Calibration of a single-diode performance model without a short-circuit temperature coefficient

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Abstract
We calibrate the seven parameters of a single-diode model (SDM) for photovoltaic device performance using current-voltage (I-V) curves measured under controlled laboratory conditions over a matrix of nominal temperature and irradiance combinations. As described in previous modeling work, we do not use a short-circuit temperature coefficient parameter, which depends on the often unknown insolation spectrum and whose validity may be questionable. Alternatively, we employ a rigorous temperature-dependent extension of the spectral mismatch correction. This standard correction is routinely used by calibration laboratories to measure an effective irradiance ratio (i.e., a particular ratio of short-circuit currents) using a calibrated reference device, thereby compensating for spectral effects of the irradiance and for any difference in spectral response between the test device and reference device. The calibrated SDM predicts the device’s current at any prescribed voltage, temperature, and effective irradiance, and thus can predict power and energy production under prescribed conditions. Our approach aligns well with the matched reference cell approach to outdoor I-V curve measurements, while clarifying the requirements of a “matched” condition for the irradiance monitoring device(s). We find evidence for significant model discrepancy in the SDM, suggesting that model improvements and measurement intercomparisons are needed.

Introduction
Equivalent-circuit performance models are commonly used for photovoltaic (PV) device performance predictions. Among these models, the single-diode model (SDM) is prevalent [26]. The effective application of the SDM rests on many inter-related factors, including the physical inaccuracies in the model, the measurements used to calibrate the model parameters from the measurement data, and the numerical algorithm used for the parameter estimation. The authors of [26] recently stated that “Developing methods to estimate these parameters remains an active research area.”

Previous work described PV performance measurement and modeling approaches that avoided the use of short-circuit temperature coefficients, whose values quoted in the literature, manufacturers’ specification sheets, and parameter databases were brought into question [10, 24, 25]. Instead, the models in [10] employed an effective irradiance ratio commonly used in calibration laboratories’ I-V curve measurements, incorporating temperature effects in the spectral mismatch corrections between a PV test device (TD, e.g., a cell, module, or array) and a PV reference device (RD).

Here, we extend the modeling work in [10] by presenting a SDM calibration algorithm in which the model parameters are fit to a collection of I-V curves measured over a matrix of nominal effective irradiance ratio and effective temperature ratio combinations. To verify our algorithm, we first present calibration results on two synthetic I-V curve matrix datasets. Analyzing these fits, we discuss the implications for parameter identifiability for our particular choice of SDM. We then present model calibration results for an actual PV cell measured over a matrix of six nominal irradiance levels and three nominal temperatures.

While our fitting algorithm is shown to be effective, comprehensive analysis of our results suggests significant
model discrepancy is possible in the SDM. Thus, improving this model or implementing a suitable alternative (or alternatives) should be the focus of follow-up work, which should also include I-V curve matrix measurement intercomparisons for a variety of PV material systems. Further research is also needed in the application of effective temperature ratios. Such advances would improve performance prediction accuracy over the full range of real operating conditions, as well as opening new opportunities to use model-calibrated devices in PV-specific irradiance and temperature measurement applications.

Model Description

As described in [10], the five-parameter SDM for a PV TD consisting of one or more equal length cell-strings wired in parallel is given by

\[ I = I_{ph} - I_n \left( e^{\frac{q(V+I R_s)}{n k T}} - 1 \right) - \Gamma_p (V+I R_s), \]  

(1)

with device-level observables: \( I \), terminal current \([A]\), \( V \), terminal voltage \([V]\), and device-level model parameters: \( I_{ph} \), photocurrent \([A]\), \( I_n \), diode reverse saturation current \([A]\), \( n^* \), modified ideality factor \([V]\), \( R_s \), series resistance \([\Omega]\), \( \Gamma_p \), parallel (shunt) conductance \([S]\), where the model parameters are independent of the values of the observables. The modified (diode) ideality factor is defined by

\[ n^* = N_s n k_b T / q, \]

where \( N_s \), number of series-wired cells in each string \([1]\), \( n \), diode ideality factor \([1]\), assumed independent of \( I \), \( V \), and \( T \), \( k_b \), Boltzmann constant, \( k_b = 1.38064852 \times 10^{-23} \) J/K, \( T \), diode junction temperature \([K]\), \( q \), elementary charge, \( q = 1.6021766208 \times 10^{-19} \) C.

To improve computational stability for near-ideal devices, we parametrized the model in terms of parallel conductance, \( \Gamma_p \), instead of parallel resistance, \( R_p = 1 / \Gamma_p \). Also, if \( T \) and \( N_s \) are known quantities, then \( n \) is readily computed from \( n^* \).

This SDM does not consider reverse bias diode breakdown or the presence of bypass diodes, whose effects are deemed negligible in forward bias under the key assumption of homogeneous cell properties, junction temperature, and insolation at any given instant. Accordingly, situations where these assumptions are violated must be treated with caution, such as with partially shaded or degraded modules.

We call equation (1) a local SDM (SDM-L) because operation conditions (OC) consisting of a single temperature and spectral and total irradiance are typically necessary for the validity of the model with constant values of the five parameters. For performance modeling over a range of temperature and spectral and total irradiance, we extend the five-parameter SDM-L to a global seven-parameter SDM (SDM-G). The seven parameters are defined at some well-defined reference conditions (RC) of junction temperature and spectral and total irradiance, so that some of the original five parameters of SDM-L change with temperature and/or irradiance through auxiliary equations. RC are typically standard reporting conditions (SRC) \([1, 2, 4]\) or standard test conditions (STC) \([16, 18]\).

Total irradiance incorporates an underlying spectrum to which PV devices are sensitive. Furthermore, the spectral response depends on the junction temperature \([10, 25]\). To properly accommodate these spectral and temperature dependencies, we formulate the irradiance dependence in terms of a unitless effective irradiance ratio, defined by

\[ F = \frac{I_{sc}}{I_{sc,r}}, \]

(2)

where \( I_{sc} \) short-circuit current at OC \([A]\), \( I_{sc,r} \) short-circuit current at RC \([A]\).

\( F \) replaces usage of a short-circuit temperature coefficient, whose spectral dependence is often neglected and whose reported values are sometimes suspect \([13, 24, 25]\).

The measurement of \( F \) is readily achieved by monitoring the short-circuit current of a calibrated RD mounted in the same plane of irradiance. Consider some TD OC and RD operating conditions (OC r) of (possibly different) temperature and spectral and total irradiance. As described in \([3, 10, 25]\), the spectral correction parameter is defined as

\[ M = \frac{I_{sc,r}}{I_{sc,r,0}}, \]

(3)

where \( I_{sc,r,0} \) short-circuit current of RD at OC r \([A]\), \( I_{sc,r,0} \) short-circuit current of RD at RC \([A]\).

