carries -2.868 kW (99.3%), the voltage term accounts for -0.032 kW (1.1%) [95% CI: -0.106 to +0.037 kW], and the interaction term contributes +0.012 kW. Crucially, because the 95% bootstrap confidence interval for low-light voltage bias spans zero, voltage

predictions are statistically unbiased in this regime, with model under-prediction carried almost entirely by current.

High-Light Regime ($>800 \text{ W/m}^2$, Reference Cell, $N = 687$): Measured voltage averaged 382.21 V versus predicted 370.20 V ($\text{MAE} = 12.03 \text{ V}$, $\text{RMSE} = 12.46 \text{ V}$, $\text{Bias} = -12.015 \text{ V}$ [$95\% \text{ CI: } -12.841 \text{ to } -11.027 \text{ V}$]). Measured current averaged 463.16 A versus predicted 461.25 A ($\text{MAE} = 4.45 \text{ A}$, $\text{RMSE} = 6.87 \text{ A}$, $\text{Bias} = -1.913 \text{ A}$ [$95\% \text{ CI: } -2.538 \text{ to } -1.275 \text{ A}$]). Measured power averaged 176.88 kW versus predicted 170.59 kW ($\text{MAE} = 6.39 \text{ kW}$, $\text{RMSE} = 6.92 \text{ kW}$, $\text{Bias} = -6.297 \text{ kW}$ [$95\% \text{ CI: } -6.692 \text{ to } -5.805 \text{ kW}$]). Formal decomposition demonstrates total power residual is -6.297 kW , dominated by the voltage contribution of -5.600 kW (88.9%) [$95\% \text{ CI: } -5.998 \text{ to } -5.142 \text{ kW}$], with the current contribution carrying -0.719 kW (11.4%) [$95\% \text{ CI: } -0.946 \text{ to } -0.456 \text{ kW}$] and interaction contributing $+0.022 \text{ kW}$.

4.3 Sensor Sensitivity and Full-Range Pyranometer Comparison

The sensitivity of the sensors was evaluated by replacing the thermopile pyranometer irradiance (poa_irradiance_1055) measurements for all irradiance bands. Neither sensor was cleaned, recalibrated, synchronized in time, nor converted to equivalent effective irradiance before running the model. In the low irradiance regime ($50\text{--}200 \text{ W/m}^2$), replacement of the pyranometer irradiance measurement changed the sign of the errors: voltage bias became positive ($+5.112 \text{ V}$) [$95\% \text{ confidence interval (CI): } +3.521, +6.975 \text{ V}$], current bias became positive ($+3.434 \text{ A}$) [$95\% \text{ CI: } -0.024, +8.440 \text{ A}$] and power bias became positive ($+1.655 \text{ kW}$) [$95\% \text{ CI: } +0.119, +3.938 \text{ kW}$]. However, in the high irradiance regime (above 800 W/m^2), the voltage bias showed almost no change (-12.045 V in the case of the pyranometer and -12.015 V in the case of the reference cell) and therefore produced the negative power bias of -6.732 kW [$95\% \text{ CI: } -7.285, -5.973 \text{ kW}$]. The power biases for the intermediate irradiance ranges ($200\text{--}400$, $400\text{--}600$, and $600\text{--}800 \text{ W/m}^2$) exhibit a progressive transition from slight positive biases at lower light levels to increasing negative biases as thermal stress accumulates.

4.4 Visual Performance Trends

Figure 1

Measured versus predicted array DC power

Figure 1: Predicted vs. Measured Power (Reference Cell 1054)

