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# Statistical Approach for Determining the Sandia Array Performance Model Coefficients that Considers String-Level Mismatch

C. Birk Jones, Clifford W. Hansen, & Bruce H. King

Prepared by
Sandia National Laboratories
Albuquerque, New Mexico 87185 and Livermore, California 94550

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# Statistical Approach for Determining the Sandia Array Performance Model Coefficients that Considers String-Level Mismatch

C. Birk Jones
Photovoltaics & Distributed Systems
Sandia National Laboratories
Albuquerque, NM 87185-9999
cbjones@sandia.gov

Bruce H. King
Photovoltaics & Distributed Systems
Sandia National Laboratories
Albuquerque, NM 87185-9999
bhking@sandia.gov

Clifford W. Hansen
Photovoltaics & Distributed Systems
Sandia National Laboratories
Albuquerque, NM 87185-9999
cwhanse@sandia.gov

**Abstract**

Commonly used performance models, such as PVsyst, Sandia Array Performance Model (SAPM), and PV_LIB, treat the PV array as being constructed of identical modules. Each of the models attempts to account for mismatch losses by applying a simple percent reduction factor to the overall estimated power. The present work attempted to reduce uncertainty of mismatch losses by determining a representative set of performance coefficients for the SAPM that were developed from a characterization of a sample of modules. This approach was compared with current practice, where only a single module's thermal and electrical properties are testing. However, the results indicate that minimal to no improvements in model predictions were achieved.

# Contents



## Appendix



# Figures



# Tables

# Nomenclature

**AOI** Angle of Incidence

**$E_b$** Beam Irradiance

**$E_{POA}$** Plane of Array Irradiance

**DOE** Department of Energy

**$I_{SC}$** Short Circuit Current

**$I_{MP}$** Max Power Point Current

**$P_{MP}$** Max Power Point Power

**POA** Plane of Array

**PV** Photovoltaic

**PVID** Photovoltaic Module Identification Number

**PVsyst** Photovoltaic Software

**SAPM** Sandia Array Performance Model

**SNL** Sandia National Laboratories

**$T_C$** Cell Temperature

**$V_{MP}$** Max Power Point Voltage

**$V_{OC}$** Open Circuit Voltage

# 1 Introduction

Photovoltaic (PV) arrays have typically been assembled by connecting multiple modules in series and then combining them in parallel. Connecting the modules in series creates what is often referred to as a string, where the overall voltage is the sum of each individual module voltage. The current, in this situation, is equal to the output of the worst performing module. The parallel connection of multiple strings forces the strings to have the same voltage, and the overall current is the sum of each string. Unfortunately, the string configuration has been susceptible to losses caused by mismatch conditions.

Several PV modules of the same type may not have the same voltage and/or current outputs due to manufacturing tolerances, degradation, or fault conditions. The connection of these modules in series will produce an overall power that is below the expected output according to the manufactures nameplate specifications. The loss in power caused by the different individual module outputs in a series can be referred to as **mismatch losses** [13]. Mismatch losses were evident in the present work. For instance, five modules were combined in series to create a string. The current and voltage (IV) curves for each module are plotted on the left side of Figure 1. It is evident that

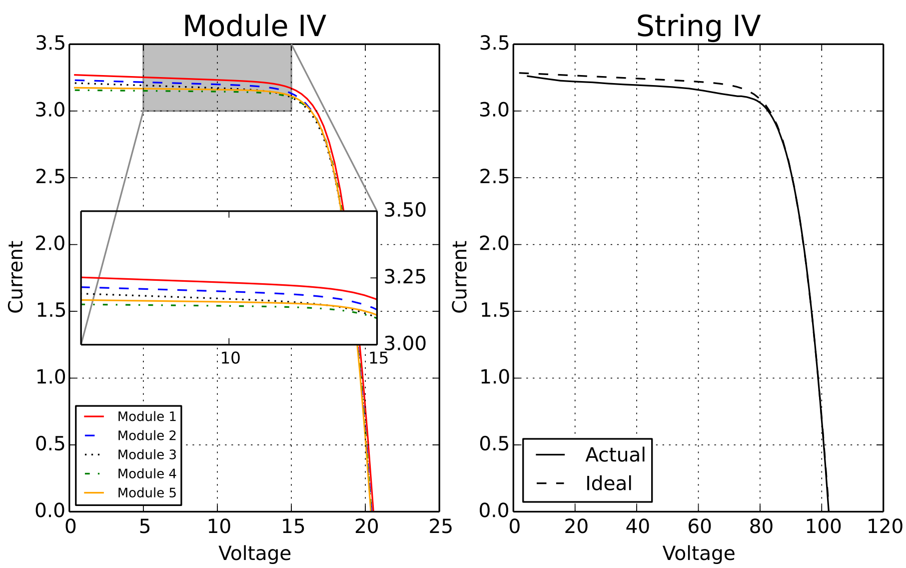


**Figure 1.** Left: Individual module current and voltage curves show a variation in current output for the five modules used in the present work. Right: The combination of the five modules, plotted on the left, connected in series provided an output that had a degraded IV curve when compared to the ideal.

the current output for each of the modules varied slightly. This variation between the individual modules created a non-ideal IV curve when the modules were combined in series as shown on the right side of Figure 1. The actual IV curve had a slightly degraded current output compared to the ideal IV curve that was created from a model. Current modeling techniques have not accurately factored this condition into the estimations.

Commonly used performance models, such as PVsyst [2], Sandia Array Performance Model (SAPM) [9], and PV_LIB [1], treat the PV array as being constructed of identical modules. Each of the models attempts to account for mismatch losses by applying a simple percent reduction factor to the overall estimated power. For instance, PVsyst has a module quality loss factor and SAPM has used a nameplate loss factor that can be applied to individual modules. The two models also have an array mismatch loss factor which derates the overall power output provided by the model. For example, PVsyst modeling software includes a tool that can estimate the array mismatch loss factor based on a statistical analysis. The analysis creates a statistical sample of modules based on a gaussian or square distribution to determine the $V_{oc}$,$I_{sc}$, etc. [3]. Beyond this tool there exists little basis for setting these derate factors except for intuition. As a consequence, additional uncertainty is ascribed to predicted system performance arising from these derate factors.

Further, these PV performance models are typically applied using a set of coefficients determined for a single, representative module rather than from a statistical sample of modules. While some manufacturers may test larger samples of modules, IEC 61215/61646 only requires that a single module be tested for electrical performance. Even when multiple modules are characterized, methods are not documented and validated to determine model coefficients that will accurate predict performance of a string of such modules. Using coefficients from only a single module is likely to introduce bias errors into the estimation of PV system power.

At a recent workshop hosted by Sandia and attended by representatives from the PV modeling, manufacturing, finance and system integrator communities, uncertainty about mismatch losses was identified as a significant gap in current performance models [4]. Field measurements of mismatch losses, however, have shown the effect to be relatively small even for modules with significantly different current-voltage characteristics [11]. Modeling studies have also shown that the effect of mismatch on power production is relatively small [5]. It is small relative to other uncertainties in performance models [7].

