A Semi-Empirical Model of PV Modules Including Manufacturing I-V Mismatch

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***Abstract*—This paper presents an analysis of the impact of manufacturing variability in PV modules when interconnected into a large PV panel. The key enabling technology is a compact semi-empirical model, that is built solely from information derived from datasheets, without requiring extraction of electrical parameters or measurements. The model explicits the dependency of output power on those quantities that are heavily affected by variability, like short circuit current and open circuit voltage. In this way, variability can be included with Monte Carlo techniques and tuned to the desired distributions and tolerance. In the experimental results, we prove the effectiveness of the model in the analysis of the optimal interconnection of PV modules, with the goal of reducing the impact of variability.**

I. Introduction

As for any electrical device, photo-voltaic (PV) cells are subject to the variability of the manufacturing process, which results in mismatches of electrical parameters among different devices. Such mismatches are usually disregarded because considered marginal; however, the widened landscape of PV panel manufacturers has increased competition due to reduced margins. As a sample figure, there has been an 80% decline in worldwide solar prices between 2008 and 2013, occurred largely due to improvements in manufacturing costs in China [1]. Competition in a market in large expansion has the unavoidable consequence of an increase of the *quality range* of the products; while quality of PV modules is usually measured in terms of electrical failures, thermal cycling, mechanical load, resistance to atmospheric events (e.g., hail) [1], [2], the variability of the basic electrical parameter of a PV module is seldom given as a figure of merit, although it can significantly impact the total power output of a PV panel assembled by interconnecting mismatched modules.

Several researchers have addressed the problem by proposing different models that incorporate variability in various ways. Most models refer to an individual cell, and focus on the variability of the electrical properties (a non-ideal diode with resistances), in analogy with the statistical variability analysis done for generic semiconductor devices [3].

More practical approaches consider the variability of a PV module (usually the series interconnection of 36–72 PV cells), which is the building block of a PV panel, and whose electrical properties can be easily measured even from a user. These works demonstrate and quantify experimentally or analytically the intuitive conclusion that "sorting" modules based on their electrical characteristics (usually, measured output power in standard conditions) and connecting them in series according the resulting order provides best results [4], [5].

However, these methods generally have at least one of two drawbacks. Firstly, many solutions build a model based on a *circuit-equivalent representation of the PV module*, which is the physical representation *of a cell, not of a module*; therefore the linear scaling of the circuit parameter from a cell to a module ignores possible shading of a cell or the presence of bypass diodes within the module [4], [6]. A second drawback is related to methods based on measurements: while results are more reliable, they are tied to a specific type of module and do not help to do comparative analysis (if not at the cost of an intensive measurement campaign) [7], [8].

In this work, we try to address these two limitations by providing a model for a PV module and by extension for a PV panel that (i) is based only on publicly available data and does not require any measurement for its derivation, and (ii) adds variability as a random variation on the basic electrical parameters of the module rather than on the output power or on the parameters of the circuit-equivalent model. Our simulations show that the model allows to estimate the impact of manufacturing variability in large PV panels, and to take into account PV module arrangement on power production.

II. Background

A. Background on PV modules

A photovoltaic (PV) cell is basically a semiconductor diode whose $p-n$ junction is exposed to light [9]: the incidence of light generates charge carriers that originate electric current.

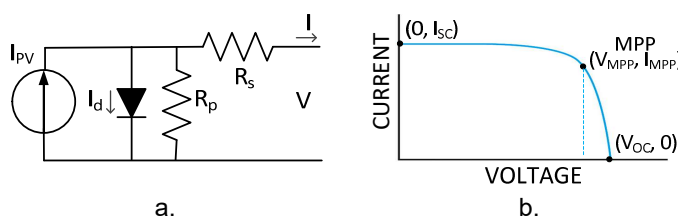

Figure 1. Circuit model of a PV cell (a), and characteristic I-V curve (b).