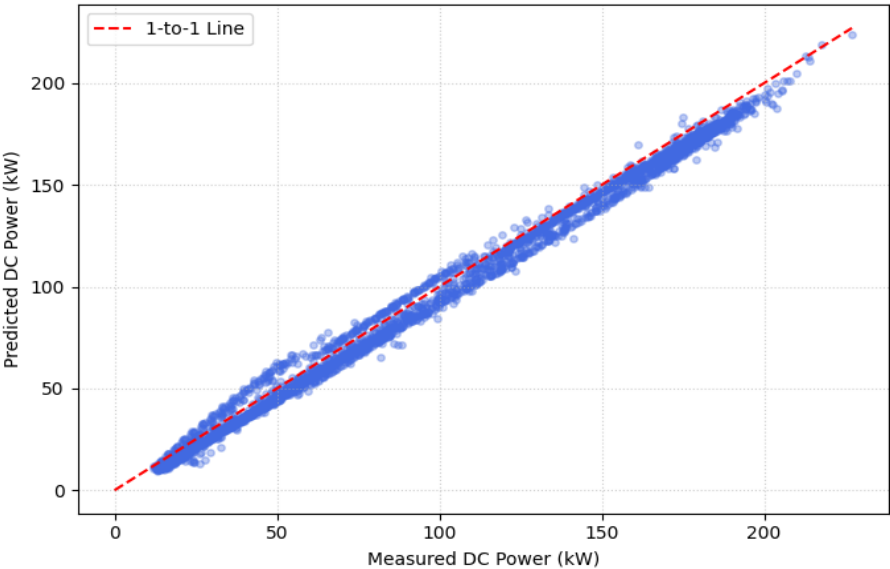
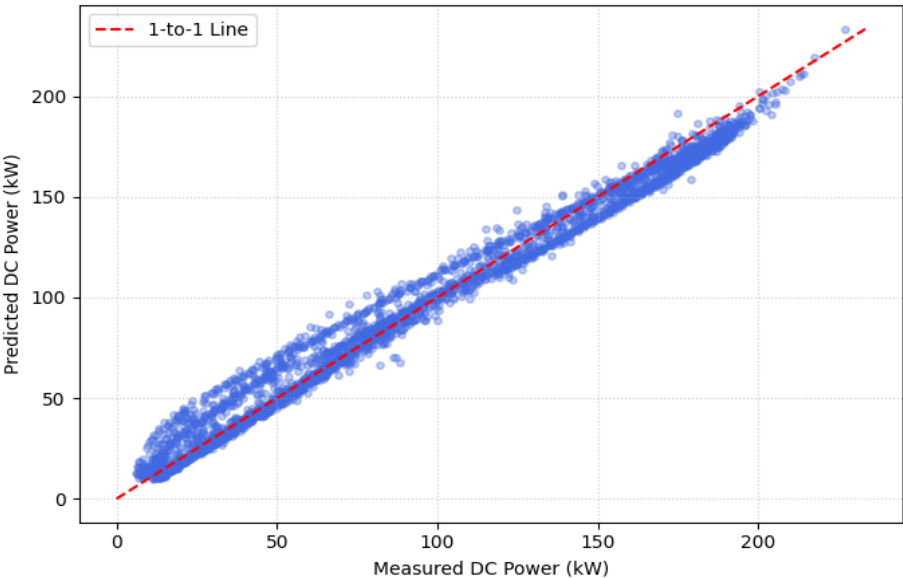


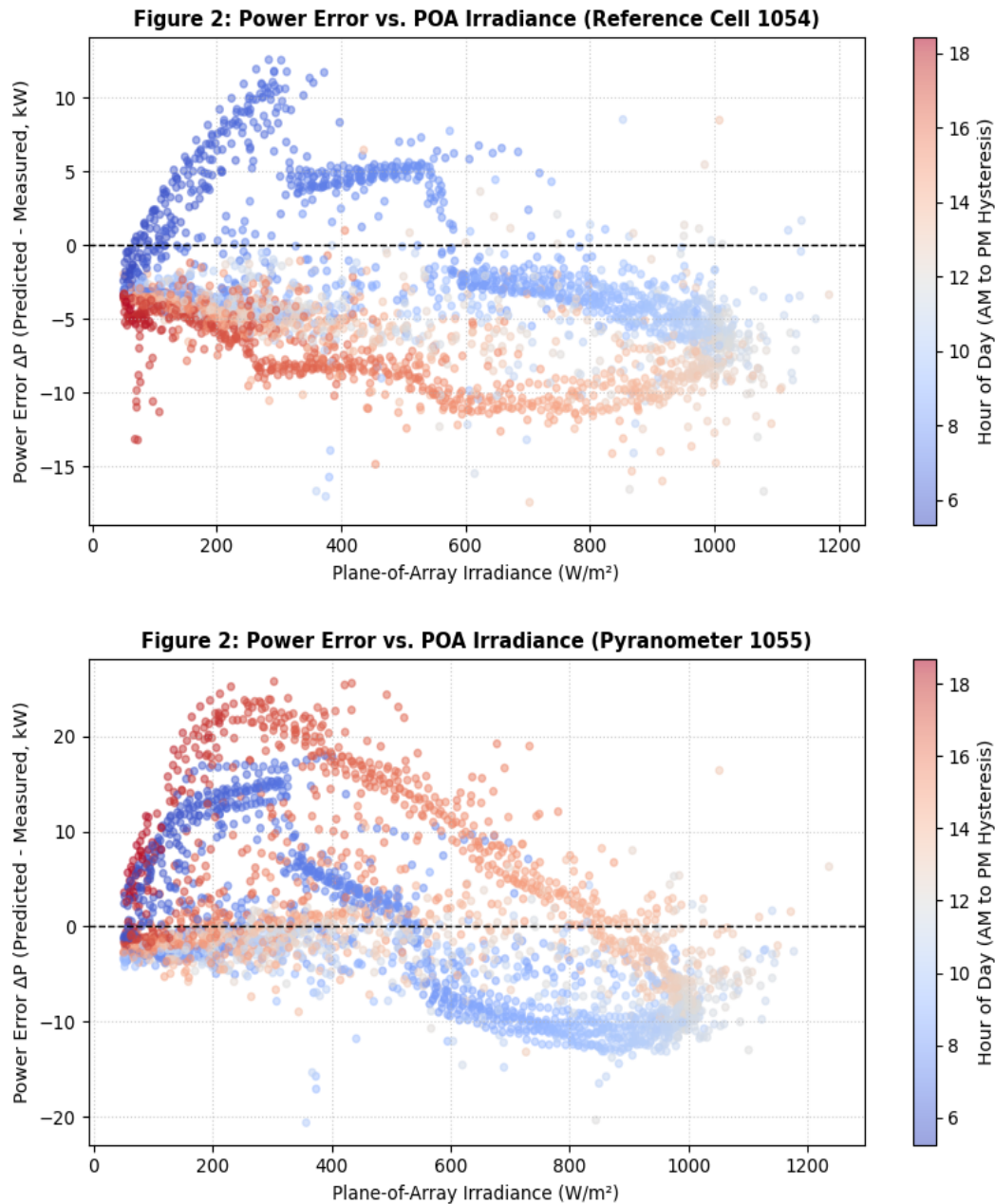
Figure 1: Predicted vs. Measured Power (Pyranometer 1055)