Although the effect of mismatch loss may be small in comparison to other modeling uncertainties, any reduction in the uncertainty of power prediction is welcome. Moreover, a 1% difference in predicted power generally translates to a proportional difference in annual energy and hence revenue from a PV system. To illustrate, the impact of power predictions using coefficients from a single module by comparing one-year system performance predictions using SAPM for two nominally identical modules recently characterized at SNL was investigated. These two modules differed in measured $P_{MP}$ by 2W, which is less than the manufacturer's binning criteria of 2.5W. To minimize all other effects, all of the derates were set to 100% (i.e. no reduction in power), and a common set of coefficients were used to represent the effects of angle of incidence (AOI), spectral irradiance and cell temperature ($T_C$). The predicted power differed by 0.7% between the two modules, highlighting the significance of the choice of coefficients used in the predictions. The mismatch derate value was then set to the standard 2%. Unsurprisingly, this did not reduce the difference in predicted system power between the two; it simply shifted the predicted power of each down by 2%.

Reducing uncertainty regarding the determination of mismatch loss factors thus will provide a meaningful improvement in performance modeling. The present work introduces a method to determine a representative set of performance coefficients for the SAPM that were developed from characterization of a sample of modules. The proposed approach was validated with field and laboratory measurements. The method combined measured module performance characteristics into a representative set of coefficients that accurately described performance of an array comprised of the characterized modules.

The intent of the present work was to define the impact of SAPM coefficients derived from three different methods. The following chapters describe the experiment methodology, results, and conclusions. The methodology, Chapter 2, describes module testing procedures, statistical analysis approach, and the formulation of the string level models. The results chapter (Chapter 3) reviews the experiment and model results. It also compares the proposed approach with current practice. Finally, Chapter 4, provides a concise conclusion that summarizes the project outcomes.

# 2 Methodology

The current work evaluated three different methods to determine coefficients for the Sandia Array Performance Model (SAPM) [King]. The intent was to test a set of modules or a string of modules in order to best represent the performance of a string of similar modules. The evaluation included individual thermal and electrical characterization of eleven Suntech STP0802-12 modules, and the characterization of two strings of five modules each. The evaluation followed a three-step process as described in Figure 2. First, each module was individually subjected to thermal and electrical

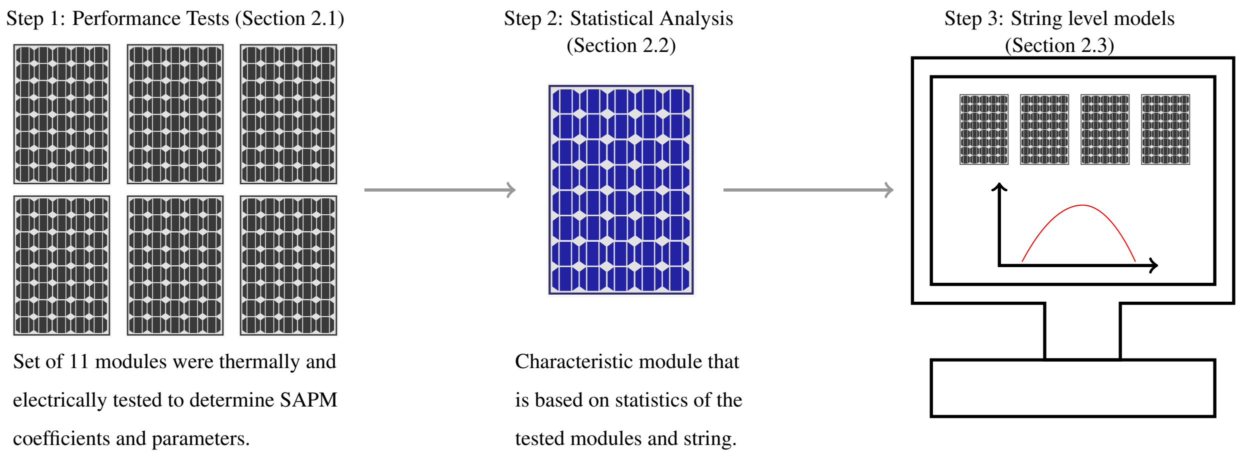


**Figure 2.** Three step process for determining module coefficients: (1) performance tests, (2) statistical analysis, and (3) string level model.

testing and module-level coefficients were determined for the SAPM. The performance tests also included the evaluation of two strings to develop SAPM coefficients for a single characteristic module. The module-level coefficients were aggregated into string-level coefficients based on a statical analysis performed in step 2. Finally, the performance of two strings comprised of five modules each was characterized, and string-level model predictions were compared with the string-level measurements.

## 2.1 Module Testing

Individual module tests were conducted over two time frames. The first modules labeled with photovoltaic identification numbers (PVID) 2691 to 2696 were tested between March 6 and May 5, 2011. The second batch of tests were done from June 12 to October 2, 2013 and included modules PVID 2697 to 2703. These tests were conducted on the two-axis solar tracker shown in Figure 3. The thermal and electrical tests measured current-voltage (IV) curves at different temperatures and irradiance values. For instance, during the thermal tests IV curves were measured while the module was subjected to steady irradiance near one sun. The electrical tests measured IV curves

