Parameter Translation for Photovoltaic Single Diode Models

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***Abstract*—We recommend methods to translate parameters between the PVsyst and California Energy Commission (CEC) single diode models. Translation adds flexibility to PV performance modeling by enabling the use of the CEC database with the PVsyst model, and PVsyst PAN files in the CEC model. We compare three approaches for translation and evaluate agreement between models using three types of monocrystalline silicon (monoSi) technologies and six climate datasets. The recommended approach yields the lowest normalized root mean square error (NRMSE) for all module technologies, never exceeding 0.89% of rated power. Annual energy yields agree within 0.32% for translated models. The recommended methods will be proposed for inclusion in *pvlib-python*.**

***Index Terms*— single diode model, parameter estimation, performance modeling, pvlib**

I. INTRODUCTION

Accurate modeling of photovoltaic (PV) systems is essential for reliable performance simulation and analysis. The PVsyst [1] and the California Energy Commission (CEC) [2] single diode models are widely used in the industry, each with distinct parameter requirements. We propose methods for translating parameters between the PVsyst and CEC models. Our tools enable the use of the CEC module database with the PVsyst model in *pvlib-python* and vice versa. A database of parameters for the CEC model is distributed with the System Advisor Model (SAM) application [4]. This database contains about 5,000 more modules than are found in the PVsyst library of *Panneau Solaire* (PAN) files. Having equivalent parameters for either model would be beneficial. For example, in the U.S. industry, PVsyst results are often requested to prove a project bankable, but a desired module may only have parameters in the CEC database. Some modelers may need to assess the uncertainty introduced by choice of model and need a way to convert one model to the other. The parameter translation method enables flexible modeling workflows, overcomes barriers due to data availability, and allows modelers to compare simulations across different models using the same input data.

Many approaches used for simulating PV system performance use a single diode model. The single diode equation (1) describes a current-voltage (IV) curve given values for five parameters: I_L - photocurrent, I_0 – diode current, n – diode ideality factor, R_S – series resistance, and R_{SH} – shunt resistance.

$$I = I_L - I_O\left(\exp\frac{V+IR_S}{nN_SV_{th}} - 1\right) - \frac{V+IR_S}{R_{SH}} \qquad (1)$$

A single diode model uses (1), along with auxiliary equations, to describe the IV curve at any irradiance and cell temperature. The auxiliary equations vary among single diode models, as do their required parameters. This work considers parameter translation between two popular and commercially relevant single diode models: the CEC model and the PVsyst model, described below.

Techniques for extracting the five parameters for the single diode equation (1) are numerous (e.g., [5], [6]). By contrast, fewer methods are published for estimating parameters for single diode models (e.g., [7], [8]); thesel parameters appear in the model's auxiliary equations. Published methods tend to extract parameters from measurement data (i.e. IEC 61853-1 matrix [9], IV curves) for a specific single diode model which in many cases is different from either the CEC or PVsyst models.

In this work, we compare three methods for translating between the CEC and PVsyst single diode models. The three candidate methods are described and compared for three types of monocrystalline silicon (monoSi) technologies, using environmental data from a variety of climates. The best performing methods are proposed to be implemented in *pvlib-python* as part of a parameter translation toolkit, which includes methods for translating between PV module temperature models [10] and incidence angle modifier (IAM) models [11]. Limitations of the recommended translation methods are explained following the results.