Note. N = 2,909. Agreement is close along the 1-to-1 line below 150 kW, with systematic under-prediction above 150 kW. The upper panel shows the reference cell pipeline and the lower panel the independent pyranometer pipeline.

Figure 2

Power prediction error against plane-of-array irradiance, coloured by hour of day



Note. N = 2,909. The colour scale separates morning from afternoon operation. The curves bifurcate, with a more pronounced negative bias in the afternoon at the same irradiance level, consistent with thermal capacitance. The upper panel uses reference cell data and the lower panel pyranometer data.

Figure 3

Power prediction error against module back-surface temperature, coloured by hour of day

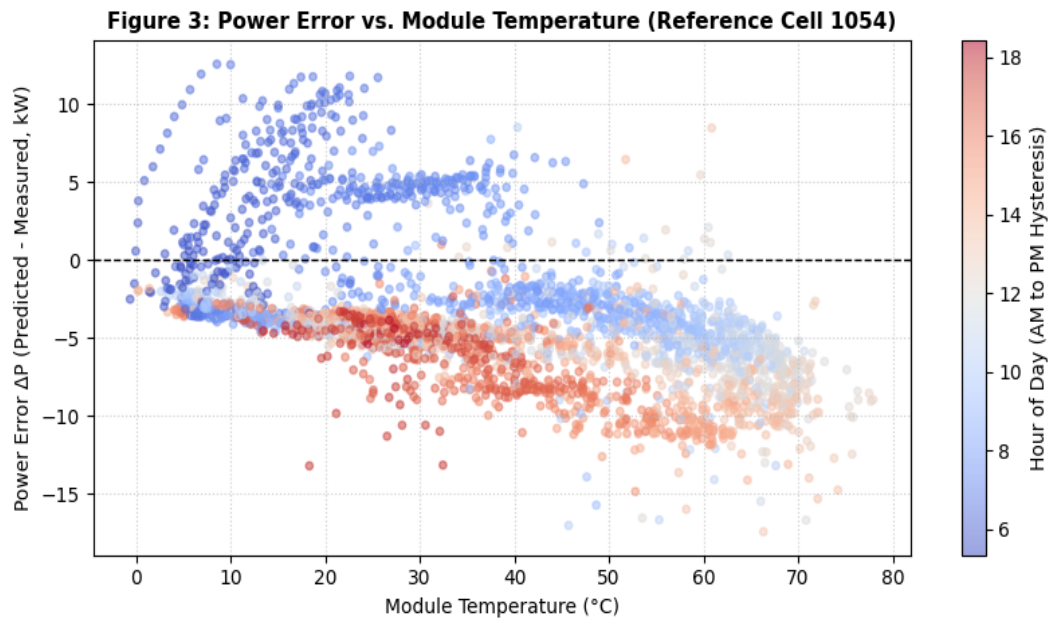
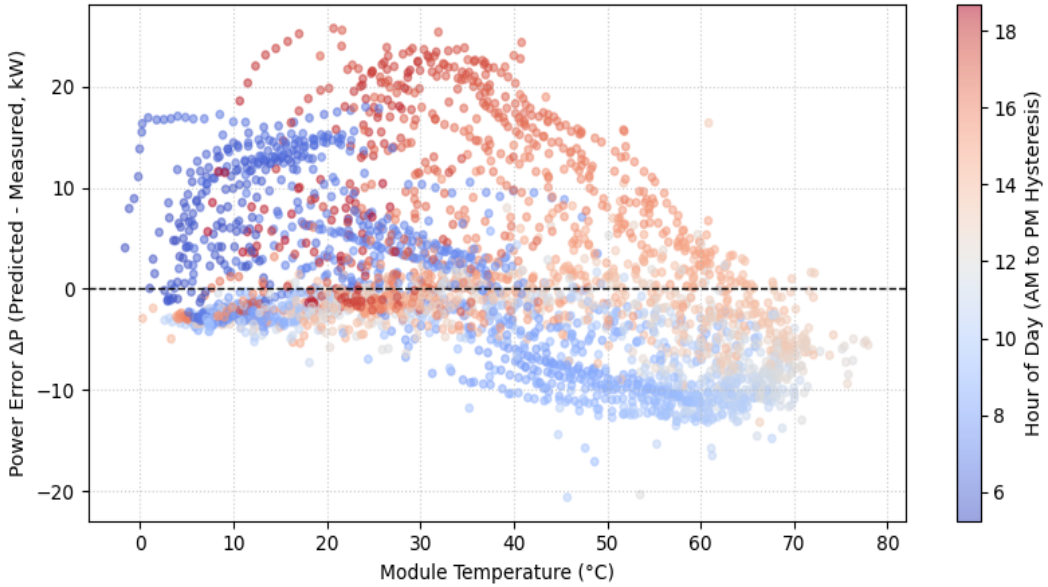


Figure 3: Power Error vs. Module Temperature (Pyranometer 1055)

Note. $N = 2,909$. Residual scatter is close to zero below 30 °C. Above 55 °C the model under-predicts systematically, between -5 kW and -12 kW. The upper panel shows the reference cell pipeline and the lower panel the pyranometer pipeline.