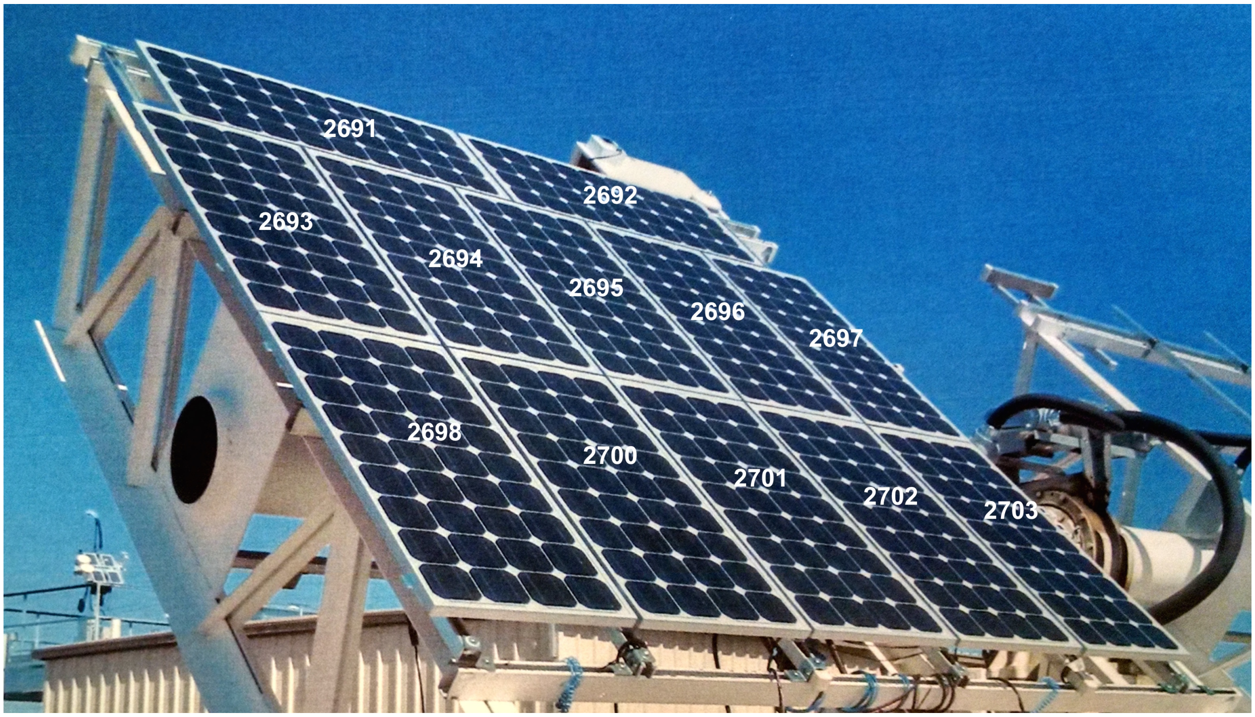


**Figure 3.** Modules under test on two-axis solar tracker.

over a wide range of different irradiance and temperature conditions. Analysis of the test results determined coefficients and parameters for the SAPM which can then be used to predict module performance at different irradiance and temperature operating conditions.

## 2.2 Statistical Analysis

The statistical analysis considered three different methods to determine coefficients and parameters for the SAPM. The intent of each technique was to find the characteristic module that could be used to accurately model a string. A physically-informed method, termed here the “Average Module Method”, generally, estimated string-level coefficients and parameters by averaging the corresponding values for individual modules. The “Average Module Method” was compared with two other methods for determining string-level model coefficients and parameters: random selection of a single, individual module as representative of all modules comprising a string (the “Random Module Method”), and direct determination of string-level coefficients and parameters from electrical testing of the string (the “Average String Method”). The “Random Module Method” simply selected (at random) one of the characterized modules as representative of all modules in the string and models the string by scaling the module-level coefficients for the selected module. The “Average String Method” required electrical characterization of the actual string of modules, from which string-level coefficients and parameters for the SAPM can be determined using the same methods as are used for module data.

**Random Module**

The SAPM depends on sets of coefficients and parameters to define each module type. The "Random Module Method" was considered common practice. The approach tests and evaluates a single module to determine the coefficients and parameters for a particular type of module. This approach assumes that the module chosen for testing was representative of all modules from a particular manufacturer. This method was applied to the present work as a control to compare with the two other methods ("Average String Method" and "Average Module Method").

**Average String Method**

The "Average String Method" considered the average of the coefficients and parameters derived from tests performed on two strings. More specifically, electrical and thermal tests were conducted on two strings that each had five modules. The tests revealed the SAPM coefficients and parameters which were then used to model the string. The third method, known as the "Average Module Method" evaluated a set of modules to determine the SAPM coefficients and parameters.

**Average Module Method**

The proposed "Average Module Method" for determining string-level coefficients and parameters considers a sub-set of modules. Here, the notation ( $\hat{}$ ) denotes a string-level coefficient to distinguish from the corresponding module level coefficient.

If all modules in a series-connected string are identical in electrical performance, then the performance model for the string is found by multiplying voltage terms by the number of modules in series, $N$. Consequently, string-level coefficients are obtained in the obvious manner, e.g.:

$$\hat{I}_{SC0} = I_{SC0}, \hat{\alpha}_{Isc} = \alpha_{Isc} \tag{1}$$

$$\hat{N}_S = NN_S, \hat{V}_{OCO} = NV_{OCO}, n = n, \hat{\beta}_{V_{oc}} = N\beta_{V_{oc}} \tag{2}$$

When modules are similar in performance, but not identical, as is often observed when several modules from a production lot are characterized, the coefficients for the performance models for each module vary.

Here, we obtain the coefficients for a string of modules from N sets of coefficients for individually-characterized modules. We assume that each characterized module represents an equal fraction of the production lot and we weight each module equally. We assume that irradiance and temperature conditions are uniform across all modules in the string.

*Coefficients for $V_{OC}$: $\hat{V}_{OCO}$, $\hat{n}$, $\hat{\beta}_{V_{OC}}$*
At open circuit string voltage is the sum of the voltage for each module:

$$\hat{V}_{OC} = \sum_{i=1}^{N} V_{OC,i} = \sum_{i=1}^{N} V_{OC,i} + N_S n_i \delta(T_C) ln(E_e) + \beta_{V_{OC,i}}(T_C - T_0) \tag{3}$$

Accordingly

$$\hat{V}_{OC} = \sum_{i=1}^{N} V_{OC,i} \tag{4}$$

$$\hat{n} = \frac{1}{N} \sum_{i=1}^{N} n_i \tag{5}$$

$$\hat{\beta}_{V_{OC}} = \sum_{i=1}^{N} \beta_{V_{OC,i}} \tag{6}$$

The value for the diode factor n is estimated by averaging rather than summation because for a string of N modules each with $N_S$ cells in series, the number of cells in series is $\hat{N}_S = NN_S$.

*Coefficients for $I_{SC}$: $\hat{\alpha}_{I_{SC}}$, $\hat{I}_{SC0}$*

In a string of slightly mismatched modules operating at short circuit, some cells in the string will be in reverse bias. If mismatch is sufficient and bypass diodes are present, these diodes may conduct current to protect cells from damage. In theory string short circuit current is determined from the module-level I-V curves provided that the curves are measured for both negative and positive biases. However, module characterization rarely includes measuring current at reverse bias, and here we apply several assumptions to overcome the limits of the data:

1. We assume that bypass diodes are present across $N_B$ series-connected cells in each module for a total of $B = N_S/N_B$ bypass diodes in each series-connected string of cells in a module.
2. We represent the nominal turn-on voltage for a bypass diode as $V_B$. We adopt a convention here that $V_B$ is always positive, i.e., $V_B$ is the magnitude of the turn-on voltage.
3. We assume that the IV curve out to a reverse bias of $V_B$ can be approximated by a linear extrapolation from the IV curve at positive bias.
4. We assume that either all bypass diodes in a module are conducting or that no bypass diodes in the same module are conducting. In other words, we treat each module in the string as an electrical element, which either conducts current through cells or through bypass diodes but not a combination of both cells and bypass diodes.

We first estimate the temperature coefficient by averaging:

$$\hat{\alpha}_{I_{SC}} = \frac{1}{N} \sum_{i=1}^{N} \alpha_{I_{SC},i} \tag{7}$$

Averaging seems appropriate because the magnitude of $\alpha_{I_{SC}}$ is typically small (i.e., on the order of 0.1% or less) and the noise in short circuit current measurements transfers to a fairly wide range of uncertainty around $\alpha_{I_{SC}}$.