Given definitions (2) and (3), it follows that the effective irradiance ratio \( F \) can be determined by measuring \( I_{sc,r} \) relative to \( I_{sc,r,0} \) and multiplying by \( M \),

\[ F = \frac{I_{sc}}{I_{sc,r}} = M \frac{I_{sc,r}}{I_{sc,r,0}}, \]

(4)

Following \([10]\), the definition (3), along with sufficient short-circuit linearity with respect to irradiance for both the TD and RD, gives the following temperature-dependent spectral correction function for \( M \):

\[ M = M_b(T, T_r, T_0, S, \Sigma E, \Sigma E) = \int_{\lambda = \lambda_0}^{\lambda_{\infty}} S(\lambda, T_0) E(\lambda) d\lambda \int_{\lambda = \lambda_0}^{\lambda_{\infty}} \Sigma S(\lambda, T_r) E(\lambda) d\lambda \int_{\lambda = \lambda_0}^{\lambda_{\infty}} \Sigma S(\lambda, T_0) E(\lambda) d\lambda \int_{\lambda = \lambda_0}^{\lambda_{\infty}} S(\lambda, T_r) E(\lambda) d\lambda \]

(5)
where $\lambda$, wavelength of irradiance [nm], $T$, junction temperature of TD at OC [K], $T_r$, junction temperature of RD at OC$_T$ [K], $T_{g0}$, junction temperature at RC [K], $S(\lambda,T)$, absolute spectral response of TD at OC $\frac{\Lambda/W/m^2}{\text{nm}}$, $S(\lambda,T_{g0})$, absolute spectral response of TD at RC $\frac{\Lambda/W/m^2}{\text{nm}}$, $S(\lambda,T_{0})$, absolute spectral response of RD at OC$_T$ $\frac{\Lambda/W/m^2}{\text{nm}}$, $S(\lambda,T_{g0})$, absolute spectral response of RD at RC $\frac{\Lambda/W/m^2}{\text{nm}}$, $E(\lambda)$, absolute spectral irradiance on TD at OC $[W/m^2]$, $E_r(\lambda)$, absolute spectral irradiance on RD at OC$_T$ $[W/m^2]$, $E_{g0}(\lambda)$, absolute spectral irradiance at RC $[W/m^2]$.

In common practice, the TD and RD are illuminated by light with essentially the same spectrum. This allows $E(\lambda)$ and $E_r(\lambda)$ to be replaced by a common relative spectral irradiance in the computation of (5), denoted as $E(\lambda) = E_r(\lambda)$. Here, any difference in total irradiance between TD and RD, say due to spatial nonuniformity, is compensated by a measured correction factor, denoted as $P$. This practice is also robust to a scaling error in the spectrum measurement. Likewise, a relative spectral irradiance at RC, denoted as $E_{g0}$, as well as relative spectral responses, denoted as $S$ and $S_{g0}$, can be used in (5), because each factor appears once in both the numerator and denominator.

Analogously to $F$, we define the unitless effective temperature ratio by

$$H = \frac{T}{T_{g0}}.$$  \hfill (6)

The determination of $H$ can be complicated by spatial inhomogeneities in temperature across the device (e.g., temperature gradients and hot spots), which is why we conceive of $H$ as an effective temperature ratio. Indeed, calibrated model parameter values can be strongly influenced by the irradiance conditions (e.g., continuous vs. flashed) and temperature measurement techniques (e.g., dry bulb temperature with wind speed vs. back of module temperature(s)) [14]. Even though we view more elaborate modeling of effective temperature as an important area for further investigation, it was not needed for the cell measurement dataset analyzed in the present work.

The auxiliary equation for $n^*$ depends on junction temperature and is given by

$$n^* = \frac{N_n n_kT}{q} = \frac{N_n n_kT}{q} \frac{T}{T_{g0}} = n^*_0 H,$$  \hfill (7)

where at RC: $n^*_0$, modified ideality factor [V], $n^*_0 = N_n n_k T_{g0} / q$.

Note that the diode ideality factor $n$ was recently validated for several crystalline Silicon (c-Si) modules in work by Lee [21].

The auxiliary equation for $I_{ph}$ depends on junction temperature and is given by

$$I_{ph} = I_{sc} \left( e^{\frac{qV}{kT}} - 1 \right) + \frac{I_{ph} R_s}{\frac{1}{I_{ph}} + \frac{I_{ph} R_s}{N_{sc} F}}.$$  \hfill (8)

The auxiliary equation for $I_{ph}$ includes a short-circuit temperature coefficient in the auxiliary equation for $I_{ph}$. This temperature coefficient is spectrally dependent [13, 25], and has been shown in popular PV module parameter databases to be lacking the attendant spectral information and sometimes questionably valued [14, 25].

The auxiliary equation for $R_s$ is assumed to be independent of device temperature and spectral and total irradiance and is given by

$$R_s = R_{s0},$$  \hfill (10)

where at RC: $R_{s0}$, series resistance [Ω].
The auxiliary equation for $\Gamma_p$ is assumed to be independent of device temperature and spectral and total irradiance and is given by

$$\Gamma_p = \Gamma_{p_0},$$

(11)

where at RC: $\Gamma_{p_0}$, parallel conductance [S].

This constant value differs from the photo-conductive parallel conductances found in the PVsyst and DeSoto models [11, 22]. For the c-Si cell model calibrated in the next section, calibration using the DeSoto-like photo-conductive parallel conductance model $\Gamma_p = \Gamma_{p_0} F$ did not produce clearly better fits. However, this auxiliary equation is readily changed should the PV material system exhibit significant photo-conductive parallel conductance. Likewise, the auxiliary equation for $R_s$ is readily changed to incorporate, say, a temperature effect [21].

Altogether, SDM-G for a PV device (e.g., cell, module, or array) consisting of one/more equal-length series-wired strings of identical cells wired in parallel is given by

$$I = I_{ph} - I_n \left(e^{\frac{qV}{nRT_s}} - 1\right) - \Gamma_p (V + IR_s),$$

(12)

with five auxiliary equations

$$I_{ph} = I_{sc0} F + I_n \left(e^{\frac{qE_s}{nRT_s}} - 1\right) + \Gamma_p I_{sc0} FR_s,$$

(13)

$$I_n = I_{nc0} H + I_n \left(e^{\frac{qE_n}{nRT_s}} - 1\right),$$

(14)

$$n^* = n^n H,$$

(15)

$$R_s = R_{s0},$$

(16)

$$\Gamma_p = \Gamma_{p_0},$$

(17)

four device-level observables at OC: $I$ terminal current [A], $V$ terminal voltage [V], $F$ effective irradiance ratio [1], $H$ effective temperature ratio [1], and seven device-level model parameters at RC: $I_{sc0}$ short-circuit current [A], $I_{nc0}$ diode reverse saturation current [A], $n^n$ modified ideality factor [V], $R_{s0}$ series resistance [Ω], $\Gamma_{p0}$ parallel (shunt) conductance [S], $E_s$ modified material band gap [eV], $E_n$ modified material band gap [eV], $\alpha_p^T$ modified temperature coefficient of material band gap [1/°C], where the model parameters are independent of the values of the observables. Unlike the development in [10], we do not reparametrize SDM-G in terms of open-circuit voltage, because we have found this to cause issues with numerical computation in certain cases.