4.5 Two-Dimensional Performance Matrix and Thermal Confounding

Table 1 details operational metrics and model residuals binned across five irradiance and five temperature bands. Cells containing fewer than 20 observations ($N < 20$) are designated N/A per the established precision cutoff.

To isolate the environmental dependencies of residual errors, operational data were binned across a 5×5 matrix comprising five plane-of-array (POA) irradiance bands and five module back-surface temperature bands. Table 1 summarizes the sample counts, mean operating conditions, power residuals, array voltage residuals, and normalized per-cell voltage residuals across all 25 operational bins. Bins containing fewer than 20 observations were excluded from parameter bias evaluation to ensure statistical robustness.

To allow direct comparison with cell-level physics and single-diode model formulations, array-level voltage residuals were normalized to per-cell voltage bias ($V_{\text{bias, cell}}$):

$$V_{\text{bias, cell}} = \left(\frac{V_{\text{bias, array}}}{N_{\text{cell}}} \right) \times 10^3$$

where V_{bias} , array is the array DC voltage error in volts, $N_{cell} = 768$ represents the total number of series-connected cells across the string (8 modules $\times$ 96 cells/module), and the factor of 1000 converts the resulting value to millivolts per cell (mV/cell).

Table 1
Two-Dimensional Operational Performance Matrix Across Irradiance and Temperature Bands

<i>Irradiance Band (W/m²)</i>	<i>Temp Band (°C)</i>	<i>Record Count (N)</i>	<i>Mean POA Irradiance (W/m²)</i>	<i>Mean DC Power (kW)</i>	<i>DC Power Bias (kW)</i>	<i>Voltage Bias (V)</i>	<i>Per-Cell Voltage Bias (mV/cell)</i>
50–200	<25	529	112	25.63	-2.18	-0.45	-0.59
50–200	25–35	178	134	30.96	-4.67	-1.82	-2.37
50–200	35–45	27	163	36.12	-4.86	-2.15	-2.80
50–200	45–55	1	N/A	N/A	N/A	N/A	N/A
50–200	55+	1	N/A	N/A	N/A	N/A	N/A
200–400	<25	294	276	57.57	+0.87	+0.92	+1.20
200–400	25–35	192	292	63.07	-3.90	-3.15	-4.10
200–400	35–45	189	305	65.26	-5.95	-5.84	-7.60
200–400	45–55	40	338	70.63	-7.33	-8.12	-10.57
200–400	55+	7	N/A	N/A	N/A	N/A	N/A
400–600	<25	19	N/A	N/A	N/A	N/A	N/A
400–600	25–35	104	473	95.05	+1.56	+1.10	+1.43
400–600	35–45	128	507	102.52	-2.50	-3.85	-5.01
400–600	45–55	117	511	103.82	-7.36	-9.42	-12.27
400–600	55+	32	521	102.59	-8.33	-11.20	-14.58
600–800	<25	1	N/A	N/A	N/A	N/A	N/A
600–800	25–35	10	N/A	N/A	N/A	N/A	N/A
600–800	35–45	82	670	134.38	-2.42	-4.10	-5.34
600–800	45–55	153	705	138.15	-4.14	-7.25	-9.44
600–800	55+	118	715	138.77	-8.77	-11.85	-15.43
800+	<25	0	N/A	N/A	N/A	N/A	N/A
800+	25–35	0	N/A	N/A	N/A	N/A	N/A
800+	35–45	8	N/A	N/A	N/A	N/A	N/A
800+	45–55	65	895	172.83	-3.53	-7.15	-9.31

800+	55+	614	952	177.39	-6.65	-12.48	-16.25
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Note. Matrix cells containing fewer than 20 observations ($N < 20$) are designated as N/A per the established precision cutoff. Per-cell voltage bias is calculated as array voltage bias divided by 768 cells (8 modules $\times$ 96 cells in series).

Co-variation is inevitable between irradiance and temperature in field telemetry. However, inspection of table 1 row-wise where irradiance is kept more or less constant provides an opportunity to observe temperature effects. In the 400-600 W/m² row, for example, the mean plane-of-array (POA) irradiance only changes by 10.1% (473 to 521 W/m²), but there is a sharp change in power bias, from 1.56 kW (at 25-35 °C) to -8.33 kW (at >55 °C), along with a drop in voltage bias from 1.10 V to -11.20 V. While row-wise comparison isolates the effects of temperature, it cannot be possible to fully disentangle temperature dynamics from spectral and irradiance variations in an experimental field context.