We estimate $\hat{I}_{SC0}$ by first estimating an IV curve for each module at STC conditions, extrapolating each module?s STC IV curve to reverse bias, and then iterative solving Kirchoff?s equations to determine the voltage drop over each series-connected module and the current. Iteration is used in order to account for conduction through bypass diodes that introduces a cusp in each module's I-V characteristic at -$V_B$. The following algorithm solves the Kirchoff equations for voltage and current through a string of series-connected modules accounting for modules for which current flows through the bypass diode. The system of equations for voltage and current is solved without constraining voltage, i.e., as if no bypass diodes were present, then voltage for modules with bias less than -$V_B$ is set to -$V_B$ to represent conducting bypass diodes, then the system of equations is reduced in dimension to omit these modules and the reduced system is solved.

1. For each module define an STC IV curve by translating a measured IV curve to STC conditions.
2. Linearly extend each STC IV curve to negative bias, e.g., by fitting a line using least squares to IV curve data for $0 \leq V \leq 0.5 V_{MP}$, to obtain a slope $m_i$ corresponding to each intercept $I_{SC0,i}$
3. Initialize $V_i = 0$, $i$=1, K, N and converge = false.
4. White NOT(converge)
   (a) Set P = $\#\{i \mid V_i \leq -V_B \}$. P counts the number of modules with conducting bypass diodes.
   (b) Define an index J($i$), $i$ = 1, K, N-P such that $V_{J(i)} \leq -V_B$.
   (c) Form the (N-P+1)x(N-P+1) design matrix

$$X = \begin{bmatrix} 1 & K & 1 & 0 \\ -m_{J(1)} & 0 & 0 & 1 \\ 0 & 0 & 0 & M \\ 0 & 0 & -m_{J(N-P)} & 1 \end{bmatrix}$$

   and solve

$$X \begin{bmatrix} V_{J(1)} \\ M \\ V_{J(N-P)} \\ 1 \end{bmatrix} = \begin{bmatrix} PV_B \\ I_{SC,J(i)} \\ M \\ I_{SC,J(N-P)} \end{bmatrix}$$

   (d) If any $V_{j(i)} \leq -V_B$ set converge = false and $V_{J(i)} = \max\{-V_B, V_{J(i)}\}$.
5. The algorithm produces values $V_i$ for the bias for each module, and a value $\hat{I}_{SC0} = I$ for the short circuit current for the string of modules.

*Coefficients for $V_{MP}$: $\hat{\beta}_{V_{MP}}$, $\hat{V}_{MP0}$, $\hat{C}_2$, $\hat{C}_3$*
Although voltage for a string is the sum of voltages for each module, at the string's maximum power point the voltage across each module is not the module's maximum power voltage. However,

typically for either modules or strings, in the vicinity of maximum power the voltage vs. power curve has a wide and relatively shallow peak. Thus can be predicted with an acceptably small error even when estimated $V_{MP}$ has a greater error, e.g., on the order of a few volts. We estimate string model coefficients for $V_{MP}$ by averaging:

$$\begin{aligned}\hat{V}_{MP} &= V_{MP0} + \hat{C}_2 N N_S \hat{n}\delta(T_C)\ln(E_e) + \hat{C}_3 N N_S (\hat{n}\delta(T_C)\ln(E_e))^2 + \beta_{V_{MP}}(T_C - T_0) \\ &= \sum_{i=1}^{N} V_{MP,i} \\ &= \sum_{i=1}^{N} V_{MP0,i} + C_{2,i} N_S n_i \delta(T_C)\ln(E_e) + C_{3,i} N_S (n_i \delta(T_C)\ln(E_e))^2 + \beta_{V_{MP,i}}(T_C - T_0)\end{aligned} \tag{8}$$

From which we obtain

$$\hat{\beta}_{V_{mp}} = \sum_{i=1}^{N} \beta_{V_{mp,i}} \tag{9}$$

$$\hat{V}_{MP0} = \sum_{i=1}^{N} V_{MP0,i} \tag{10}$$

$$\hat{C}_2 = \frac{1}{N} \sum_{i=1}^{N} C_{2,i} \tag{11}$$

$$\hat{C}_3 = \frac{1}{N} \sum_{i=1}^{N} C_{3,i} \tag{12}$$

The coefficient $\hat{n}$ is determined from $V_{OC}$ by Eq. 5

*Coefficients for $I_{MP}$: $\hat{\alpha}_{I_{MP}}$, $\hat{I}_{MP0}$, $\hat{C}_2$, $\hat{C}_3$*
As was done for $I_{SC}$we determine $\hat{\alpha}_{I_{MP}}$ by averaging, because values for $\alpha_{I_{MP}}$ are typically small and are subject to significant uncertainty:

$$\hat{\alpha}_{I_{MP}} = \frac{1}{N} \sum_{i=1}^{N} \alpha_{I_{MP,i}} \tag{13}$$

We average to obtain a value for $\hat{C}_1$ because these coefficients are typically very small in magnitude:

$$\hat{C}_1 = \frac{1}{N} \sum_{i=1}^{N} C_{1,i} \tag{14}$$

By definition, $C_0 + C_1 = 1$ so we compute

$$\hat{C}_0 = 1 - \hat{C}_1 \tag{15}$$

Finally, to make the predictive model consistent with the STC power rating $P_{MP0}$ for the module in question we set

$$\hat{I} = \frac{P_{MP0}}{\hat{V}_{MP0}} \tag{16}$$

## 2.3 String Model

The SAPM [9] was developed for flat-plate, crystalline silicon modules but has been found to adequately describe electrical performance of a wide variety of PV technologies [4]. SAPM comprises the following fundamental equations to describe the electrical performance of a single module:

$$E_{POA} = \frac{E_b f_2(AOI) + f_d E_{diff}}{E_o} SF \tag{17}$$

$$I_{SC} = I_{SC0} f_1(AM) E_{POA} (1 + \alpha(T_C - T_o)) \tag{18}$$

$$E_c = \frac{I_{SC}}{I_{SC0}(1 + \alpha_{Isc}(T_C - T_o))} \tag{19}$$

$$I_{MP} = I_{MP0}(C_0 E_e + C_1 E_e^2)(1 + \alpha_{I_{mp}}(T_C - T_o)) \tag{20}$$

$$I_X = I_{X0}(C_4 E_e + C_5 E_e^2)(1 + \alpha_{I_{sc}}(T_C - T_o)) \tag{21}$$

$$I_{XX} = I_{XX0}(C_6 E_e + C_7 E_e^2)(1 + \alpha_{I_{mp}}(T_C - T_o)) \tag{22}$$

$$\delta(T_C) = \frac{k(T_C + 273.15)}{q} \tag{23}$$

$$V_{OC} = V_{OC0} + N_s n \delta(T_C) ln(E_e) + \beta_{V_{OC}}(T_C - T_0) \tag{24}$$

$$V_{MP} = V_{MP0} + C_2 N_s \delta(T_C) ln(E_e) + C_3 N_s (\delta(T_C) ln(E_e))^2 + \beta_{V_{mp}}(T_C - T_0) \tag{25}$$