II. SINGLE DIODE MODELS

A. California Energy Commission (CEC) Model

The CEC model comprises (1) and the following auxiliary equations. The CEC model requires parameters $I_{L,ref}$, $I_{O,ref}$, n_0, $R_{S,ref}$, $R_{SH,ref}$, *Adjust*, and α_{sc} (temperature coefficient of short circuit current in A/°C), where the subscript $_{ref}$ denotes the value at standard testing conditions (STC), which is irradiance

E_0 = 1000 W/m^2 and cell temperature of T_0 = 25°C. The band gap energy (E_g) and the temperature dependance of the energy bandgap at STC ($\frac{dE_g}{dT_C}$) are usually set at 1.121 eV and 2.677E-4 eV/K, respectively.

$$I_L = \frac{E}{E_0}\left(I_{L,ref} + \alpha_{sc}^*(T_{cell} - T_0)\right) \tag{2}$$

$$\alpha_{sc}^* = \alpha_{sc}\left(1 - \frac{\text{Adjust}}{100}\right) \tag{3}$$

$$I_O = I_{O,ref}\left(\frac{T_{cell,K}}{T_{0,K}}\right)^3 \exp\left(\frac{1}{k_B}\left(\frac{E_g(T_{0,K})}{T_{0,K}} - \frac{E_g(T_{cell,K})}{T_{cell,K}}\right)\right) \tag{4}$$

$$E_g(T_{cell,K}) = E_g(T_{0,K})\left(1 - \frac{dE_g}{dT_C}(T_{cell} - T_0)\right) \tag{5}$$

$$n = n_0 \tag{6}$$

$$R_{SH} = R_{SH,ref}\frac{E_0}{E} \tag{7}$$

$$R_S = R_{S,ref} \tag{8}$$

B. PVsyst Model

For most cell technologies, the PVsyst model comprises (1) and the following auxiliary equations, described by Sauer et al. [12]. The PVsyst model requires the parameters $I_{L,ref}$, $I_{O,ref}$, $E_{g,ref}$, n_0 (referred to as γ_0 in PVsyst documentation), μ_n, $R_{S,ref}$, $R_{SH,ref}$, $R_{SH,base}$, $R_{SH,0}$ and $R_{SH,exp}$.

$$I_L = \frac{E}{E_0}\left(I_{L,ref} + \alpha_{sc}(T_{cell} - T_0)\right) \tag{9}$$

$$I_O = I_{O,ref}\left(\frac{T_{cell,K}}{T_{0,K}}\right)^3 \exp\left(\frac{qE_{g,ref}}{k_B n}\left(\frac{1}{T_{0,K}} - \frac{1}{T_{cell,K}}\right)\right) \tag{10}$$

$$n = n_0 + \mu_n(T_{cell} - T_0) \tag{11}$$

$$R_{SH}(E) = R_{SH,base} + (R_{SH,0} - R_{SH,base})\exp\left(-R_{SH,exp}\left(\frac{E}{E_0}\right)\right) \tag{12}$$

$$R_{SH,base} = \max\left[\frac{R_{SH,ref} - R_{SH,0}\exp(-R_{SH,exp})}{1 - \exp(-R_{SH,exp})}, 0\right] \tag{13}$$

$$R_S = R_{S,ref} \tag{14}$$

For cadmium telluride (CdTe) and amorphous Si technologies, PVsyst adds an additional term to (1) that represents recombination current in the intrinsic layer. This term requires new parameters: thickness of the intrinsic layer, diffusion length, and the built-in voltage. We do not consider CdTe or amorphous Si modules in our work because the underlying single diode equation is different from (1).

III. Translation Methods

We evaluate three methods to translate between the CEC and PVsyst models: 1) based on published methods, 2) an analytic equivalence approach, and 3) an optimization approach. The matrix of temperature and irradiance defined in the IEC 61853-1 is used to generate model values for the translations.

A. Published Methods

The published methods use techniques found in literature for estimating parameters for the CEC or PVsyst models. This method involves two steps:

1. Calculate a set of IV curves with a source model (either CEC or PVSyst) using *pvlib-python* [3]
2. Fit the target model to the calculated IV curves using previously published methods: Dobos [2] for the CEC model, and Hansen [13] for the PVSyst model.

i. Translating to the PVsyst Model

An IV curve is computed at each of the temperature and irradiance values of the IEC 61853-1 matrix. The IV curves' values, with the module temperature coefficient of current and the number of cells in series, are used with methods described by Hansen [14],[13] to determine the PVsyst parameters. Code for fitting is available in *pvlib-python* [3].

ii. Translating to the CEC Model

The method to fit the CEC model uses only points on the IV curve at STC. Accordingly, current, voltage, and power at STC conditions are calculated, and CEC parameters are found using code available in PySAM v.5.1.0 [15].