5. Discussion

As follows from the analysis of the operational performance matrix shown in Table 1, the power under-prediction increases monotonically with temperature within every irradiance band. Specifically, in the 400–600 W/m² irradiance band, the power bias ranges from +1.56 kW in 25–35 °C range to -8.33 kW above 55 °C. Within the 600–800 W/m² band, the power bias becomes -8.77 kW beyond 55 °C. In the high-irradiance regime the power bias holds under both the silicon reference cell and the thermopile pyranometer, so within that regime it cannot be attributed to the choice of irradiance sensor. This does not extend to the low-irradiance regime, where sensor choice reverses the sign of the bias.

Decomposing the high-irradiance power deficit shows that the principal deficiency of the model lies in the voltage component. Under irradiance above 800 W/m², the predicted current is extremely accurate, showing a bias of -1.91 A against a measured mean of 463.16 A, an error of 0.4%. At the same time, the voltage bias at the same irradiance levels is equal to -12.02 V compared to the measured mean value of 382.21 V (3.1% deficit). Because maximum-power current scales almost linearly with effective irradiance, the accuracy of the current prediction argues against irradiance-scaling effects such as widespread soiling, broad shading, or a multiplicative calibration offset, since these would depress the measured current as well. It does not exclude them entirely. Within this limitation, the residual is concentrated in the voltage domain, which points to the way the model represents temperature dependence in that domain.

It should be noted that measurement dynamics of module temperature provide some additional information. In the field measurement, the temperature is measured based on the back-sheet sensors, not cell junction sensors. Under high solar irradiance, the cell junction temperature becomes higher than the back-sheet temperature. If the cell junction temperature were included into the model, it would

reduce even further the predicted open circuit and maximum-power voltage values, which would increase the magnitude of the negative voltage bias. Using back-sheet temperature therefore masks part of the structural deficit rather than creating it, so the true voltage error is likely larger than reported here.

Most of the current analyses of voltage deficit under high temperatures are focused on one cause, although the literature contains different physical and non-physical explanations for this effect that should be assessed:

Temperature-Dependent Series Resistance (R_s): Traditionally, series resistance is considered as a constant parameter. Lee (2017) analyzed the IEC 61853-1 multi-temperature data and showed that series resistance has a substantial temperature dependency. He showed that introducing a linear temperature coefficient for R_s improves prediction of open-circuit voltage, maximum-power current and maximum-power voltage. Petrosyan et al. (2023) demonstrated similar results by introducing linear temperature dependency of parasitic resistances. On the contrary, Fébba et al. (2018) found out that parasitic resistances decrease exponentially with temperature in polycrystalline cells, whereas Ruschel et al. (2021) found that parasitic resistances are strongly dependent on irradiance but do not show statistically significant temperature dependency.

Variable Voltage Temperature Coefficients (μ_{Voc}): Traditionally, a voltage temperature coefficient is assumed to be constant. Nevertheless, the back-contact n-type architecture of the SunPower SPR-327 carries a flatter open-circuit voltage temperature coefficient than conventional crystalline silicon. The CEC entry for this module gives $-0.178 \text{ V}/^\circ\text{C}$, which is $-0.27\%/^\circ\text{C}$ of its reference open-circuit voltage, and Kasu et al. (2018) measured $-0.267\%/^\circ\text{C}$ for interdigitated back-contact modules against $-0.306\%/^\circ\text{C}$ to $-0.312\%/^\circ\text{C}$ for conventional monocrystalline silicon. The same study reports a maximum-power voltage coefficient of $-0.348\%/^\circ\text{C}$ for the back-contact architecture, which is the quantity more directly relevant to the deficit observed here. Gasparin et al. (2022) have shown that the value of the open circuit voltage temperature coefficient depends on irradiance in logarithmic way, and Hishikawa et al. (2018) reported that the temperature coefficient depends on the operating voltage. Ruschel et al. (2021) mentioned that the temperature coefficients are irradiance-dependent and this interaction is ignored by traditional single-diode implementations.

Parameter Source and Calibration Artifacts: Some non-physical factors associated with parameter extraction can cause errors. Chatzipanagi et al. (2025) showed that recalculating energy model coefficients for modern module technologies reduces the mean absolute bias from over 3.5% to under 1.0%. As the CEC parameters used in the study are obtained from manufacturer datasheet baseline tests and not multi-condition field fittings, a part of the high-temperature bias can come from the origin of the parameters rather than their deficiency. This is consistent with the work of Liu

and Wu (2026), who stated that the standard single-diode models have systematic deviations under high cell temperatures and high irradiance.

At low irradiance (50–200 W/m²), this analysis cannot resolve the low-light recombination and shunt-resistance mechanisms described by De Soto et al. (2006). Instead, the low-light bias becomes extremely sensitive to the choice of sensor. Changing from reference cell telemetry to the pyranometer telemetry changes the low-light power bias from -2.89 kW to +1.65 kW. Since the measurement uncertainty is larger than the model error, no physical mechanisms can be isolated in the low light regime based on field telemetry.