Effective plane-of-array irradiance, $E_{POA}$, (suns) is the incident broadband solar irradiance that reaches the module's cells, and is estimated from incident broadband beam irradiance $E_b$ (W/m2) and diffuse irradiance $E_{diff}$ (W/m2). $E_{POA}$ is reduced by reflection losses at the module's surface, expressed by the empirical function $f_2$ (unit-less) of angle of incidence AOI (degrees), and by soiling losses, represented by the factor SF. The coefficients $I_{SC0}$, $I_{MP0}$, $V_{OC0}$, $V_{MP0}$ define short-circuit current, maximum power current, open circuit voltage, and maximum power voltage at standard test conditions (STC); herein we assume that STC is defined at $T_0$ and $E_0$ = 1000 W/m$^2$. $I_{SC}$ is determined from $E_{POA}$ after adjustment by the empirical function $f_1$ (unit-less) of absolute air mass AM (unit-less) to account for the effect of solar spectrum on short-circuit current. Effective irradiance $E_e$ (suns) is computed from $I_{sc}$ and is used to determine all other values of current and voltage. The coefficients $I_{X0}$ and $I_{XX0}$ define current at the voltage midway between 0 and $V_{MP}$, and between $V_{MP}$ and $V_{OC}$, respectively. The coefficients $\alpha_{I_{sc}}$ (1/C), $\alpha_{I_{mp}}$(1/C), $\beta_{V_{oc}}$ (V/C), and $\beta_{V_{mp}}$ (V/C) define how current and voltage change with cell temperature; the empirical coefficients $C_0$, $C_1$, $C_2$ and $C_3$, describe how maximum power current and voltage, respectively, change with effective irradiance . The thermal voltage $\delta(T_C)$ (V) is expressed in terms of the Boltzmann's constant k=1.38x10$^{-23}$ (J/K) and the elementary charge q=1.6x10$^{-19}$ (C). The term $N_s$ is the number of series-connected cells and n (unit-less) is the diode quality factor.

Coefficients and parameters for the SAPM can be readily determined using the results of the thermal and electrical tests [8]. The SAPM can describe the performance of a string of series-connected modules if appropriate string-level coefficients are determined.The Suntech STP080S-12/Bb modules consist of 36 cSi cells in series and are rated to produce 17.2 volts, 4.65 amps, and

80 Watts at STC as described in Table 1. Analysis of the individual module tests determined the coefficients $\alpha_{I_{sc}}$, $\alpha_{I_{mp}}$, $\beta_{V_{oc}}$, $\beta_{V_{mp}}$, $C_0$, $C_1$, $C_2$, and $C_3$ and parameters $I_{sc0}$, $V_{oc0}$, $I_{mp0}$, and $V_{mp0}$ for the SAPM as shown in Table 2. The statistical analysis calculated an average value for each of the coefficients and parameters.

# 3 Results

The experiment compared predicted power using the SAPM with coefficients determined by three methods ("Average Module Method", "Random Module Method", and "Average String Method") to the measured performance of the system. The coefficients and parameters used in each of the methods are described in Section 3.1. Power prediction results for each of the methods are described in Section 3.2.

## 3.1 Method Coefficients & Parameters

### Random Module Method

The coefficients and parameters for the "Random Module Method" were derived from module 2695 as shown in Table A.1.

### Average String Method

The coefficients and parameters for the "Average String Method" were derived from the string level tests (Table A.2). The results from the two tests were then averaged to create the values used to model the PV string.

### Average Module Method

The average module was defined by first extracting coefficient and parameter values from a set of actual modules. Coefficient and parameter data from each of the modules is described in Table A.1. The "Average Module Method" defined the characteristic parameter based on the average value, which is given at the bottom of Table A.1. The only exception was the $I_{SC0}$ estimate. $I_{SC0}$ was not based on an average value; instead it was estimated based on the equations described in Section 2 due to the physical nature of the system.

The parameter values estimated for the "Average Model Method" included $I_{SC0}$, $V_{SC0}$, $I_{MP0}$, and $V_{MP0}$. The average $I_{SC0}$ value at STC was calculated to be 4.86 Amps. The distribution for $I_{SC0}$ module data was slightly skewed to the right as shown in the top right graph in Figure 4. Furthermore, the modeled $I_{SC0}$ value used in the "Average Module Method" was calculated to be 4.919 Amps, which is about 1% greater than the average. The average $I_{MP0}$ was calculated to be 4.53 Amps as shown graphically with the right skewed distribution plotted in the top left graph of Figure 4. Seven of the eleven $V_{SC0}$ values recorded were greater then 21.9 Volts. Therefore, the average value was calculated to be 21.94 Volts as shown in the graph that is located on the bottom right of Figure 4. The final parameter value, max power point voltage $V_{MP0}$, had a normal distribution as shown in the bottom right graph of Figure 4. The average $V_{MP0}$ was found to be

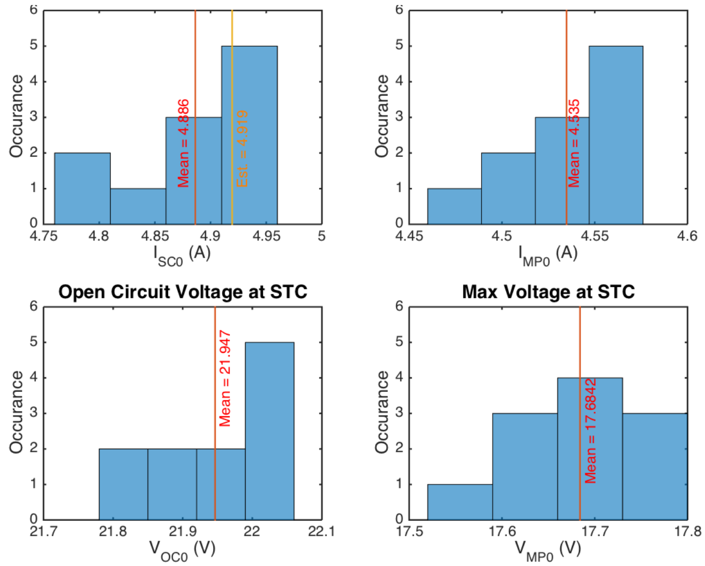


**Figure 4.** Histogram for $I_{SC0}$, $I_{MP0}$, $V_{SC0}$, and $V_{MP0}$.

17.68 Volts. The coefficients $\alpha_{I_{SC}}$, $\alpha_{I_{MP}}$, $beta_{V_{OC}}$, and $beta_{V_{MP}}$ for the characteristic module were calculated in a similar manner.