Given the complexity of the physics of PV cells, it is common to think in terms of its electric equivalent, as in the circuit in Figure 1.a: an equivalent current source I_{PV} induced by the light, shunted with a diode and resistor R_p and cascaded with a series resistor R_s [10]. The basic equation is:

$$I = I_{PV} - I_0\Big[exp\Big(\frac{qV}{akT}\Big) - 1\Big] \quad (1)$$

where I_{PV} is the current generated by the incident light, V and I represent the output voltage and current of the solar

cell, respectively, I_0 is the reverse saturation current of diode, q is the electron charge, and a is a dimensionless constant that depends on technology. The resulting I-V curve (in Figure 1.b) is characterized by its short circuit current I_{SC} (the current at which the voltage is 0), its open-circuit voltage V_{OC} (the voltage at which the current is 0), and the maximum extracted power (Maximum Power Point MPP) (V_{MPP}, I_{MPP}).

PV cells are then interconnected according to a series/parallel organization into a *PV module*, in order to increase the output power. PV modules can be further interconnected together to form a PV panel, again in series or in parallel, to achieve the desired voltage and current levels. In general, the power production of connected PV cells and modules is not simply the sum of the single power productions: the cell or module that, because of different irradiance or variability, has lower voltage or current constraints the power output of the other ones [11]. To reduce this impact, *bypass diodes* may be placed across groups of series-connected cells (usually within a PV modules) for bypassing these weaker cells.

The main limitation of Equation 1 is that manufacturers never provide the values to populate it: they rather disclose a few I-V curves, and derating factors describing the dependence of power production on irradiance and temperature. Using these limited information, it is unfeasible to reconstruct the I-V function of Equation 1. Additionally, Equation 1 does not make explicit the dependence of the I-V curve from I_{SC} and V_{OC} (i.e., the easily measurable quantities).

B. Manufacturing variability for PV modules

Manufacturing variability is caused by the complexity of the manufacturing process, e.g., by the presence of impurities in the silicon material or approximation in the control of process parameters. Efficient quality assurance can identify slight defects, thus allowing to reduce tolerance at the Maximum Power Point (MPP) [6]. However, even small variations of the characteristics of the I-V curve can affect power production, and manufacturing tolerance is still high, in the order of $\pm 5\%$ up to $\pm 10\%$ for rated power [4], [6].

To minimize the impact of manufacturing variability, it is necessary to reduce as much as possible the bottleneck effects caused on the MPP of PV panels by those PV modules that are more affected by variability. To face this issue, parameters of the I-V curve (like I_{SC} and V_{OC}) are used to sort the PV modules and to determine their arrangement. In [5], the operating conditions at the MPP are used to analyse both parallel and series power losses given uniform irradiance. [4] compares the impact of using the operating conditions at the MPP to sort PV modules: the outcome of the analysis is that sorting by current is the most effective solution. [7] compares a I_{MPP}-based sorting with a random sort of the PV modules, with the former solution being the optimal one.

III. Model of a PV Module

The proposed model of PV modules is a semi-empirical one, built based on information extracted solely from datasheets (as the ones in Figure 2 for the Mitsubishi PV-MF165EB3 module) to derive an equation that yields module voltage and current as a function of irradiance G and temperature T.

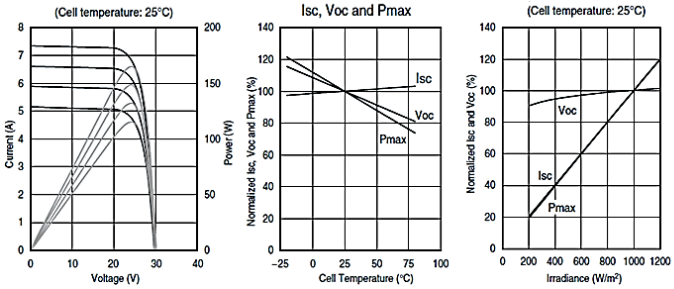

Figure 2. Datasheet graphs for Mitsubishi's PV-MF165EB3 PV module [12].