Model Calibration

Our SDM-G calibration algorithm infers point estimates of the seven model parameters from I-V curves measured over a matrix of nominal temperature and irradiance combinations. We use both a cell-like and a module-like synthetic dataset generated from the seven-parameter model to verify the calibration algorithm. We demonstrate our technique with an I-V curve matrix dataset on a small c-Si cell measured under the controlled conditions of a calibration laboratory.

Model calibration algorithm

We now describe the model calibration algorithm and identified fitting issues in more detail. We present the algorithm for the seven-parameter SDM-G in equations (12–17), noting that a slightly simpler algorithm for the five-parameter SDM-L in equation (1) was also developed for I-V curves taken at (or corrected to) a single temperature and irradiance.

Inputs and outputs

In a general setting, the data inputs to our model calibration algorithm are a collection of measured quadruples ($I$, $V$, $F$, $H$) that are the device's observed terminal current, terminal voltage, effective irradiance ratio, and effective temperature ratio respectively. These data are typically from I-V curves measured at different combinations of nominal temperature and nominal irradiance. For example, IEC 61853-1 specifies 22 such combinations for a standard spectral irradiance with total irradiance ranging over 100, 200, 400, 600, 800, 1000, and 1100 W/m² and module temperature ranging over 15°C, 25°C, 50°C, and 75°C [19]. For our algorithm there is no need to apply preparatory temperature or irradiance corrections such as [17] to the I-V curve data, thus avoiding any introduction of correction artifacts.

The primary outputs from our model calibration algorithm are the seven parameters of SDM-G that are inferred from the observed data. The seven parameters are at RC, but because $F$ and $H$ are ratio quantities, these RC need not be explicitly provided to the algorithm. However, providing the number of series-wired cells in each string, $N_s$, the RC temperature, $T_{ps}$, and the PV material system (e.g., c-Si, CdTe, CIGS) as inputs to the algorithm allows much more effective scaling of the automated choice of initial conditions for $E_s^{\text{e}}$, initial values for material band gap, $E_n^{\text{e}}$, and band gap temperature coefficient, $\alpha_p^T$, are taken from nominal values in the literature [11, 22]).

The computed fit parameters can subsequently be used in SDM-G to compute eight model-derived parameters of interest at various OC. These values at RC ($F = 1$ and $H = 1$) are denoted by: $I_{ph0}$, photocurrent [A]; $R_{s0}$, resistance at short circuit [Ω]; $I_{mp0}$, current at maximum power point [A]; $P_{mp0}$, power at maximum power point.
[W]; \(V_{mp}\), voltage at maximum power point [A]; \(R_{oc}\), resistance at open circuit [\(\Omega\)]; \(V_{oc}\), voltage at open circuit [V]; \(FF_p\), fill factor.

Furthermore, a maximum power time-series computed over dynamic OC defined by a time-series of \((F, H)\) can be used in subsequent performance simulations.

**Orthogonal distance regression**

The computational core of our model calibration algorithm is orthogonal distance regression (ODR), which is capable of directly handling the implicit nonlinear model relationship between the observables [5–8]. Implicit model relations such as equation (1) or equations (12–17) typically define a smooth curve, surface, or higher dimensional manifold in the space of observables. Simply put, ODR searches for a choice of model parameters that minimizes the sum of squared orthogonal distances from each data point to the model surface.

Several reasons influenced our choice to use ODR. Foremost, model relationships such as equations (1) and (12) are based on a Kirchhoff’s current conservation law at the diode node of a lumped element equivalent circuit model of a PV device. Such conservation laws are naturally written as an implicit mathematical relation among the observable variables. In this case, the implicit model is a collection of current terms that must sum to zero. For example, SDM-L equation (1) can be rewritten as

\[
0 = I_{ph} - I_n \left( e^{\frac{V}{k T}} - 1 \right) - I_{f} \left( V + I R_{p} \right) - I
\]

\[
= g_{local} \left( V, I, I_n, I_s, R_s, \Gamma \right).
\]  

(18)

Likewise, SDM-G equations (12–17) can be rewritten as

\[
0 = g_{global} \left( V, I, F, H_n, I_{ph}, I_{ir}, I_{f}, I_{in}, I_s, R_s, \Gamma, E_s, \alpha_{s} \right).
\]  

(19)

Importantly, the ODR’s minimization of the sum of squared orthogonal distances is not the same as minimizing the sum of squared residuals of, say, \(g_{global}\). However, the latter residuals are physically intuitive because they indicate the degree of violation of a physical conservation law and thus are useful for examining goodness of fit.

Conveniently, ODR does not require one to arbitrarily solve an implicit model relationship for one “output” observable in terms of the others taken as “inputs” (e.g., \(I\) as a function of \(V, F, \) and \(H\)). Instead, ODR puts all the observable variables on equal footing, without any underlying statistical assumption that only the output observable is measured with non-negligible error. Computationally programming the sum of the current terms is also much more straightforward and efficient than numerically solving a mathematically equivalent explicit formulation.

ODRPACK, the ANSI Fortran 77 ODR algorithm developed by Boggs et al. [6] is available via the scipy.odr wrapper in the open source Python package SciPy [20]. The only limitation we have found in using the current SciPy implementation of ODR is the lack of bounded constraints on the parameters, which became available in ODRPACK95, an updated Fortran 95 version of ODRPACK [33]. Such constraints are useful because, for example, series resistance is non-negative. We circumvent this limitation by using log-transformed variables where necessary to impose positivity constraints. We also log transform the reverse saturation current for better variable scaling, although ODRPACK also attempts detection and autoscaling of poorly scaled variables.

**Initial conditions**

As with most nonlinear model calibration algorithms, proper numerical convergence can be strongly influenced by the choice of initial conditions for the parameters. Our algorithm expects that at least one of the \(I-V\) curves is sufficiently close to the RC (\(F = 1\) and \(H = 1\)) and sufficiently well-sampled between \(I_{ph}\) and \(V_{oc}\), so that these data can be used to algorithmically estimate the five parameters \(I_{ph}, I_n, n_p, R_s, \) and \(\Gamma_p\). As mentioned previously, initial condition choices for the remaining two parameters \(E_s^*\) and \(\alpha_{s}^*\) are aided by knowledge of \(N_{s}, T_{oc}\) and the PV material system. Optionally, one or more initial conditions for the parameters may be provided explicitly, and the remaining initial conditions are determined automatically and in accordance with those provided.

**Parameter nonidentifiability**

Parameter nonidentifiability is another issue that affects model calibration. Parameter nonidentifiability arises when additional data collection is never sufficient to better estimate unique values for all model parameters [32]. Identifiability means that the model’s parameters will be uniquely determined in the conceptual limit of an infinite amount of measurement data. However, significant measurement noise can limit the accuracy of fit parameters given practical datasets with limited measurement data. Interestingly, parameter nonidentifiability does not necessarily mean that a calibrated model has poor predictive power. However, the physical meaning of the fit value of a nonidentifiable parameter is certainly questionable.