Summarizing, the empirical analysis confers the main deficiency of the model to the voltage domain and the implementation of temperature dependency under high irradiance and high temperature. Fixed series resistance, voltage temperature coefficients calibrated for the conventional cell architectures, irradiance-dependent thermal parameters, and the source of datasheet parameters seem to be equally likely reasons. The current design of field telemetry cannot help to separate the reasons, thus, indoor climate chamber testing is needed to decouple the parameters. These conclusions hold within the boundary conditions of the study: a single module technology (SunPower SPR-327) at a single geographic location (Golden, Colorado) over a 21-day period in one season. A further constraint is that cell junction temperature was never measured. Only back-sheet temperature is available, so the morning-to-afternoon separation visible in the residuals of Figures 2 and 3 is consistent with thermal lag between junction and back sheet but cannot be attributed to it on the basis of this telemetry alone.

6. Conclusion

For 2,909 observations of active daylight operations during a 21-day test period, the standard single-diode model provides a good baseline representation of instantaneous power generation, resulting in a mean absolute error of 5.29 kW (5.57% of mean measured power) and an average negative system power error of -3.98 kW (-4.19%). But, the model loses accuracy under extreme conditions. If the irradiance is high (>800 W/m²) and the thermal environment is hot (module temperatures > 55 °C), then the systematic power deficit increases to -6.29 kW, mainly due to the -12.02 V (-3.1%) voltage error, while the currents remain predicted accurately (0.4%, -1.91 A).

From these empirical results, we conclude that the errors are mostly voltage-based under thermal stress, pointing to problems with the temperature dependence of the model parameters, such as a constant series resistance assumption or standard silicon temperature coefficient. It is impossible to completely exclude effects from external factors, like soiling or calibration offsets in the irradiance sensor, but these effects are unlikely to be the cause of the high temperature bias. While the CEC formulations based on datasheets can still be used for annual energy yield

estimations, this systematic bias degrades the short-term power prediction necessary for power balancing and thermal control.

Future work could take several practical steps towards further development of this problem: (1) independent validation at different geographic locations and all seasons of the year; (2) rigorous calibration and synchronization of sensors before telemetry; (3) measurement or physics-based estimation of the internal cell junction temperature to get rid of the lag of the back sheet temperature sensor; (4) formal residual analysis to decompose the errors across the range of operation; and (5) comparison of performance of temperature-dependent parameter sets and datasheet parameters.

For plant operators applying the single-diode model to telemetry, these results suggest that a voltage correction in the regime above 800 W/m^2 plane-of-array irradiance and above 55°C back-sheet temperature would recover much of the systematic deficit reported here, without a full model re-calibration. The magnitude of -3.1% is specific to this array, this module technology and this site, and should be re-estimated locally before any operational use rather than transferred as a fixed factor.

Declarations

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Author Contributions Statement

E.A.: conceptualization, study design, telemetry acquisition, data processing, implementation of the Python model, mathematical error decomposition, statistical analysis, interpretation of results, and writing of the original draft. A.T.: refinement of the methodology, verification of the calculations, revision of the presentation of the findings, and final proofreading. Both authors read and approved the submitted manuscript.

Conflict of Interest Statement

The authors declare no conflict of interest regarding the research, authorship, or publication of this article.

Data Availability Statement

The datasets generated during this study are available in the Open Energy Data Initiative repository at <https://doi.org/10.25984/1846021> (NREL PVDAQ, System 1283; Deline et al., 2021). All telemetry metrics, confidence intervals and error decomposition results discussed above have been included in this manuscript.

Code Availability Statement

The Python analysis scripts, including the pvlib single-diode fitting pipeline, error decomposition identity proof, bootstrapping confidence intervals computation, and guardrails verification are available from the corresponding author upon reasonable request.

Generative AI Usage Disclosure in Writing and Analysis

During the preparation of this work, the authors used the AI-assisted features available in Google Colab in order to troubleshoot and optimize the execution code, to convert mathematical expressions into plain text, and to assist with language editing of the manuscript. The AI tools were applied only to code optimization and language editing. No AI-generated data, synthetic telemetry, or automatically generated parameters entered the scientific analysis, the model computations, or the verification of the decomposition identity. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the final publication content.