B. Analytic Equivalence Approach

The analytic equivalence approach equates model parameters that have the same value at STC as determined from the auxiliary equations – I_L, I_O, R_S, and R_{SH}. For translating to the PVsyst model, E_g, μ_n, $R_{SH,0}$ and $R_{SH,exp}$ must be found whereas the *Adjust* model parameter must be found for the CEC model,.

i. Translating to the PVsyst Model

$E_{g,ref}$, and μ_n. are found by using the CEC model to compute $I_{0,CEC}$ at T_C = 0,1, . . . 75°C and then find $E_{g,ref}$ and μ_γ to minimize:

$$\sqrt{\sum_{T_C=0}^{75}\left(\log_{10} I_{O,CEC}(T_C) - \log_{10} I_{0,PVsyst}(T_C)\right)^2} \tag{16}$$

Similarly, $R_{SH,0}$ and $R_{SH,exp}$ are found by using the CEC model to compute $R_{SH,CEC}$ at E = 100, 200, . . . 1100 W/m^2 and minimizing:

$$\sqrt{\sum_{E=100}^{1100}\left(\log_{10} R_{SH,CEC}(E) - \log_{10} R_{SH,PVsyst}(E)\right)^2} \tag{17}$$

I_O and R_{SH} can range over several orders of magnitude, hence we transform by $\log_{10}$ to avoid basing the PVsyst parameters primarily on agreement at the largest values.

ii. Translating to the CEC Model

The *Adjust* parameter serves to match the CEC model's temperature dependence to a value specified on a module datasheet. Accordingly, *Adjust* is found to match the temperature dependence of the source PVsyst model. Temperature dependence is calculated as the derivative of P_{mp} with respect to temperature using a five-point centered difference formula with 1°C increments:

$$\left.\frac{dP_{mp}}{dT}\right|_{T=25°C} \approx \frac{1}{12}\begin{pmatrix} P_{mp}(23°C) - 8P_{mp}(24°C) + \\ 8P_{mp}(26°C) - P_{mp}(27°C) \end{pmatrix} \quad (18)$$

Denoting $\left.\frac{dP_{mp}}{dT}\right|_{T=25°C}$ as γ_{mp}, *Adjust* is found from:

$$\gamma_{mp,PVSyst} = \gamma_{mp}, CEC \times \left(1 + \frac{\text{Adjust}}{100}\right) \quad (19)$$

C. Optimization Approach

The optimization approach determines all parameters in the target model by fitting the target model to five points on the IV curve (P_{mp}, I_{sc}, V_{oc}, I_{mp}, and V_{mp}) computed using the source model at the different combinations of irradiance and temperature conditions in the IEC 61853-1. Parameters are optimized subject to bounds defined based on physical possibility. The Nelder-Mead simplex algorithm [16] as implemented in *scipy-python* v.1.11.4 [17] is used. For the PVsyst and CEC models the optimization procedure differs only in the error function. Different error functions were tested, and it was found that the mean of the absolute percentage error (APE) (20) of the current, voltage, and power values yields the best results for determining PVsyst parameters, while the best error function for determining CEC parameters is the mean of the root sum of squares (RSS) (21) errors of current, voltage, and power.