Often, certain regions of the observables space are more informative about a given parameter, which can affect how effectively one can determine parameters in an identifiable model given limited data. For example, \(I-V\) data
points near open-circuit voltage are known to carry more information about series resistance, because of the strong dependence of the local derivative there on this parameter. Furthermore, measurement noise generally produces worse parameter inferences for a given fixed data sample size. Because such factors are generally intertwined for any given model and measurement dataset, we use the term parameter nonidentifiability here in a somewhat broader, qualitative sense than in [32]. Specifically, parameter nonidentifiability here means general difficulty in identifying effective model parameter values, especially given limited noisy data collection and an imperfect model.

As described later, our numerical studies using matrices of synthetic I-V curve data generated from SDM-G show evidence of problematic nonidentifiability when locally fitting SDM-L to a single I-V curve. In particular, series resistance is difficult to identify at low irradiance and shunt conductance is difficult to identify at high irradiance, with temperature having a secondary effect. Furthermore, these local parameters become more difficult to identify with increasing measurement noise. In addition, ODR problems tend to be under-determined as compared to ordinary (non)linear least squares, and nonunique minimizers have been observed [7].

Model discrepancy

Model discrepancy (sometimes called model error) arises from an imperfect model and also adversely affects model calibration. For example, a double-diode model (DDM) could be a significantly better representation of a given PV device than a SDM for a particular operating condition or range of conditions [27]. Sources of model discrepancy include the simplification of device physics and poor assumptions about the measurement noise distribution or the lack of measurement bias. Furthermore, additional data collection, by itself, does not generally reduce the parameter inference inaccuracy caused by model discrepancy [9], and sometimes measurement artifacts (e.g., bias) can be mistaken for model discrepancy.

As described later using real data for a particular c-Si solar cell, we see evidence of model discrepancy for SDM-G, which appears to complicate the parameter estimation of series resistance. This suggests the need for measurement intercomparisons to guard against measurement artifacts, and that the auxiliary equations could be improved in order to reduce model discrepancy, or that possibly a global DDM would be preferable.

Verification: synthetic datasets

We verified our fitting algorithm by using synthetic datasets generated for two separate PV device types. First, we generated noisy V-I-F-H datasets representative of a small area, 65.5 mW at STC, mono-crystalline Silicon (mono-Si) PV reference cell similar to the real device whose calibration is discussed subsequently. Second, we generated noisy V-I-F-H datasets representative of a 72-cell, 275 W at STC, multicrystalline Silicon (multi-Si) PV module.

The number of factor combinations that could have been explored in these synthetic dataset studies was large, with dimensions such as the number and spacing of data points in each I-V curve, the level and distribution of noise in the observable data channels, and the choice of initial condition for the parameters in the fit algorithm. Two main factors that we varied between the two device studies presented here were: (1) the functional variation in the $F_{\text{true}}$ and $H_{\text{true}}$ values at each nominal combination ($F_{\text{nom}}$, $H_{\text{nom}}$), and (2) the number of points $N$ in each I-V curve. We did not study synthetic datasets with a known model discrepancy, such as fitting a SDM to a DDM, although this might prove useful in follow-up studies.

In both device studies, I-V curves were synthetically generated at each nominal combination of $F_{\text{nom}}$ from 0.1, 0.2, 0.4, 0.6, 0.8, 1.0, 1.1 and $T_{\text{nom}}$ from 15°C, 25°C, 50°C, 75°C. These 28 combinations include all 22 combinations specified in IEC 61853-1 [19]. Taking $T_0 = 25°C$ gives $H_{\text{nom}}$ values of 0.966, 1, 1.0838, and 1.1677. For each nominal combination ($F_{\text{nom}}$, $H_{\text{nom}}$), $N$ true irradiance values and $N$ true temperature values were generated around the respective nominal values. True voltages were generated as $N$ equally spaced values between zero and (approximately) the nominal open circuit voltage. Lastly, a true current value, $I_{\text{true}}$, was computed at each combination ($V_{\text{true}}$, $F_{\text{true}}$, $H_{\text{true}}$) by solving SDM-G for $I$ in terms of $V$, $F$, and $H$ and the seven model parameters.

After computing the quadruples of true data, normally distributed multiplicative noise was independently added to all components of the V-I-F-H points at some level $s$. For both synthetic datasets, $s = 0.1\%$, so that, for example, noisy voltage values were computed from the true voltage values by

$$V = V_{\text{true}} (1 + sr) = V_{\text{true}} (1 + 0.001r),$$

where $r$ is a random variate drawn independently for each component of each V-I-F-H point from the standard normal distribution. To examine potential parameter identifiability issues with respect to noisy data (and other factors), 100 samples of each curve at each nominal combination ($F_{\text{nom}}$, $H_{\text{nom}}$) were realized using a Monte Carlo simulation.

A sufficient characterization of the measurement system’s noise was not available. Thus, we chose a seemingly conservative noise level that was approximately two orders of magnitude larger than the “% of reading” error for
measuring DC voltage with a 6 1/2-digit digital multimeter (DMM). In future work, we would like to develop a better characterization of a given measurement system’s noise distribution and estimate its scale parameters from the data.

**Synthetic cell dataset**

Data generation for the synthetic cell dataset used known true parameter values for SDM-G given in Table 1, representative of a small area mono-Si PV reference cell \( (N_s = 1) \) producing a maximum power of \( P_{mp0} = 65.5 \) mW at STC. For this device, the true values \( F_{\text{true}} \) and \( H_{\text{true}} \) were not varied during each \( N = 101 \)-point I-V curve. Figure 1 shows three examples of noisy synthetic V-I-F-H data for one realization from the 100-sample Monte Carlo simulation. Figure 1 also shows the residuals for the SDM-G fit according to equation (19).

Table 1 summarizes the parameter identifiability for fitting SDM-G to the synthetic dataset for a cell in the absence of model discrepancy. Table 2 summarizes the same information for the eight model-derived parameters of interest at RC.

The mean fit parameters values over the 100 Monte Carlo simulations were generally very accurate, with the exception of the modified temperature coefficient of material band gap at RC, \( a_{Eg}^\ast \), whose 46% coefficient of variation (C.V.) was relatively large. Despite this large variation and more moderate variations in other parameters, parameters such as \( I_{sc0} \) and \( P_{mp0} \) appeared to have reasonably good identifiability for this synthetic dataset.

For this synthetic dataset, the true values \( F_{\text{true}} \) and \( H_{\text{true}} \) were not varied from the nominal values \( F_{\text{nom}} \) and \( H_{\text{nom}} \) during each \( N = 101 \)-point I-V curve. This allowed for a reasonable comparison of the different five-parameter SDM-L

| \( I_{sc0} \) | \( I_{rs0} \) | \( n_s^\ast \) | \( R_s0 \) | \( \Gamma_{p0} \) | \( E_{g0}^\ast \) | \( a_{Eg}^\ast \) |
|---------------|---------------|-------------|-----------|--------------|----------------|----------------|
| Truth         | 150.0 mA      | 1.000 nA    | 30.0 mV   | 100.0 mΩ     | 1.000 mS       | 1.177 eV       | −0.0758        |
| Mean          | 150.0 mA      | 0.993 nA    | 30.0 mV   | 100.4 mΩ     | 1.004 mS       | 1.177 eV       | −0.0775        |
| C.V. (%)      | 5.4 × 10\(^{-3}\) | 4.0       | 0.22      | 1.21         | 2.9            | 4.9            | 46             |

C.V., coefficient of variation.