The "Average Model Method" calculated $\alpha_{I_{SC}}$, $\alpha_{I_{MP}}$, $beta_{V_{OC}}$, and $beta_{V_{MP}}$ values to be 5.73e-4, 6.98e-5, -0.069, and -0.073 respectively. These values are the average of the sample tested as shown in Table 2. The histogram for each of the coefficients are plotted in Figure 5. The $\alpha_{I_{SC}}$ values for the sample set ranged from 4.93e-4 to 6.47e-4 as shown in the top left graph of

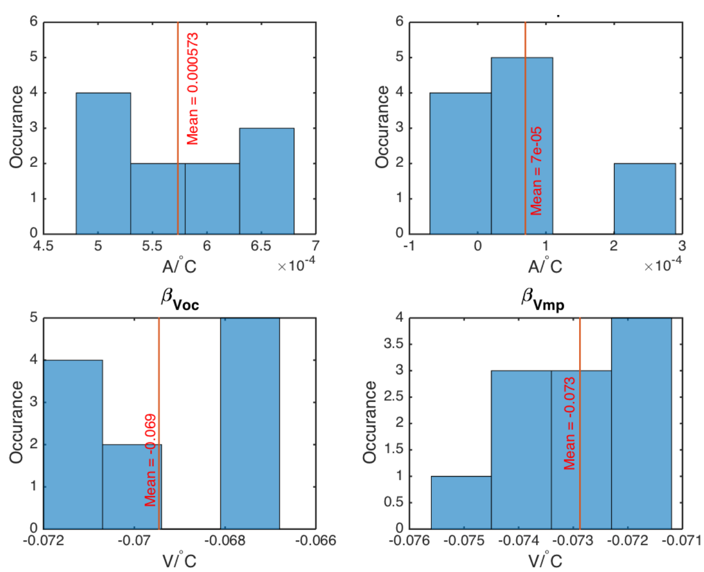


**Figure 5.** Histogram for $\alpha_{I_{SC}}$, $\alpha_{I_{MP}}$, $\beta_{V_{OC}}$, and $\beta_{V_{MP}}$.

Figure 5. The $\alpha_{I_{MP}}$ values ranged from -3.1e-5 to 2.72e-4 and have a mean value of 6.98e-5. The histogram for the voltage coefficient, $\beta_{V_{OC}}$, and $\beta_{V_{MP}}$, are plotted on the bottom of Figure 5. The voltage coefficient $\beta_{V_{OC}}$ had an average value of -0.069. The $\beta_{V_{MP}}$ coefficient had a distribution that was skewed to the right and an average value of -0.073. These coefficients helped define the

module?s dependence on temperature. The modules dependency on irradiance was captured with the coefficients $C_0$, $C_1$, $C_2$, and $C_3$.

The distribution of $C_0$, $C_1$, $C_2$, and $C_3$ coefficients extracted form the set of modules tested is shown in Figure 6. The frequency of coefficient values remains constant for $C_0$ as shown in the top left graph in Figure 6. The minimum and max values were found to be 0.96 and 0.99 respectively. The average value was calculated to be 0.98, which was very close to the median value of 0.979. The $C_1$ coefficient had a similar distribution to $C_0$ as shown in the top right graph of Figure 6. The average and median values were calculated to be 0.019 and 0.02 respectively. The $C_2$ coefficient had a left skewed distribution with an average value of -0.37. Finally, the $C_3$ coefficient histogram resembled a normal distribution with an average value equal to -18.19.

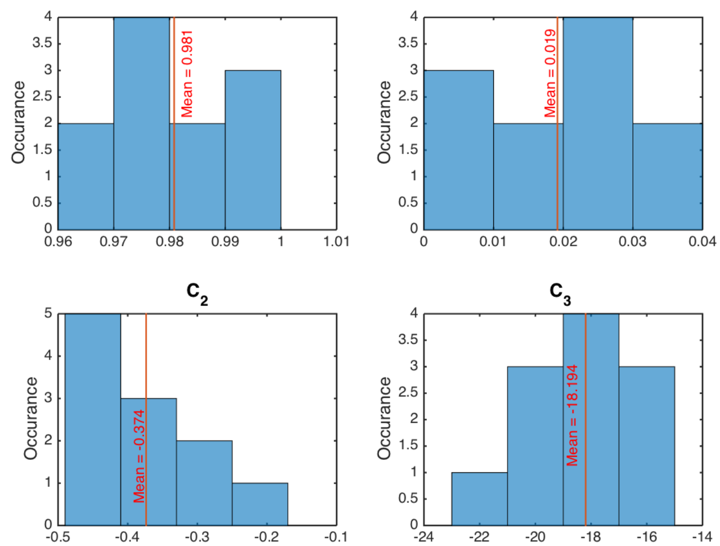


**Figure 6.** Histogram for $C_0$, $C_1$, $C_2$, and $C_3$.

The average values for the coefficients and parameters, with the exception of $I_{SC0}$, represented a characteristic module for the "Average Module Method". The coefficients and parameters calculated for this approach were used to model string performance at different operating conditions. The results were compared with the other two approaches that included "Random Module Method" and the "Average String Method".

## 3.2 String Level Model Results

The string level models used the coefficients and parameters defined by the characteristic module and applied the SAPM equations to estimate performance. The evaluation of the model's abilities first compared the coefficients from the "Average Module Method" with the "Random Module Method" and the "Average String Method". The performance results from each of the methods were compared to discover the most effective approach.

## Sandia Performance Model Coefficients & Parameters

The SAPM coefficients and parameters were slightly different for the three methods evaluated in the present work. The respective values for each method are plotted against each other in Figure 7. The parameter values, $I_{SC0}$, $I_{MP0}$, $V_{OC0}$, and $V_{MP0}$ were very similar for each method. For instance the Imp0 values did not vary by more than 2%. The temperature dependent coefficients, on the other hand, had slight variations for the different methods. For instance, the $I_{MP}$ values were calculated to be 6.98e-5, 2.72e-4, and -2.7e-5 for the "Average Module Method", "Random Module Method" and the "Average String Method" respectively. The irradiance dependent values also had variations between the three methods. $C_1$, $C_2$, and $C_3$ had different results for the three methods as shown in Figure 7. However, $C_0$ was the exception for the irradiance dependent coefficients and each method produced very similar values.