$$APE = \left|\frac{Value_{Target} - Value_{Source}}{Value_{Source}}\right| \quad (20)$$

$$RSS = \sqrt{\sum (\text{Value}_{Target} - Value_{Source})^2} \quad (21)$$

IV. Comparison of Methods

To compare the methods' accuracy in parameter translation, we translate models for three types of monoSi module technologies (Table 1). CEC model parameters are taken from the SAM database and PVsyst parameters are obtained from the PVsyst PAN file database. Model agreement is evaluated by applying the models to 1) the IEC 61853-1 matrix of temperature and irradiance values [9], and 2) six reference climatic datasets provided in IEC 61853-4 [18]: high elevation, subtropical arid, subtropical coastal, temperate coastal, temperate continental, tropical humid. Each dataset provides POA irradiance, ambient temperature, and wind speed at hourly intervals over a year for a fixed tilt, equator-facing system. The datasets are used to generate current, voltage, power and energy yield for the source and target models, which are compared using percentage error (22), residuals (23), and normalized root mean square error (NRMSE) as a percent of nominal module power (24):

$$Percentage\ Error = 100 \times \frac{Value_{Target} - Value_{Source}}{Value_{Source}} \quad (22)$$

$$Residuals = Value_{Target} - Value_{Source} \quad (23)$$

$$NRMSE\ (\%) = 100 \times \frac{\sqrt{\frac{1}{\text{N}}\sum (Value_{\text{Target}} - Value_{\text{Source}})^2}}{Nominal\ Module\ Power} \quad (24)$$

where N is the length of the dataset.

Residual analysis provides insight into trends that may exist within errors of a method, e.g. greater error at high irradiance. NRMSE can be used to quantify the spread and average magnitude of residuals, reflecting the overall performance of a translation method. Annual energy yield was also used as a method of comparison.

Table I: Modules used to compare translation methods.

Module Name	Technology Type
Trina Solar 660W (TSM-DEG21C-20-660W)	monoSi – High Current (Isc = 18.45A)
Sunket Solar 415W (SKT415M10-108S1)	monoSi – TOPCon[1] Half Cell
Hanwha Q Cells 595W (Q.Peak-Duo-XL-G11S.3)	monoSi – PERC[2]

[1]Tunnel Oxide Passivated Contact
[2]Passivated Emitter and Rear Contact

A. Translating to the PVsyst Model

Figure 1 shows the percentage errors in current, voltage, and power calculated from the source model (CEC) and the target model, at all conditions in the IEC 61853-1 matrix, with colors representing the used method of translation. The analytic equivalence method exhibited the largest error in power across all technologies, with inaccuracies as large as -2.98% while using the high current module parameters. For all module types, the published and optimization methods never exceeded ±1% error in power.

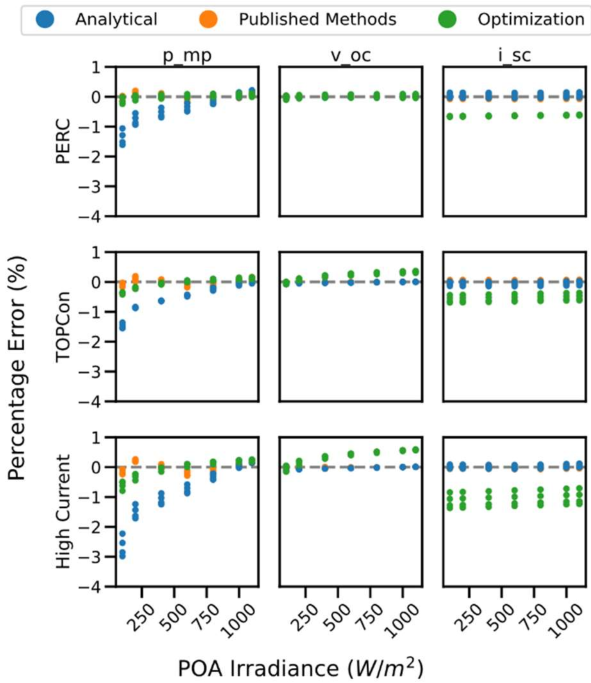

Figure 1: Percentage errors in power (p_mp), voltage (v_oc), and current (i_sc) at the IEC 61853-1 matrix conditions; due to density of the datapoints temperature levels are not individually labelled. Applying the analytic equivalence method to the high current module parameters yields the largest errors in power.