Table 1. SDM-G fit to synthetic cell dataset: model parameters. Identifiability over 100 noisy I-V curve samples.
fits for each I-V curve to the seven-parameter SDM-G fit. Analysis of the trends in the five SDM-L parameters with respect to $F_{\text{nom}}$ and $H_{\text{nom}}$ revealed issues with using SDM-L to identify the five model parameters in different parts of the $(F_{\text{nom}}, H_{\text{nom}})$ space. Tables 3–7 summarize the parameter identifiability results for SDM-L (1) for each $(F_{\text{nom}}, H_{\text{nom}})$ combination in the measurement matrix over the 100 Monte Carlo simulations. In particular, we observed that $R_s$ and $\Gamma_p$ were not identified as well in certain parts of the $(F_{\text{nom}}, H_{\text{nom}})$ space, as compared to the identifiability of the $R_s0$ and $\Gamma_p0$ parameters in the seven-parameter SDM-G fit that uses the entire measurement matrix.

## Synthetic module dataset

Data generation for the synthetic module dataset used known true parameter values for SDM-G given in Table 8, which is representative of a multi-Si PV module ($N_s = 72$) producing a maximum power of $P_{\text{mp}} = 275$ W at STC. For this device, the true values $F_{\text{true}}$ oscillated sinusoidally with a constrained, uniformly random period and phase offset and the true values $H_{\text{true}}$ ramped linearly during each $N = 51$-point I-V curve. Figure 2 shows three examples of noisy synthetic V-I-F-H data from one realization from the 100-sample Monte Carlo simulation. Figure 2 also shows the residuals for the SDM-G fit according to equation (19).

Table 2. SDM-G fit to synthetic cell dataset: derived parameters. Identifiability over 100 noisy I-V curve samples.

| Parameter | Truth | Mean | C.V. (%) |
|-----------|-------|------|----------|
| $I_{n0}$  | 150.0 mA | 150.0 mA | 5.6 × 10^{-3} |
| $R_{sc0}$ | 1000 $\Omega$ | 997 $\Omega$ | 2.9 |
| $I_{mp0}$ | 140.3 mA | 140.3 mA | 9.7 × 10^{-3} |
| $P_{mp0}$ | 65.5 mW | 65.5 mW | 0.025 |
| $V_{mp0}$ | 467 mV | 467 mV | 0.023 |
| $R_{oc0}$ | 0.301 m$\Omega$ | 0.301 m$\Omega$ | 0.37 |
| $V_{oc0}$ | 565 mV | 565 mV | 0.020 |
| $FF_0$   | 0.774 | 0.774 | 0.038 |

C.V., coefficient of variation.

Table 3. $I_{ph}$ fits for cell SDM-L synthetic dataset. Identifiability over 100 noisy I-V curve samples.

| $F$ | Temperature [°C] | $I_{ph}$ [mA] | Mean [mA] | C.V. (%) |
|-----|------------------|---------------|-----------|----------|
| 1.1 | 165.0            | 165.0         | 0.027     | 1.0      |
| 1.0 | 150.0            | 150.0         | 0.026     | 0.8      |
| 0.8 | 120.0            | 120.0         | 0.025     | 0.6      |
| 0.6 | 90.0             | 90.0          | 0.027     | 0.4      |
| 0.2 | 30.0             | 30.0          | 0.039     | 0.1      |
| 0.1 | 15.0             | 15.0          | 0.042     |          |

C.V., coefficient of variation.

Table 4. $I_{rs}$ fits for cell SDM-L synthetic dataset. Identifiability over 100 noisy I-V curve samples.

| $F$ | Temperature [°C] | $I_{rs}$ [nA] | Mean [nA] | C.V. (%) |
|-----|------------------|---------------|-----------|----------|
| 1.1 | 165.0            | 0.209         | 0.212     | 1.1      |
| 1.0 | 150.0            | 0.209         | 0.218     | 1.0      |
| 0.8 | 120.0            | 0.209         | 0.227     | 0.8      |
| 0.6 | 90.0             | 0.209         | 0.239     | 0.6      |
| 0.2 | 30.0             | 0.209         | 0.230     | 0.2      |
| 0.1 | 15.0             | 0.209         | 0.1961    | 0.1      |

C.V., coefficient of variation.
Table 5.  $n^*$ fits for cell SDM-L synthetic dataset. Identifiability over 100 noisy I-V curve samples.

| $F$ | Temperature [°C] |
|-----|------------------|
|     | 15   | 25   | 50   | 75   |
| 1.1 | 29.0 | 30.0 | 32.5 | 35.0 |
| 28.9| 30.0 | 32.4 | 35.0 | Mean [mV] |
| 1.71| 1.30 | 1.34 | 1.19 | C.V. (%) |
| 1.0 | 29.0 | 30.0 | 32.5 | 35.0 |
| 29.0| 30.0 | 32.5 | 35.0 | Mean [mV] |
| 1.65| 1.47 | 1.25 | 1.17 | C.V. (%) |
| 0.8 | 29.0 | 30.0 | 32.5 | 35.0 |
| 29.0| 30.1 | 32.5 | 35.0 | Mean [mV] |
| 1.69| 1.73 | 1.36 | 1.11 | C.V. (%) |
| 0.6 | 29.0 | 30.0 | 32.5 | 35.0 |
| 29.1| 29.8 | 32.5 | 35.0 | Mean [mV] |
| 2.0 | 2.1  | 1.52 | 1.43 | C.V. (%) |
| 0.4 | 29.0 | 30.0 | 32.5 | 35.0 |
| 29.0| 29.9 | 32.6 | 35.0 | Mean [mV] |
| 2.1 | 2.1  | 2.0  | 1.69 | C.V. (%) |
| 0.2 | 29.0 | 30.0 | 32.5 | 35.0 |
| 28.9| 30.0 | 32.5 | 35.0 | Mean [mV] |
| 2.8 | 2.4  | 2.1  | 2.3  | C.V. (%) |
| 0.1 | 29.0 | 30.0 | 32.5 | 35.0 |
| 28.7| 29.8 | 32.4 | 34.8 | Mean [mV] |
| 2.8 | 2.6  | 2.0  | 1.91 | C.V. (%) |

C.V., coefficient of variation.