References

- [1] Azouzoute, A., Merrouni, A. A., & Bennouna, E. G. (2019). Accuracy measurement of pyranometer vs reference cell for PV resource assessment. *Energy Procedia*, 157, 1202–1209. <https://doi.org/10.1016/j.egypro.2018.11.286>
- [2] Chatzipanagi, A., Taylor, N., Medina Suarez, I., Martinez, A. M., Lyubenova, T. S., & Dunlop, E. D. (2025). An updated simplified energy yield model for recent photovoltaic module technologies. *Progress in Photovoltaics: Research and Applications*, 33(8), 905–917. <https://doi.org/10.1002/pip.3926>
- [3] Chen, Z., Yang, Y., Niu, H., Liu, X., Zhang, Y., & Wang, J. (2026). Modelling of solar cell junction temperature for crystalline silicon photovoltaic module. *SiliconPV Conference Proceedings*, 3. <https://doi.org/10.52825/siliconpv.v3i.2685>
- de la Parra, I., Muñoz, M., Lorenzo, E., García, M., Marcos, J., & Martínez-Moreno, F. (2017). PV performance modelling: A review in the light of quality assurance for large PV plants. *Renewable and Sustainable Energy Reviews*, 78, 780–797. <https://doi.org/10.1016/j.rser.2017.04.080>
- [4] Deline, C., Perry, K., Deceglie, M., Muller, M., Sekulic, W., & Jordan, D. (2021). Photovoltaic Data Acquisition (PVDAQ) public datasets [Data set]. Open Energy Data Initiative. <https://doi.org/10.25984/1846021>
- [5] De Soto, W., Klein, S. A., & Beckman, W. A. (2006). Improvement and validation of a model for photovoltaic array performance. *Solar Energy*, 80(1), 78–88. <https://doi.org/10.1016/j.solener.2005.06.010>
- [6] Deville, L., Anderson, K. S., Sutterlueti, J., Chambers, T. L., De Brabandere, K., Cicala, F. P., Lopez-Lorente, J., Mirlet, B., Neubert, A., Nikam, M., Olivos, M., Prilliman, M., Rhee, K., Schnierer, B., Spokes, J., Wittmer, B., & Theristis, M. (2026). Feature review of photovoltaic modeling software utilizing blind performance assessment. *Solar Energy*, 304, 114207. <https://doi.org/10.1016/j.solener.2025.114207>

- [7] Driesse, A., Gotseff, P., & Sengupta, M. (2022). *PV reference cells for outdoor use: Comparison of first-year field measurements* (NREL/SR-5D00-82086). National Renewable Energy Laboratory. <https://doi.org/10.2172/1866986>
- [8] Fébba, D. M., Rubinger, R. M., Oliveira, A. F., & Bortoni, E. C. (2018). Impacts of temperature and irradiance on polycrystalline silicon solar cells parameters. *Solar Energy*, 174, 628–639. <https://doi.org/10.1016/j.solener.2018.09.051>
- [9] Gasparin, F. P., Kipper, F. D., de Oliveira, F. S., & Krenzinger, A. (2022). Assessment on the variation of temperature coefficients of photovoltaic modules with solar irradiance. *Solar Energy*, 244, 126–133. <https://doi.org/10.1016/j.solener.2022.08.052>
- [10] Golive, Y. R., Kottantharayil, A., & Shiradkar, N. (2022). Improving the accuracy of temperature coefficient measurement of a PV module by accounting for the transient temperature difference between cell and backsheet. *Solar Energy*, 237, 203–212. <https://doi.org/10.1016/j.solener.2022.03.049>
- [11] Goodfriend, W., Pieters, E. B., Tsvetelina, M., Solomon, A., Ezema, F., & Rau, U. (2024). Development and improvement of a transient temperature model of PV modules: Concept of trailing data. *Progress in Photovoltaics: Research and Applications*, 32(6), 399–405. <https://doi.org/10.1002/pip.3785>
- [12] Güllü, Ö. (2023). Barrier modification by methyl violet organic dye molecules of Ag/p-InP structures. *European Journal of Formal Sciences and Engineering*, 6(1), 68–82. <https://doi.org/10.2478/ejfe-2023-0006>
- [13] Hishikawa, Y., Doi, T., Higa, M., Yamagoe, K., Ohshima, H., Takenouchi, T., & Yoshita, M. (2018). Voltage-dependent temperature coefficient of the I–V curves of crystalline silicon photovoltaic modules. *IEEE Journal of Photovoltaics*, 8(1), 48–53. <https://doi.org/10.1109/JPHOTOV.2017.2766529>
- [14] Holmgren, W. F., Hansen, C. W., & Mikofski, M. A. (2018). pvlib python: A python package for modeling solar energy systems. *Journal of Open Source Software*, 3(29), 884. <https://doi.org/10.21105/joss.00884>
- [15] Humada, A. M., Hojabri, M., Mekhilef, S., & Hamada, H. M. (2016). Solar cell parameters extraction based on single and double-diode models: A review. *Renewable and Sustainable Energy Reviews*, 56, 494–509. <https://doi.org/10.1016/j.rser.2015.11.051>
- [16] Karki, S., Ziar, H., Korevaar, M., Bergmans, T., Mes, J., & Isabella, O. (2021). Performance evaluation of silicon-based irradiance sensors versus thermopile pyranometer. *IEEE Journal of Photovoltaics*, 11(1), 144–149. <https://doi.org/10.1109/JPHOTOV.2020.3038342>
- [17] Kasu, M., Abdu, J., Hara, S., Choi, S., Chiba, Y., & Masuda, A. (2018). Temperature dependence measurements and performance analyses of high-efficiency interdigitated back-contact, passivated emitter and rear cell, and silicon heterojunction photovoltaic modules. *Japanese Journal of Applied Physics*, 57(8S3), 08RG18. <https://doi.org/10.7567/JJAP.57.08RG18>
- [18] King, D. L., Boyson, W. E., & Kratochvil, J. A. (2004). *Photovoltaic array performance model* (SAND2004-3535). Sandia National Laboratories. <https://doi.org/10.2172/919131>