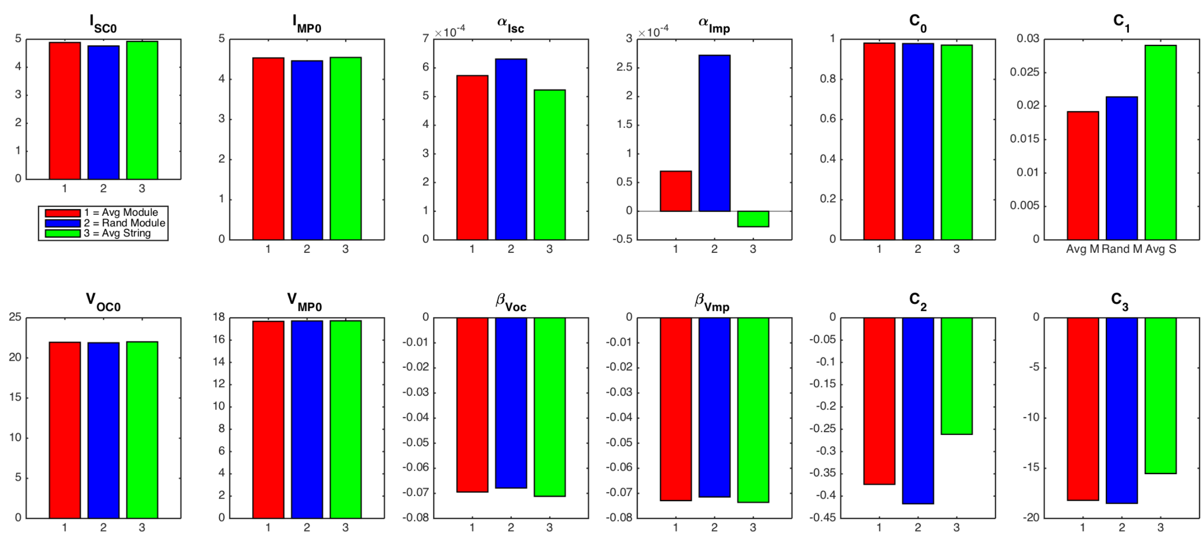


**Figure 7.** SAPM coefficients and parameters extracted from the "Average Module Method", "Random Module Method", and the "Average String Method".

The comparison of the SAPM coefficients and parameters for each of the methods indicated small differences. This suggested that the string level model results for each method would have small variations. Section 4.2.2 provides an assessment of each method versus the actual string performance to define the degree of fit. It also compared each method's residual results with each other.

## Estimated Power

The calculated coefficients and parameters provided by each of the three methods were applied to the SAPM to represent a string of five modules. The model was provided with actual weather inputs such as outside air temperature, solar irradiance, and average module temperature. The model was run for two sets of weather conditions. First, the model was subjected to weather that was experienced by String 1. The String 1 actual system contained modules 2691 to 2696. The second iteration was weather that String 2, which contained modules 2697 to 2703, was exposed to. The model results for the two iterations were compared with the actual performance from the respective string. The actual and modeled results were plotted against each other as shown in the left graph of Figures 8 and 9. Also, the percent difference between the actual and modeled was plotted with respect to actual power and is shown in the right graph of Figure 8 and 9.

The String 1 results are shown in Figure 8. The graph on the left side of Figure 8 plots the prediction for each method versus the actual results. The three methods all follow the best-fit line that has a slope of one and an intercept of 0. Additionally, the percent error results for each method were very similar and basically plot right on top of one another. There were slight differences between the three methods as indicated by the calculated mean squared error (MSE). The MSE was 8.122, 7.213, and 7.218 for the "Average Module Method", "Random Module Method", and the "Average String Method" respectively.

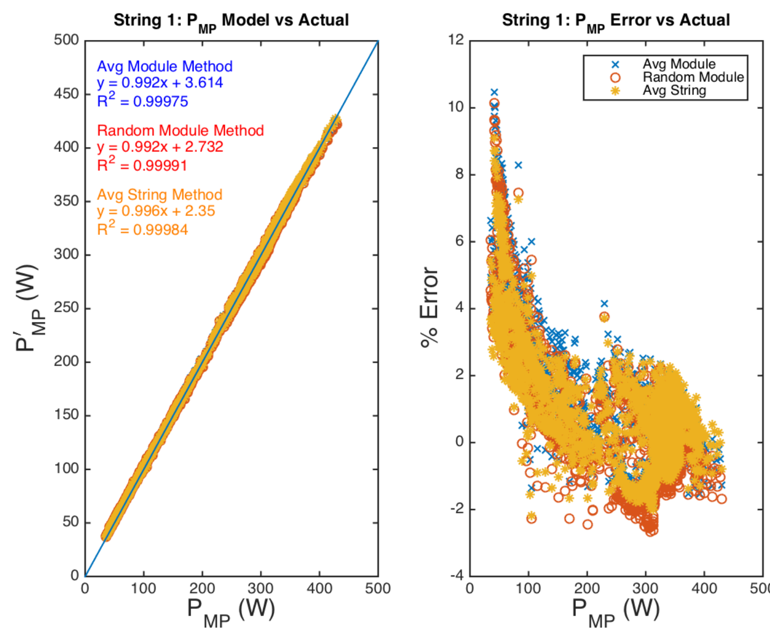


**Figure 8.** String 1 model versus actual fit and percent error results.

The results form the second model iteration was compared with String 2. Similar to String 1, the three methods performed very similar. The graph on the left side of Figure 9 shows a strong linear correlation between the model and actual performance. Each of the methods had an $R^2$ value very close to 1. Also, the percent error versus actual power for each of the methods was very close. The MSE results for each of the methods varied slightly. The "Random Module Method" had a MSE error of 10.0, followed by "Average Module Method" at 9.81, and then the "Average String Module Method" with a MSE of 8.211.

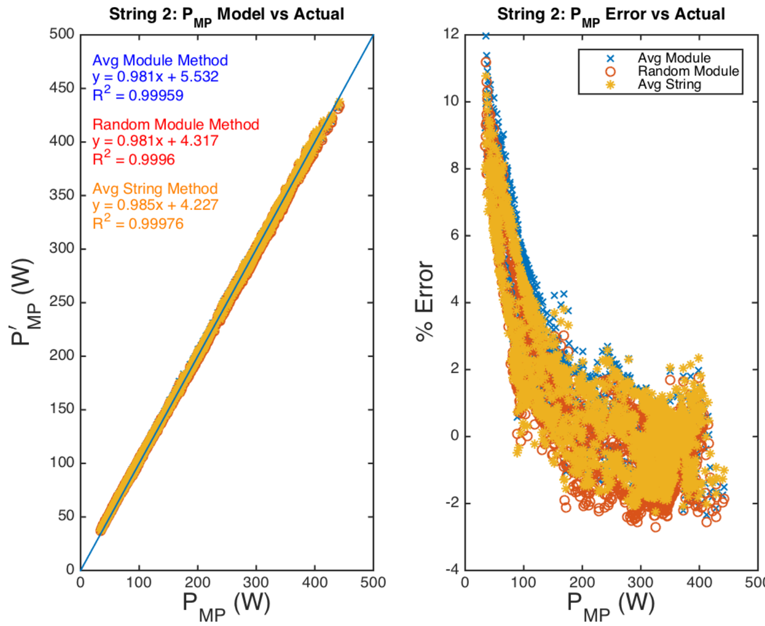


**Figure 9.** String 2 model versus actual fit and percent error results.

The two model iterations that compared results with String 1 and 2 indicated that the three methods provided very similar results. The overall model fit, as described by the linear correlation between the actual and modeled results are very good. For instance the slopes of the linear fit line were all above 0.98 as shown in Table 1 for the String 1 and 2 results, which was very close to the optimal value of 1.0. Additionally, the intercepts for the two model iterations for each of the methods were close to zero with a minimal value of 2.35 and a max of 5.53. The results from each of the methods were very close, but the “Average String Method” had the best overall slope, intercept, $R^2$, and MSE for each of the string level model iterations.