Table 6.  $R_f$ fits for cell SDM-L synthetic dataset. Identifiability over 100 noisy I-V curve samples.

| $F$ | Temperature [°C] |
|-----|------------------|
|     | 15   | 25   | 50   | 75   |
| 1.1 | 100.0| 100.0| 100.0| 100.0| Truth [mΩ] |
| 101.0| 100.3| 101.1| 100.6| Mean [mΩ] |
| 9.0 | 6.7  | 6.9  | 6.4  | C.V. (%) |
| 1.0 | 100.0| 100.0| 100.0| 100.0| Truth [mΩ] |
| 99.8| 100.5| 99.6 | 100.1| Mean [mΩ] |
| 10.0| 8.8  | 7.5  | 7.1  | C.V. (%) |
| 0.8 | 100.0| 100.0| 100.0| 100.0| Truth [mΩ] |
| 99.1| 97.6 | 99.6 | 100.8| Mean [mΩ] |
| 11.6| 11.9 | 10.4 | 8.4  | C.V. (%) |
| 0.6 | 100.0| 100.0| 100.0| 100.0| Truth [mΩ] |
| 97.4| 105.4| 99.6 | 100.0| Mean [mΩ] |
| 18.3| 17.6 | 14.8 | 12.2 | C.V. (%) |
| 0.4 | 100.0| 100.0| 100.0| 100.0| Truth [mΩ] |
| 99.4| 104.6| 96.3 | 100.6| Mean [mΩ] |
| 28  | 27   | 28   | 23   | C.V. (%) |
| 0.2 | 100.0| 100.0| 100.0| 100.0| Truth [mΩ] |
| 110.0| 98.4 | 99.4 | 104.0| Mean [mΩ] |
| 64  | 61   | 54   | 57   | C.V. (%) |
| 0.1 | 100.0| 100.0| 100.0| 100.0| Truth [mΩ] |
| 132.6| 133.0| 106.5| 121.5| Mean [mΩ] |
| 99  | 100  | 101  | 87   | C.V. (%) |

C.V., coefficient of variation.

Fitting issues

We checked the sensitivity of convergence of our SDM-G parameter fit algorithm to its choice of initial condition for the seven parameters. The algorithm computes an initial condition by requiring at least one I-V curve at/ close to RC, as well as from knowledge of the material type and the number of series-wired cells in each string, $N_s$. We compared fit solutions from using our algorithm to fit solutions using our algorithm except with the true parameter values for the initial condition. In no cases did we find a significant difference in the two solutions, which suggests that our initial condition selection is reasonably robust, including with respect to the potential nonuniqueness of the ODR minimizer.

For the SDM-L five parameter fit algorithm, in rare instances (5 of 5600 fits) for the lowest irradiance curves ($F = 0.1$), the ODR solver would stop prematurely due to numerical issues, even though the parameter fits still appeared reasonable. We continue to investigate the resolution of these apparent edge cases, such as by providing model derivatives to the ODR solver, normalizing current and voltage data, and other numerical optimizations and checks.

As expected, higher noise and fewer data points adversely affected parameter identifiability in both the SDM-L and SDM-G parameter fitting algorithms, potentially requiring additional iterations for the ODR solver to converge or even causing failure to converge due to numerical issues. For SDM-L, this noise effect was generally more pronounced, due to the limited data covering only a small portion of the ($V, I, F, H$) space. Given the number of factors involved, we have found it hard to conclude exactly which measurement systems might be too noisy or otherwise limited for effective parameter fitting using our algorithm. However, we have identified several important factors for carrying out such an in depth analysis, and our SDM-L and SDM-G algorithms have successfully computed fits on a variety of datasets.

Validation: cell measurement dataset

We demonstrated both the SDM-L and SDM-G parameter fitting algorithms on an I-V curve measurement matrix for a 2 cm by 2 cm mono-Si cell of reference cell quality. This TD was property of the Photovoltaic Characterization Laboratory at the National Institute of Standards and Technology (NIST) [23]. NIST also performed all spectral response and I-V curve measurements. The primary-calibrated RD was a similarly sized mono-Si cell [15].

The matrix of I-V curve measurements required an extension of the standardized procedures at STC of 25°C...
and 1000 W/m² with a standard terrestrial spectrum [18]. There were three nominal cell junction temperatures, specifically, 15°C, 25°C, and 50°C (corresponding to $H = 0.966, 1.000, 1.084$ with ratios calculated using Kelvin equivalents). There were six nominal irradiance levels with effective irradiance ratio ranging from approximately $F = 0.12$ to $F = 1.15$, see Table 10.

### I-V curve measurements

For the I-V curve measurements, the irradiance source was a class AAA continuous Xenon solar simulator with a 156 mm by 156 mm illumination area. The simulator’s irradiance had non-negligible fluctuations during each I-V curve measurement, so that $F$ was not treated as fixed for each I-V curve. The junction temperatures of the TD and RD were monitored with a resistance temperature detector (RTD) and K-type thermocouple (TC), respectively, which were affixed to the cell backsides within the cell packages. The TD and RD were continuously illuminated on a temperature-controlled plate that kept the junction temperature variability during each I-V curve to less than ± 0.05°C. Furthermore, the junction temperatures of the TD and RD differed by less than ± 1°C from the three nominal values used in the I-V curve measurements, so that $H$ was treated as fixed at the nominal value for each I-V curve and the TD and RD junction temperatures differed from each other by less than ± 2°C.

For each nominal $H$ value, the I-V curves were collected as $(I, V, F)$ data triplets. The RD’s short-circuit current was used to monitor $F$ for each V-I-F point. The RD was colocated on the temperature controlled plate and in the plane of irradiance immediately adjacent to the TD. Over the range of $F$, the RD was maintained within 30 mV of short circuit using a 203 mΩ terminal shunt resistor, across which the voltage was measured to determine $I_{sc,r}$ (30 mV is ~6.25 of $V_{oc}$). The TD’s current and voltage were measured using a commercially available source measure unit (SMU). Each I-V curve consisted of 69 data points, swept from $V_{oc}$ to $I_{sc}$ in 60 msec. The range of $F$ varied by less than ± 1 about the middle value of the range over the duration of each sweep.

#### Correction factors

The computation of $F$ for each $(V, I, F)$ datum required a different computation of the spectral correction parameter, $M$, for each I-V curve, using definition (5). The measurement system was controlled such that we could consider $F = T_{r}$ and $E = E_{r}$ for each I-V curve measurement at one of the three nominal temperatures, which included the RC temperature $T_{r}$. Thus, the absolute spectral response functions $S$ and $S_{r}$ were measured only at the three nominal temperatures. In addition, the TD and RD were each illuminated by perinormal irradiation from a solar simulator, which greatly minimized angular response differences that are not handled by definition (5). Because the spectral irradiance distribution changed with each nominal (total) irradiance level, the relative spectral irradiance $E (= E_{r})$ was measured at every nominal irradiance level.

The temperature dependence of $M$ required measurement of the spectral responses of both TD and RD as a function of junction temperature. In this work the TD and RD had similar mono-Si material composition, and thus similar spectral response functions (as a function of both wavelength and temperature). Furthermore, the non-brupt dropoff in spectral response for the indirect bandgap of mono-Si made the convolution integral with the Xenon simulator spectrum less sensitive to temperature changes. Thus, the potential ± 1°C temperature discrepancy between each device and a nominal temperature value was considered sufficiently small to allow the usage of spectral response measurements at that nominal value in the computation of (5).¹

The six nominal irradiance levels were realized through a combination of neutral density filters and current adjustments to the simulator lamp. Thus, the spectrum of the solar simulator changed to some degree between nominal irradiance levels, although the spectrum on both

| $F$ | Temperature [°C] |
|-----|-----------------|
| 1.1 | 1.000           |
| 1.036 | 1.005           |
| 0.995 | 1.002           |
| 1.012 | 1.002           |
| 0.982 | 0.997           |
| 1.015 | 1.013           |
| 1.02 | 0.996           |
| 0.955 | 0.972           |
| 0.6 | 0.981           |
| 1.28 | 1.48            |
| 0.4 | 1.000           |
| 0.995 | 1.002           |
| 0.92 | 10.3            |
| 0.2 | 1.000           |
| 1.012 | 1.002           |
| 0.6 | 6.5             |
| 0.1 | 1.000           |
| 0.34 | 3.7             |

C.V., coefficient of variation.