Figure 2 shows the mean percentage errors in V_{mp} averaged across ambient temperature intervals (left) and I_{mp} averaged across POA irradiance intervals (right). Grey bars represent the amount of data in each interval. For V_{mp} values, the optimization method showed the lowest errors and smallest variation across the ambient temperature intervals. For all technologies the range of V_{mp} error was < 1% when using optimization, while the other methods varied by up to ±1.7% across the temperature intervals. When comparing I_{mp} values, the optimization and published methods performed similarly, with an error up to 0.5%. The analytic equivalence method has the highest spread of errors across the varying levels of irradiance, reaching -2.9% at low irradiances.

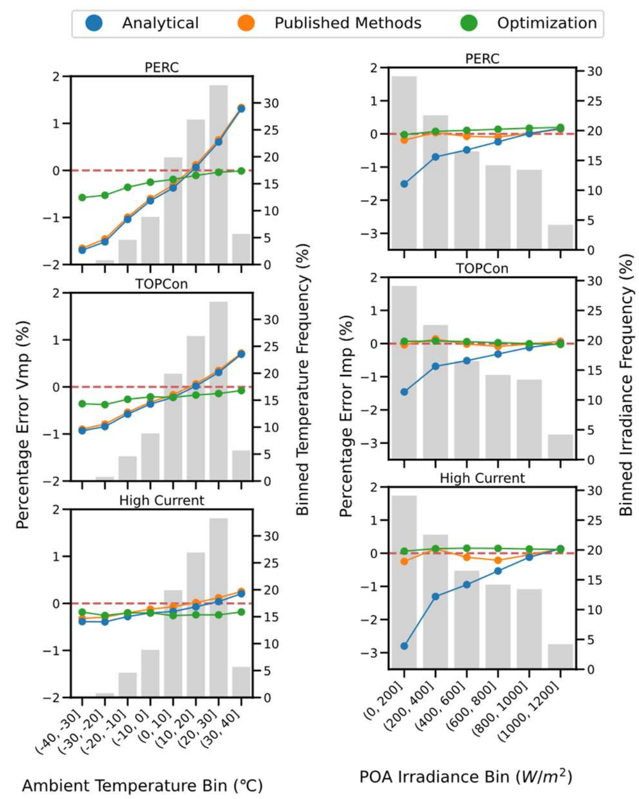

Figure 2: Average percentage error in V_{mp} over ambient temperature intervals (left) and in I_{mp} over POA irradiance intervals (right) considering the IEC 61853-4 climate profiles. The optimization approach exhibits the most consistently low error values.

Figure 3 shows the P_{mp} residuals plotted against irradiance and each method's power NRMSE values. For all module types, the optimization method yields the lowest NRMSE of < 0.07%, while the analytic equivalence method yields the highest NRMSE (0.53%). The lowest NRMSE of 0.04% is seen when suing the optimization method with the TOPCon module, while the highest NRMSE of 0.53% is seen when using the analytic equivalence method with the PERC module. For all module technologies, the analytic equivalence and published methods show a larger spread of residuals and more inconsistent performance than the optimization method across levels of irradiance. The NRMSE of analytic equivalence and published methods ranges from 0.29% to 0.53% and 0.12% to 0.50%, respectively. The NRMSE of the optimization method has a much smaller range of 0.04% to 0.07% across technologies.