The equation explicits V_{OC} and I_{SC}, so that it is possible to simulate the impact of manufacturing variations.

A. Estimation of V_{OC} and I_{SC}

The value of V_{OC} and I_{SC} is strongly affected by irradiance G and temperature T, as evident from the sensitivity coefficients provided in datasheets (Figure 2).

To make this dependency explicit, cell temperature T_c is first derived from ambient temperature T by using the relations in [13], which correlate with G and with characteristic coefficients of the PV module, such as its temperature coefficient. Then, the curves in the center and right plot of Figure 2 are empirically fitted to the templates of Equations 2 and 3:

$$V_{OC}(G, T_c) = V_{OC,nom}(c_1 T_c + c_2) \cdot (c_3 G^{c_4} + c_5) \quad (2)$$

$$I_{SC}(G, T_c) = \alpha \cdot \ I_{SC,nom}(c_6 T_c + c_7) \cdot (c_8 G - c_9) \quad (3)$$

where $V_{OC,nom}$ and $I_{SC,nom}$ are the *nominal* V_{OC} and I_{SC}, c_i are coefficients obtained through curve fitting, α is an PV module aging factor (assumed to be 0.4%/year [14]).

B. Injecting Manufacturing Variability

Manufacturing variability may affect any or all of the characteristic values of I_{SC}, V_{OC}, and consequently the MPP operating conditions. Sources of variability on each quantity are statistically independent and random [15]. Therefore, it is reasonable to model manufacturing variations as *independent random variables with a normal distribution* [6], [8].

To emulate variability, we use Monte Carlo simulations to generate the values of $I_{SC,mv}$ and $V_{OC,mv}$ according to a normal distribution: the mean value is the value of I_{SC} or V_{OC} calculated using Equations 2 and 3, and the variance is expressed as standard deviation determined by manufacturing tolerance (σ_{Isc} and σ_{Voc}, respectively):

$$I_{SC,mv} = \sigma_{Isc} \cdot r + I_{SC}(G, t) \quad (4)$$

$$V_{OC,mv} = \sigma_{Voc} \cdot r' + V_{OC}(G, T) \quad (5)$$

where r, r' are the randomly generated variability factors.

C. I-V Curve Model of a PV module

The last step is to derive a function describing the I-V curve for different values of G and T. We use an equation template that matches the diode equation, but replacing I_{SC} and V_{OC} with their randomized versions:

$$I = I_{SC,mv} - a \cdot (e^{b \cdot \ V} - 1) \quad (6)$$

where a is obtained through curve fitting as explained in [16] and b is derived by imposing that $I(V_{OC}) = 0$:

$$b = V_{OC,mv}^{-1} \cdot ln(1 + I_{SC,mv} \cdot \ a^{-1}) \tag{7}$$

D. Connecting PV modules

The expression of total power depends on the internal structure of a module. PV modules generally contain one or more *bypass diodes* that are used to "break" the long series strings into shorter sub-strings to decrease the cost of shaded portions of a module [11]. Our analysis considers the effect of cell (and module) mismatches at a given, uniform irradiance condition; therefore, partial shading is not considered. Since the magnitude of the mismatches is less than $\pm 10\%$, such difference would not be sufficient to trigger the activation of the bypass diodes, which would require a significant difference of current and voltage of a cell to activate the bypass. For this reason, the presence of diodes in our analysis is immaterial, and the following expressions do not consider the diode bypass effect. Under these assumptions, the weakest (i.e., with the least current) PV module acts as a bottleneck on current in case of series connection, and on voltage in case of parallel connection. The total power of the PV panel is thus obtained as $P_{panel} = V_{panel} \cdot I_{panel}$, where:

$$\begin{cases} V_{panel} & = & \min_{j=1,\ldots,p}(\sum_{i=1,\ldots,s} V_{ij}) \\ I_{panel} & = & \sum_{j=1,\ldots,p}(\min_{i=1,\ldots,s} I_{ij}) \end{cases}$$

and V_{ij} and I_{ij} are voltage and current of the i-th PV module of the j-th string [17], [18].