¹ The six nominal irradiance levels were realized through a combination of neutral density filters and current adjustments to the simulator lamp. Thus, the spectrum of the solar simulator changed to some degree between nominal irradiance levels, although the spectrum on both
devices was essentially identical at each nominal irradiance level. Accordingly, the spectrum for each level was measured in the plane of irradiance where the cells were mounted, using a spectroradiometer calibrated against an FEL lamp from 250 to 1700 nm [31]. Considering the spectral irradiance and temperature effects altogether, a separate spectral correction parameter $M$ was calculated and applied to compute the $F$ values for each I-V curve in the measurement matrix. These $M$ values are provided in Table 11.

The neutral density filters had the side effect of changing the spatial non-uniformity at the plane of irradiance, which also affected the calibrated measurement of $F$ by the RD adjacent to the TD. The average of this effect between TD and RD positions was measured for each filter as the nonuniformity correction factor $P$, and this

Table 8. SDM-G fit to synthetic module dataset: model parameters. Identifiability over 100 noisy I-V curve samples.

| $I_{sc0}$ | $I_{rs0}$ | $n^*_0$ | $R_s$ | $r_p$ | $E_{g0}$ | $a^*_{r_0}$ |
|-----------|-----------|---------|-------|-------|----------|-------------|
| Truth     | 8.30 A    | 0.330 mA| 1.880 V| 527 mΩ| 2.59 mS  | 78.7 eV     |
| Mean      | 8.30 A    | 0.332 mA| 1.880 V| 527 mΩ| 2.59 mS  | 78.8 eV     |
| C.V. (%)  | 7.8 x 10^{-3} | 4.9 | 0.22   | 0.30   | 0.67     | 0.076       |

C.V., coefficient of variation.

Table 9. SDM-G fit to synthetic module dataset: derived parameters. Identifiability over 100 noisy I-V curve samples.

| $I_{ph0}$ | $R_{sc0}$ | $I_{mp0}$ | $P_{mp0}$ | $V_{mp0}$ | $R_{oc0}$ | $V_{oc0}$ | FF0 |
|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----|
| Truth     | 8.31 A    | 387 Ω     | 7.75 A    | 275 W     | 35.5 V    | 756 mΩ    | 45.0 V |
| Mean      | 8.31 A    | 387 Ω     | 7.75 A    | 275 W     | 35.5 V    | 756 mΩ    | 45.0 V |
| C.V. (%)  | 8.5 x 10^{-3} | 0.67 | 0.012   | 0.025   | 0.021    | 0.20      | 0.020   |

C.V., coefficient of variation.

Figure 2. Example sampled noisy synthetic module data with SDM-G fit residuals for (A) $F \approx 0.1$ and $T \approx 15^\circ$C, (B) $F \approx 1$ and $T = T_0 = 25^\circ$C, and (C) $F \approx 1.1$ and $T \approx 75^\circ$C. The true values of $F$ and $H$ vary around a nominal value during each I-V curve measurement. Some vertical scales change to show detail.

Table 8.

Table 9.

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factor was applied in the computation of the $F$ values in each I-V curve by dividing $M$ in equation (4) by $P$. These $P$ values are provided in Table 12.

Table 10. I-V curve measurement matrix: average $F$ values for each I-V curve at each nominal operating condition.

| Irradiance | Temperature [°C] |
|------------|-----------------|
| Setting    | 15  | 25  | 50  |
| 6          | 1.130 | 1.144 | 1.152 |
| 5          | 0.938 | 0.944 | 0.958 |
| 4          | 0.725 | 0.731 | 0.739 |
| 3          | 0.321 | 0.321 | 0.326 |
| 2          | 0.155 | 0.157 | 0.157 |
| 1          | 0.120 | 0.122 | 0.123 |

Table 11. Spectral correction parameter matrix: $M$ values for each I-V curve at each nominal operating condition.

| Irradiance | Temperature [°C] |
|------------|-----------------|
| Setting    | 15  | 25  | 50  |
| 6          | 0.9970 | 0.9985 | 0.9971 |
| 5          | 0.9967 | 0.9982 | 0.9969 |
| 4          | 0.9963 | 0.9978 | 0.9966 |
| 3          | 0.9974 | 0.9988 | 0.9974 |
| 2          | 0.9972 | 0.9986 | 0.9972 |
| 1          | 0.9972 | 0.9986 | 0.9972 |

Table 12. Nonuniformity correction factor matrix: $P$ values for each I-V curve at each nominal operating condition.

| Irradiance | Temperature [°C] |
|------------|-----------------|
| Setting    | 15  | 25  | 50  |
| 6          | 1.0182 | 1.0182 | 1.0182 |
| 5          | 1.0167 | 1.0167 | 1.0167 |
| 4          | 1.0164 | 1.0164 | 1.0164 |
| 3          | 1.0267 | 1.0267 | 1.0267 |
| 2          | 1.0438 | 1.0438 | 1.0438 |
| 1          | 0.9946 | 0.9946 | 0.9946 |

Model calibration results

Table 13 gives the seven SDM-G parameters fit to the dataset by our algorithm, while Table 14 gives the eight model-derived parameters of interest at STC. Figure 3 shows three examples of measured I-V curves in the matrix dataset. Model discrepancy was apparent from the residual plots in Figure 3, in which the residuals are nonrandomly distributed about zero. Furthermore, the “shape” of the residuals was observed to change systematically over the $(F, H)$ space. Figure 4 provides a temperature-projected $(V, I, F)$ surface view of the SDM-G fit to the data, where the ODR solver chose model parameters that minimized the sum of squares of the orthogonal distance from each data point to its respective surface.

Fitting issues

As with the synthetic cell dataset, we found it useful to calibrate SDM-L to each individual I-V curve measurement. For these SDM-L parameter fits, each I-V curve’s currents were corrected for irradiance fluctuation by scaling current to the nominal effective irradiance ratio, $F_{nom}$, for the entire curve, i.e.,

$$I_{corr} = \frac{F_{nom}}{F} I.$$  \hspace{1cm} (20)

No corrections for the (small) temperature variations were applied to either current or voltage. See Figure 5. As indicated by Figure 6, the SDM-L fits further suggested model discrepancy in SDM-G. For example, both $I_{rs}$ and $n^*$ change considerably at the lowest $F$, even though SDM-G presumes them to be constant with respect to $F$. The local $R_s$ fit values are also nonconstant and suspect, with values constrained at their boundary at lower $F$ values.\textsuperscript{2}

To further investigate the performance prediction accuracy of SDM-G, we compared the maximum power predicted by SDM-G to the maximum power predicted by SDM-L at each combination $(F_{nom}, H_{nom})$. We did this under the caveat that the SDM-L fits using equation (20) were themselves observed to have model
discrepancy, as seen in Figure 5. However, the SDM-L fit residuals according to equation (19) were roughly an order of magnitude smaller than the SDM-G fit residuals according to equation (19). Table 15 shows that the SDM-G could exceed the SDM-L power prediction by as much as 3.7% at low irradiance and 2.4% near STC. A second caveat to interpreting these results was that an I-V curve measurement matrix intercomparison could reveal measurement artifacts that manifest as model discrepancy.