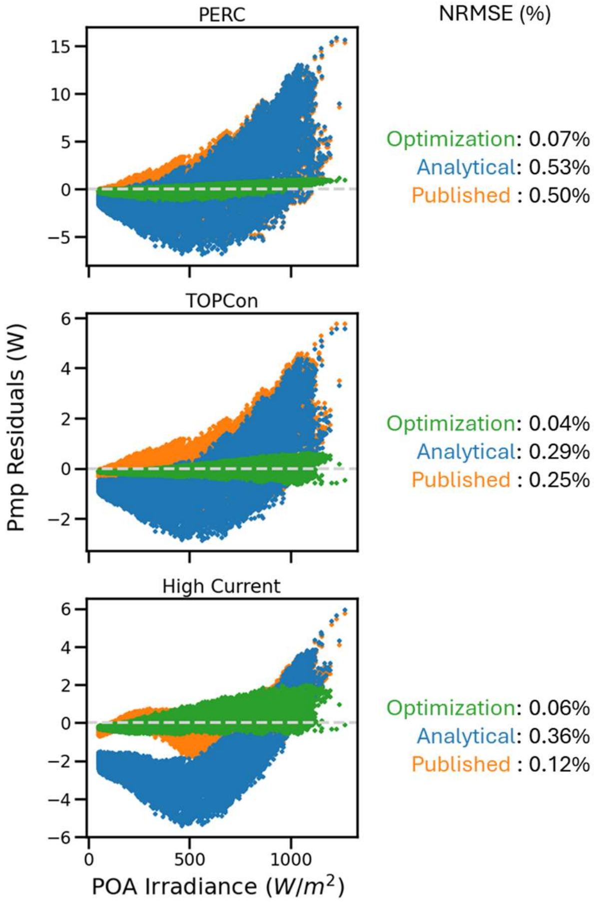

Figure 3: P_{mp} residuals plotted against irradiance. NRMSE values for each method show that the optimization method yields the best performance for all modules, while the analytic equivalence method consistently exhibits the highest NRMSE.

Figure 4 shows the average percentage error in annual energy yield across all climate profiles. For all module types, the optimization method provided the lowest error within ±0.06% in annual energy yield. This result indicates that, by starting with CEC coefficients, applying the optimization method to derive PVsyst coefficients can achieve annual energy differences within 0.06%. Both the published and analytic equivalence methods are within 0.50% and 0.75%, respectively.

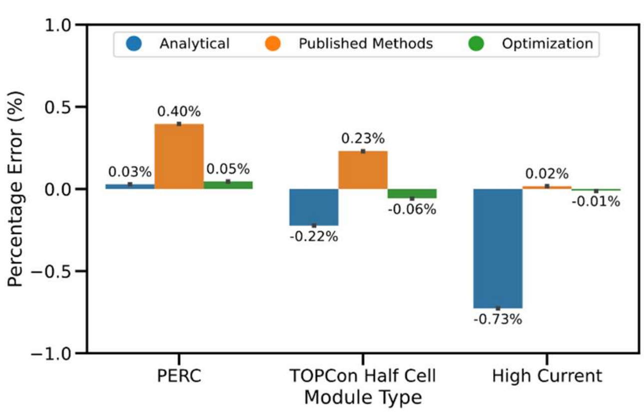

Figure 4: Percentage error in annual energy yield when translating from CEC to PVsyst. The optimization method demonstrates the lowest errors.

B. Translating to the CEC Model

Figure 5 shows the percentage errors in power, voltage, and current under the IEC 61853-1 matrix conditions when translating CEC parameters to PVsyst parameters. The optimization method never exceeds 5% in either direction for power values, while the analytic equivalence and published methods reach up to 9.5% and 10.3% negative bias, respectively.