IV. Experimental Results

This section demonstrates the effectiveness of the proposed model in the context of the design of large PV panels, by assessing the impact of variability on the operating conditions on single PV modules and on their interconnection, and by quantifying the impact of sorting the PV modules based on the characteristic points of the I-V curves.

A. Simulation setup

We implemented the model in Matlab R2019a and characterized it for two different PV modules:

- the PV-MF165EB3 PV module by Mitsubishi, a polycrystalline silicon module with rated power of 165W [12];
- a polycrystalline PV module by Centsys with rated power of 250W [19].

To represent manufacturing I-V mismatch, we randomly generated nominal I_{SC} and V_{OC} that follow a normal distribution with variance $\pm 8\%$ and $\pm 4\%$, respectively.

B. Exhaustive Exploration for a Small PV Panel

As a first experiment, we considered a small 3×2[1] PV panel, to quantify the impact of different interconnections of its PV modules in the presence of mismatches. In order to focus on manufacturing I-V mismatch, we assumed all the PV modules are subject to the same solar irradiance ($G = 1000W/m^2$), and same ambient temperature ($T = 25°C$), and we focused only on Mitsubishi PV modules.

[1]A $s \times p$ PV panel is organized in p parallel strings of s PV modules.

To ensure consistency, we run the experiment twice on different random variability factors. We generated all the $6! = 720$ possible interconnections of modules and analyzed the distribution of the generated power: Figure 3 shows the histogram of total power generation for the different arrangements of PV modules for the two experiment runs. The two histograms show that the proposed model allows to appreciate the impact of variability on output power production, given the same G and T for all PV modules. Additionally, note that the ranges of power values are different for the two simulations, as an effect of different variability factors.

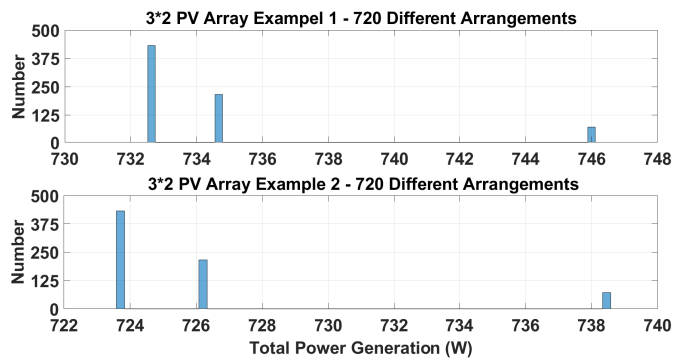

Figure 3. Power generation from all different arrangements of 3×2 PV panel.

The most interesting results provided by these histograms is their distribution. The distribution and the difference between the best and worst case do not differ much between the two simulation runs (13.4W and 14.8W respectively). In both cases, the probability of worst case (leftmost bar) is significantly higher than the best case: 432 configurations out of 720 (60%) yield the lowest value of total power, whereas only 72 (10%) configurations yielding the largest power value. Moreover, the remaining 216 (30%) in the middle bar are much closer to the worst case than to the best one. This means that it is highly probable that a "random" arrangement that does not use information about the variability mismatches will fall close to the worst case.