**Discussion**

We now discuss key findings and ramifications of this work.

**A better model**

The convergence of our algorithm was satisfactory in the SDM-G fit and in each of the SDM-L fits. However,
Figure 5. Example corrected cell measurement data with SDM-L fit residuals for (A) $F_{\text{nom}} = 0.120$ and $T_{\text{nom}} = 15^\circ\text{C}$, (B) $F_{\text{nom}} = 0.94$ and $T_{\text{nom}} = T_{0} = 25^\circ\text{C}$, and (C) $F_{\text{nom}} = 1.15$ and $T_{\text{nom}} = 50^\circ\text{C}$. Current values were corrected to $F_{\text{nom}}$ for each curve, according to equation (20). Vertical scales change to show detail.

Figure 6. Cell measurement data fits for the five parameter SDM-L over the I-V curve measurement matrix of $(F, H)$. 

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residual analyses and the SDM-L parameter fits suggested that model discrepancy was significant in the SDM-G parameter fitting. This model discrepancy has brought into question physical interpretation of the model parameters, and also appeared to degrade the predictive capability of the performance model by producing significant biases in maximum power that depend on \( (F, H) \).

Examination of the SDM-L parameter fit results suggests that the predictive capability of SDM-G might be improved by better choice of auxiliary equations (13–17). However, if better auxiliary equations are merely empirical adjustments that are not justifiable from physics, then it may be preferable to use a more physically sound DDM. Based on our preliminary DDM investigations that appear to reduce model discrepancy, we are inclined to pursue DDM’s in subsequent work, and our fitting algorithm is quickly adapted to alternative models with implicit formulations in terms of the observables \( V, I, F, \) and \( H \) [10].

We are eager to repeat and extend this analysis on a variety of PV devices of different material systems, from cells to arrays, as well as using intercomparison measurements from multiple calibration laboratories. We view the elimination of significant model discrepancy and possible measurement artifacts, in addition to better characterization of measurement system noise and algorithm refinement, as preliminary to exploiting any statistical properties of ODR. Such statistical properties would be useful for quantifying the (epistemic) uncertainty in the estimated model parameters. However, they do not appear to be as fully elucidated in the literature for the implicit case [5–8].

### Matching issues

For a calibration lab, measurement of temperature-dependent \( M \) should be straightforward for cells [24], with additional measurement time required (and thus some additional cost). In modules, controlling temperature over the full OC range for direct \( M \) measurements certainly adds complexity, time, and cost, which is in addition to the potential need to measure/verify \( M \) across multiple cells in a given module or across multiple modules in an array. However, our approach does not exclude extending existing methods that use surrogate cell measurements and rely on sufficient cell homogeneity across a module or batch of modules.

Care must be taken that factors such as inhomogeneous cell degradation, including degradation in the reference monitoring device(s), do not violate the homogeneity assumptions. As noted in [10], employing a “matched” RD (i.e., with \( M = 1 \)) requires not only matched spectral response between the TD and RD over the range of OC temperatures, but also matching temperatures for the TD and RD, cf. [28]. Exact temperature matching is unrealistic in modules and arrays with significant spatial temperature gradients, and we see further research opportunities in refining the usage of an effective temperature ratio, \( H \), and temperature modeling and monitoring for field applications. Furthermore, field applications with global irradiance also require consideration of matched angular responses between TD and RD, which may have been calibrated using the direct irradiance of a solar simulator in a calibration lab [12, 29].

### Weather data

Opportunities exist to use our modeling methodology with “self-referenced” measurements of effective irradiance ratio, \( F \), and effective temperature ratio, \( H \), which could be significantly better matched to a given PV array of like modules. If operating conditions are reasonably stable and the model discrepancy is sufficiently small, then an I-V curve tracer with a model-calibrated module can serve as a well-matched \( (F, H) \) monitor. That is, once the seven model parameters in SDM-G have been calibrated, an I-V curve for the device under stable F and H conditions can be used to infer the value of \( F \) and \( H \) over that period of time. This approach also alleviates any angular response differences, as well as relaxes the irradiance-response linearity requirement, between TD and RD in the temperature-dependent computation of \( M \).

A self-referential effective irradiance ratio and effective temperature ratio monitor could serve to gather ground campaign weather data for device-, orientation-, and location-specific energy performance predictions. These predictions would have much less reliance on traditional meteorological station data with attendant spectral effect and decomposition/transposition modeling issues [30]. The attendant I-V curves would also allow direct validation of the device model’s maximum power predictions over the collection of a site’s measured \( (F, H) \) values. We hope to be able to validate such alternative approaches
in future work, including cost comparisons and the tuning of historical satellite data to \((F, H)\) time-series.

**Conclusion**

We calibrated both a local five-parameter single-diode model, SDM-L, and a global seven-parameter single-diode model, SDM-G, for photovoltaic device performance using I-V curves measured under controlled laboratory conditions over a matrix of temperature and nominal irradiance combinations. By using the effective irradiance ratio, \(F\), derived from a rigorous temperature-dependent extension of the spectral mismatch correction factor, \(M\), we avoided employing a physically questionable short-circuit temperature coefficient parameter in the SDM-G.

Synthetic dataset studies on cell- and module-like data-sets show the excellent ability of our ODR-based algorithm to fit model parameters in the absence of model discrepancy, with some parameters harder to identify in SDM-L from single I-V curves in certain parts of the \((F, H)\) measurement space. Fitting SDM-G parameters to a real V-I-F-H dataset for a small area mono-Si cell revealed apparent model discrepancy that significantly affected the accuracy of maximum power performance prediction.

Important issues identified for further investigation were (1) intercomparison of V-I-F-H measurement datasets from multiple calibration laboratories; (2) model definition and calibration issues related to the effective temperature ratio, \(H\); and (3) overcoming significant model discrepancy in SDM-G. When paired with a device performance model with sufficiently small model discrepancy, our combined modeling and model calibration approach opens significant opportunities to improve device-, orientation-, and location-specific energy performance predictions.

**Computational Service at pv-fit.com**

A user-friendly online fitting service for SDM-L and SDM-G is available at www.pv-fit.com. Example datasets are provided, and a RESTful application programming interface (API) is available. Fits for datasets with several thousand points are possible in seconds.

**Conflict of Interest**

None declared.

**Notes**

1. A method has been described previously for computing \(M\) over a temperature continuum [24, 25]. In addition, [24] described further measurement considerations when using relative spectral response measurements, which were not an issue given the absolute spectral response measurements used throughout this work.

2. When the non-negativity constraint was removed, the ODR solver was observed in some cases to return nonphysical negative resistance values.

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