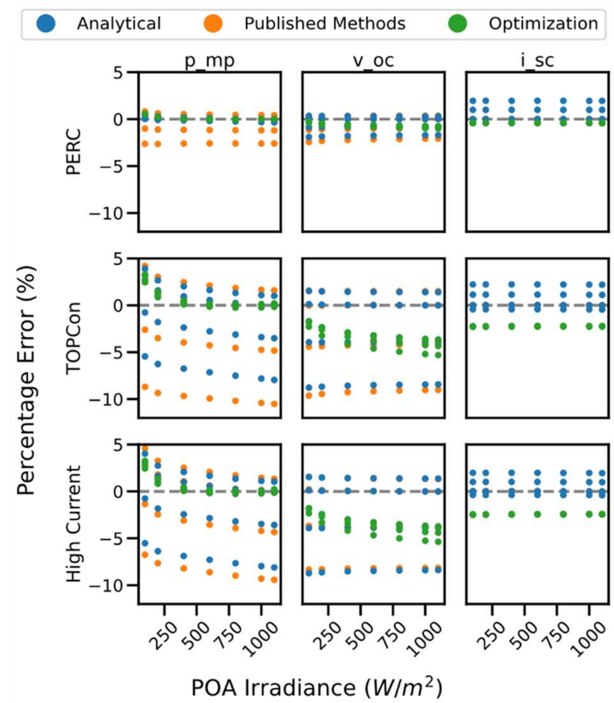

Figure 5: Percentage errors in power (p_mp), voltage (v_oc), and current (i_sc) at the IEC 61853-1 matrix conditions; due to density of the datapoints temperature levels are not individually labelled. The published and analytic equivalence methods' power errors exceed 9%, while the optimization method's power errors never exceed 5%.

Figure 6 shows that the optimization method yields the lowest errors and smallest variation in V_{mp} values across temperature intervals. The overall range of V_{mp} errors is 1.2% when using optimization, while other methods vary by ±6.2%. When comparing I_{mp} values, no method exceeds a 3% average error, though the optimization method has the least amount of change across irradiance levels.

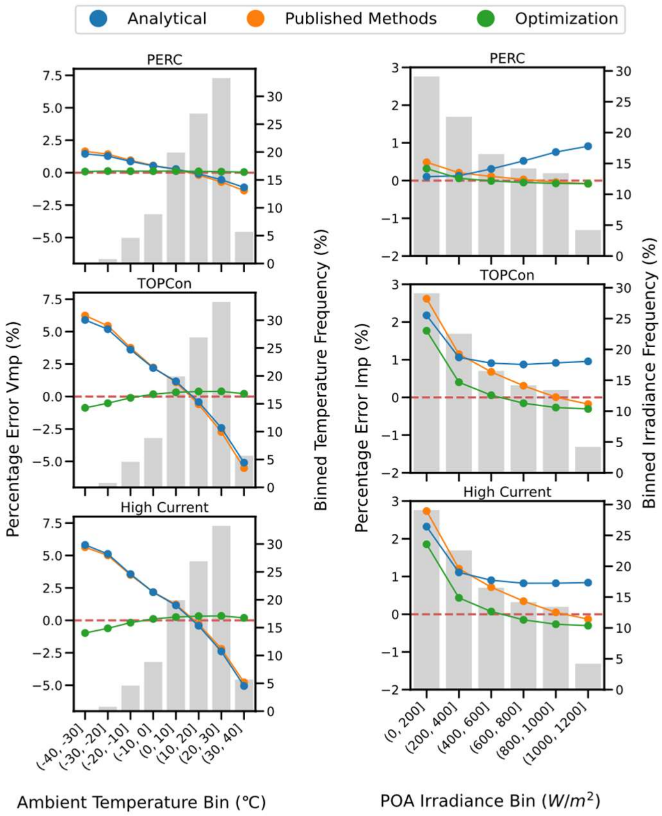

Figure 6: Average percentage error in V_{mp} over temperature intervals (left) and I_{mp} over irradiance intervals (right) considering the IEC 61853-4 climate profiles. The optimization approach demonstrates the lowest errors.

Figure 7 shows the power residuals plotted over irradiance and each method's NRMSE values. The optimization method consistently exhibits the lowest NRMSE across all module types down to 0.03%. Unlike the previous translation however, the published method consistently has the highest NRMSE across technologies, reaching up to 2.10%.