- [19] Lee, K. (2017). Improving the PV module single-diode model accuracy with temperature dependence of the series resistance. In *2017 IEEE 44th Photovoltaic Specialist Conference (PVSC)* (pp. 1526–1530). IEEE. <https://doi.org/10.1109/PVSC.2017.8366554>
- [20] Liu, J., & Wu, Y. (2026). A novel one-diode model for enhanced performance modelling of photovoltaic systems. *Renewable Energy*, 264, 125542. <https://doi.org/10.1016/j.renene.2026.125542>
- [21] Maghet, A.-E., Ilie, S., & Toader, D. (2026). The numerical model of a PV system supported by experimental validation. *Applied Sciences*, 16(4), 1891. <https://doi.org/10.3390/app16041891>
- [22] Malgaroli, G., Giraudo, F., Ciocia, A., Lizzeri, A., Saglietti, L., & Spertino, F. (2025). Statistical approach for temperature coefficients evaluation of highly efficient PV modules tested in Northern Italy. In *2025 IEEE International Conference on Environment and Electrical Engineering and 2025 IEEE Industrial and Commercial Power Systems Europe* (pp. 1–6). IEEE. <https://doi.org/10.1109/EEEIC/ICPSEurope64998.2025.11169064>
- [23] Mayer, M. J., & Gróf, G. (2021). Extensive comparison of physical models for photovoltaic power forecasting. *Applied Energy*, 283, 116239. <https://doi.org/10.1016/j.apenergy.2020.116239>
- [24] Musleh, Y. J. K., Bachour, D. A., Rodríguez-Gallegos, C. D., Perez-Astudillo, D., Braga, M., & Rüther, R. (2026). Climatic and atmospheric determinants of sensor-type biases in measured solar irradiance. *Solar Energy*, 312, 114592. <https://doi.org/10.1016/j.solener.2026.114592>
- [25] Newir, A. E., & Ibrahim, M. A. (2020). Experimental and numerical investigation for mechanical ventilated greenhouse (Comparison between different turbulence models). *European Journal of Formal Sciences and Engineering*, 3(1), 10–20. <https://doi.org/10.26417/ejef.v2i3.p107-115>
- [26] Ozden, T., Carr, A. J., Geerligs, B. (L. J.), Turan, R., & Akinoglu, B. G. (2020). One-year performance evaluation of two newly developed back-contact solar modules in two different climates. *Renewable Energy*, 145, 557–568. <https://doi.org/10.1016/j.renene.2019.06.045>
- [27] Petrosyan, O. H., Muradyan, S. T., & Simonyan, A. T. (2023). Introduction of new temperature dependences of parameters in a single-diode five-parameter model of solar panels. In *2023 IEEE East-West Design & Test Symposium (EWDTS)* (pp. 1–4). IEEE. <https://doi.org/10.1109/EWDTS59469.2023.10297091>
- [28] Prilliman, M., Stein, J. S., Riley, D., & Tamizhmani, G. (2020). Transient weighted moving-average model of photovoltaic module back-surface temperature. *IEEE Journal of Photovoltaics*, 10(4), 1053–1060. <https://doi.org/10.1109/JPHOTOV.2020.2992351>
- [29] Roberts, J. J., Mendiburu Zevallos, A. A., & Cassula, A. M. (2017). Assessment of photovoltaic performance models for system simulation. *Renewable and Sustainable Energy Reviews*, 72, 1104–1123. <https://doi.org/10.1016/j.rser.2016.10.022>
- [30] Ruschel, C. S., Gasparin, F. P., & Krenzinger, A. (2021). Experimental analysis of the single diode model parameters dependence on irradiance and temperature. *Solar Energy*, 217, 134–144. <https://doi.org/10.1016/j.solener.2021.01.067>

- [31] Santiago, I., Trillo-Montero, D., Moreno-Garcia, I. M., Pallarés-López, V., & Luna-Rodríguez, J. J. (2018). Modeling of photovoltaic cell temperature losses: A review and a practice case in South Spain. *Renewable and Sustainable Energy Reviews*, 90, 70–89. <https://doi.org/10.1016/j.rser.2018.03.054>
- [32] Sen, S., & Manik, N. B. (2021). Effect of different concentrations of titanium dioxide nanoparticles on the potential barrier of organic device. *European Journal of Formal Sciences and Engineering*, 4(1), 1–10. <https://doi.org/10.26417/633bir74y>
- [33] Theristis, M., Riedel-Lyngskær, N., Stein, J. S., Deville, L., Micheli, L., Driesse, A., Hobbs, W. B., Ovatt, S., Daxini, R., Barrie, D., Campanelli, M., Hodges, H., Ledesma, J. R., Lokhat, I., McCormick, B., Meng, B., Miller, B., Motta, R., Noirault, E., Parker, M., Polo, J., Powell, D., Moretón, R., Prilliman, M., Ransome, S., Schneider, M., Schnierer, B., Tian, B., Warner, F., Williams, R., Wittmer, B., & Zhao, C. (2023). Blind photovoltaic modeling intercomparison: A multidimensional data analysis and lessons learned. *Progress in Photovoltaics: Research and Applications*, 31(11), 1144–1157. <https://doi.org/10.1002/pip.3729>