**Table 1.** Modeled versus actual power prediction results for each method used in the present work.

| Method | Slope | Intercept | R2 | MSE |
|---|---|---|---|---|
| **String 1** | | | | |
| Average Module | 0.992 | 3.614 | 0.99975 | 8.122 |
| Random Module | 0.992 | 2.732 | 0.99991 | 7.213 |
| Average String | 0.996 | 2.350 | 0.99984 | 7.218 |
| **String 2** | | | | |
| Average Module | 0.981 | 5.532 | 0.99959 | 9.815 |
| Random Module | 0.981 | 4.317 | 0.9996 | 10.00 |
| Average string | 0.985 | 4.227 | 0.99976 | 8.211 |

# 4 Conclusion

The present work evaluated the potential benefit of testing multiple modules to generate SAPM coefficients and parameters. The experiment performed a statistical evaluation of eleven modules with the intent to define a characteristic module. The characteristic module, which theoretically would provide an optimal representation of the module type, could then be used to model string level performance. The model could then take into account string level degradation due to module mismatch system behavior. This approach, defined as the "Average Module Method", was implemented on a set of Suntech STP080S-12/Bb modules. The results produced by the "Average Module Method" were compared with two other approaches. The first approach was the "Random Module Method" that represented current testing techniques at PSEL. The third approach was named the "Average String Method" used the thermal tests from a string of five modules to develop the SAPM characteristic coefficients and parameters. Each of the methods was subjected to actual weather data and was compared with the actual system.

The three methods performed very similarly. Each of them was able to represent system behavior very well and produce an $R^2$ value very close to 1.0. There were slight variations in the linear correlation tests but all of their slopes were close to 1.0 and their intercepts were less 5.5. The method with the best results was the "Average String Method" that had the best overall slope, intercept, $R^2$, and MSE for each of the model iterations. The next best approach was the "Average Module Method" followed by the "Random Module Method". However, the variations between the methods was very small and may not be justify extra effort to perform an increased number of electrical and thermal tests to derive the SAPM coefficients and parameters.

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# A Module test results

**Table A.1.** Module thermal & electrical test results

| **ID** | $\mathbf{I}_{sc0}$ | $\mathbf{V}_{oc0}$ | $\mathbf{I}_{mp0}$ | $\mathbf{V}_{mp0}$ | $\alpha_{I_{Isc}}$ $(\mathbf{10}^{-4})$ | $\alpha_{I_{Imp}}$ $(\mathbf{10}^{-5})$ | $\beta_{V_{oc}}$ | $\beta_{V_{mp}}$ | $\mathbf{C}_0$ | $\mathbf{C}_1$ | $\mathbf{C}_2$ | $\mathbf{C}_3$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2692 | 4.94 | 22.05 | 4.57 | 17.74 | 5.76 | 9.3 | -0.067 | -0.071 | 0.97 | 0.03 | -0.47 | -22.21 |
| 2693 | 4.85 | 22.00 | 4.49 | 17.78 | 6.17 | 26.6 | -0.068 | -0.073 | 0.96 | 0.04 | -0.18 | -16.00 |
| 2694 | 4.76 | 21.88 | 4.46 | 17.72 | 6.31 | 27.2 | -0.068 | -0.071 | 0.99 | 0.02 | -0.41 | -18.49 |
| 2695 | 4.79 | 21.84 | 4.51 | 17.64 | 6.47 | 6.3 | -0.0676 | -0.071 | 0.99 | 0.003 | -0.42 | -17.4 |
| 2696 | 4.87 | 21.99 | 4.53 | 17.77 | 6.47 | 6.3 | -0.0676 | -0.071 | 0.98 | 0.02 | -0.39 | -20.56 |
| 2697 | 4.89 | 21.91 | 4.55 | 17.65 | 5.52 | -3.10 | -0.0716 | -0.075 | 0.99 | 0.009 | -0.45 | -19.34 |
| 2698 | 4.95 | 21.94 | 4.56 | 17.63 | 4.93 | 4.10 | -0.070 | -0.073 | 0.97 | 0.028 | -0.37 | -18.29 |
| 2700 | 4.91 | 21.95 | 4.54 | 17.66 | 5.16 | -0.70 | -0.0715 | -0.074 | 0.98 | 0.014 | -0.34 | -17.87 |
| 2701 | 4.89 | 21.81 | 4.53 | 17.53 | 5.19 | 2.90 | -0.070 | -0.073 | 0.99 | 0.008 | -0.32 | -15.25 |
| 2702 | 4.92 | 22.0 | 4.55 | 17.66 | 5.85 | 0.60 | -0.072 | -0.074 | 0.97 | 0.024 | -0.41 | -19.50 |
| 2703 | 4.92 | 21.99 | 4.55 | 17.69 | 5.23 | -2.70 | -0.0712 | -0.074 | 0.98 | 0.014 | -0.31 | -15.18 |
| Avg | 4.88 | 21.94 | 4.53 | 17.68 | 5.73 | 6.98 | -0.069 | -0.073 | 0.98 | 0.019 | -0.37 | -18.19 |

**Table A.2.** String thermal & electrical test results

| **ID** | $\mathbf{I}_{sc0}$ | $\mathbf{V}_{oc0}$ | $\mathbf{I}_{mp0}$ | $\mathbf{V}_{mp0}$ | $\alpha_{I_{Isc}}$ $(\mathbf{10}^{-4})$ | $\alpha_{I_{Imp}}$ $(\mathbf{10}^{-5})$ | $\beta_{V_{oc}}$ | $\beta_{V_{mp}}$ | $\mathbf{C}_0$ | $\mathbf{C}_1$ | $\mathbf{C}_2$ | $\mathbf{C}_3$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| String 1 | 4.92 | 109.84 | 4.54 | 88.53 | 5.23 | -2.7 | -0.35 | -0.37 | 0.97 | 0.03 | -0.34 | -17.1 |
| String 2 | 4.92 | 110.2 | 4.55 | 88.75 | 5.23 | -2.7 | -0.36 | -0.37 | 0.96 | 0.03 | -0.18 | -13.9 |
| Avg | 4.92 | 110.0 | 4.5 | 88.64 | 5.23 | -2.7 | -0.36 | -0.37 | 0.96 | 0.03 | -0.26 | -15.5 |

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