C. Comparison of Sorting Strategies on Large PV Panels

As a second analysis, we evaluated two PV panels with realistic sizes, 50×4 and 25×8 respectively, to assess the distance of a "random" assignment from the optimal one.
An exhaustive exploration of all possible configurations is not feasible, so we randomly generated 500 different arrangements and compared them with the optimal solution adopted in literature, i.e., based on sorting PV modules by I_{SC} [4]. Figure 4 shows the histograms of the power generated by the 500 random arrangements plus the optimal one for both the Mitsubishi (top) and Centsys (bottom) PV modules and for both panel topologies. Even if 500 is a small subset, the randomly generated configurations tend to be clustered around the lower end of the distribution, and relatively far from the optimal value. Notice that for such large panel sizes the absolute difference becomes sizable (1 to 2 KW depending on the type of module), and that this result holds for both PV

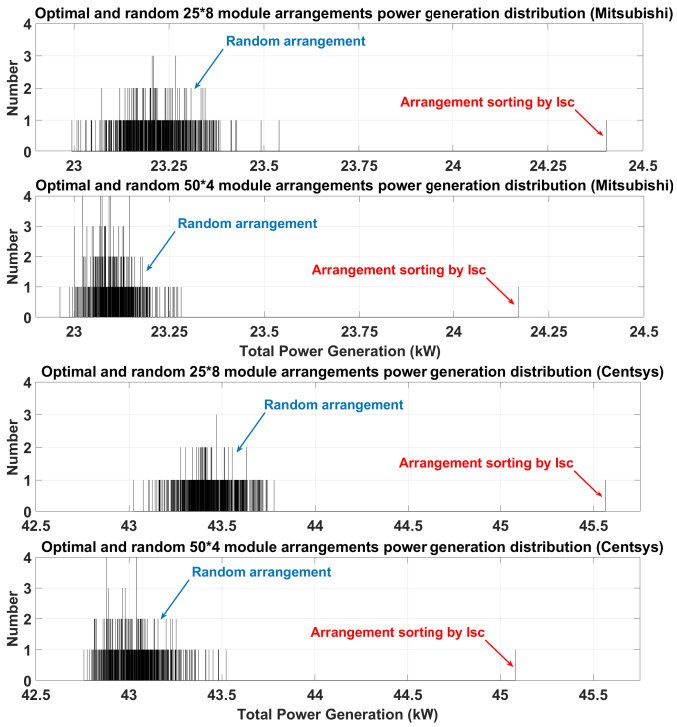

Figure 4. Power generation difference between best and random arrangements of 50×4 and 25×8 PV panel.

modules: the difference only gets amplified for the Centsys modules, that generate more power.

D. Impact of Variable Irradiance

In order to assess the impact of different irradiance conditions with mismatches, we ran a one-year long simulation for the two above panels. Irradiance and temperature traces were taken from the NREL datasets [20] and refer to recorded values at the University of Arizona.

Table I
YEARLY ENERGY GENERATION: RANDOM VS. BEST TOPOLOGIES (SORTED BY I_{SC}).

PV Module	Panel Config.	Random			Optimal [kWh]
		Max [Kwh]	Min [Kwh]	Avg [Kwh]	
Mitsubishi	25×8	62,155	61,471	61,896	64,569
	50×4	61,765	61,283	61,539	63,987
Censys	25×8	123,547	121,903	122,885	128,941
	50×4	123,777	123,021	123,532	128,496

As in the previous experiment, we generated 100 random interconnections of modules by using a given set of PV modules, and compared the results of these 100 random runs with the optimal arrangement (i.e., sorted by I_{SC}). Table I illustrates the distribution of total energy generation over the year (min, max, and average over the 100 instances). Results are consistent with those shown in Figure 4; even if in periods of lower irradiance the variability in the modules translates into smaller power penalties, the accumulated difference between the best "random" arrangement and the one sorted by I_{SC} is in excess of 2 kWh and 5 kWh for the the two types of modules, respectively.

V. CONCLUSIONS

This paper proposed a model for PV modules that takes into account manufacturing variability and that is built solely from available datasheets, thus being applicable to any PV module and not requiring extraction of electrical parameters or measurements. Our simulations show that the model effectively includes variability: it allows to make statistical evaluations of the impact of the resulting mismatch on power production, and to evaluate the effectiveness of the sorting strategies adopted in the literature. Future work will focus on the inclusion of more refined statistical distributions for the modeling of variability.

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