Figure 8 shows the average percentage error in annual energy yield across all IEC 61853-4 climate profiles. The optimization method yields the lowest errors for all technologies. This result indicates that, when starting with PVsyst parameters, using the optimization method to obtain CEC parameters could yield the same annual energy result within 0.32%. The published methods and analytic equivalence approaches reached errors up to 1.35% and 0.72%, respectively.

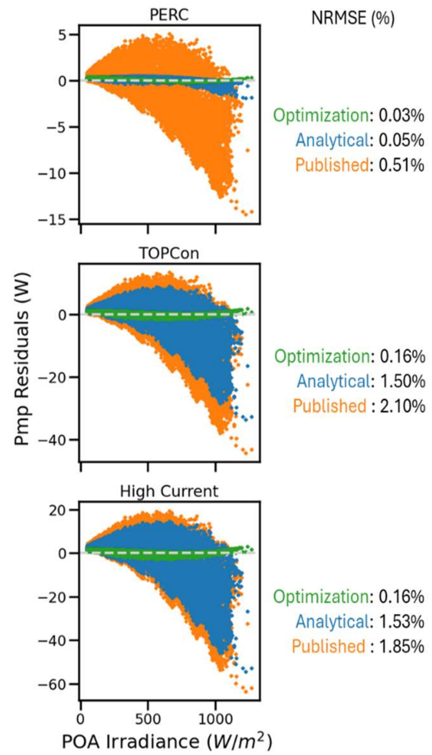

Figure 7: P_{mp} residuals plotted over POA irradiance for all PV modules and methods. The optimization approach yields the lowest NRMSE values, while the published methods has the highest NRMSE.

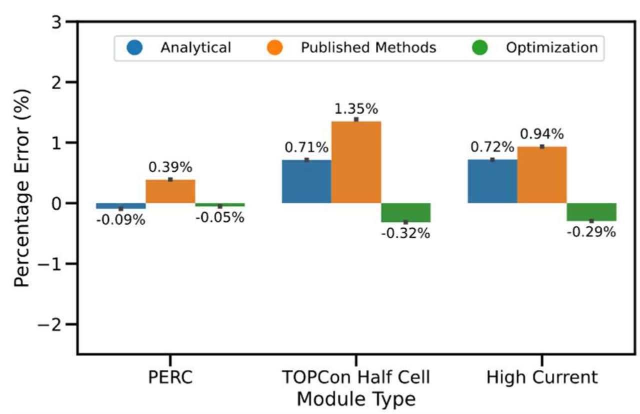

Figure 8: Percentage error in annual energy yield when translating from the CEC to PVsyst. The optimization method demonstrates the lowest percentage errors.

V. Discussion

Overall, the optimization method is the best when considering results from all modules and climate datasets. It exhibits the lowest NRMSE for both translations: CEC to PVsyst and vice versa. Additionally, it has consistently low errors across various irradiance and temperature intervals and also has the lowest annual energy yield error.

The PVsyst model has more parameters than the CEC model, which means the CEC model cannot capture all the nuances of PVsyst model's output. As a result, power residuals and annual energy estimation errors are larger when translating to the CEC model. Finally, it is important to note that our work addresses the accuracy of the translation methods, not the models themselves, as no measured module performance data were used to compare the models.

VI. Summary And Conclusion

Currently, there are no published methods for translating parameters between two of the most popular single diode models: CEC and PVsyst. We evaluated three translation methods: 1) based on published methods, 2) an analytic equivalence approach, and 3) an optimization approach. To assess these methods, we used three monoSi module technologies with weather data from six locations of varying climates. Despite some limitations, the optimization method demonstrated the best overall performance, with annual energy errors lower than 0.32%. The power NRMSE for the optimization method never exceeded 0.16%, whereas other methods reached up to 2.10%. The parameter translation method enables flexible modeling workflows, overcomes barriers due to data availability, and allows modelers to compare simulations across different models using the same input data. Last, the optimization method will be a proposed addition to *pvlib-python* as part of a parameter translation toolkit, which features translation methods for incidence angle modifier and module temperature models.

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