NUMERICAL APPROACH TO UNCERTAINTY AND SENSITIVITY ANALYSIS IN FORECASTING THE MANUFACTURING COST AND PERFORMANCE OF PV MODULES

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ABSTRACT: Forecasting of the manufacturing cost of PV modules is governed by a large number of uncertain factors. Cost estimates are frequently based upon imperfect information and, as a result, may not be perfectly accurate. Existing studies of these uncertainties focus on the sensitivity of the manufacturing cost to individual cost inputs, examining the effects of each input in isolation. Such methods of analysis neglect statistical correlations between inputs, provide no measure of the uncertainty in the projected manufacturing cost, and do not permit the assignment of probability distributions to the inputs in the case that one range of values is thought to be more likely than another. This work describes the development of a stochastic modeling framework that addresses these deficiencies. Furthermore, it demonstrates how sensitivity to particular inputs may be ranked in order to help determine the most effective path to cost reduction. The result is a method with great potential for exploring the link between engineering design, PV module cost, and the manufacturing process.
Keywords: Cost reduction, economic analysis, modeling.

1 INTRODUCTION

The manufacturing cost of a PV module is determined by a large number of factors, collectively representing the cumulative total of materials, labor, capital, and financing costs attributable to the module. Predicting the manufacturing cost of a module requires accurate estimation of both the costs and quantities required of each of these components. However, estimates are often based on imperfect information and, as a result, may not be perfectly accurate. The sensitivity of manufacturing cost with respect to uncertainty has been studied previously [1–4]. However, in these studies the sensitivity to errors in each input was examined in isolation. That is, a single parameter would be varied while all others were held constant, and sensitivity to that parameter would be inferred from the associated change in cost.

The above methods of cost analysis have three major shortcomings. First, they neglect statistical correlations in the input parameters. For example, the well known correlation between bulk resistivity and bulk lifetime leads to a higher optimum value of resistivity than is be predicted by considering resistivity and lifetime independently.

Second, it provides no measure of uncertainty in the estimated manufacturing cost, nor does it strongly bound its estimate. Third, it does not permit the assignment of probability distributions to the inputs, which one might do to emphasize a subrange of values as being more likely than other possible values. Associating uncertain inputs with statistical distributions offers modeling flexibility, the convenience of assigning probability metrics to forecasts, and confidence ranges to bound the forecasts.

This work describes the development of a stochastic modeling framework that addresses these deficiencies. Using well-established Monte Carlo methods, it assesses uncertainty in manufacturing cost projections and performs sensitivity analysis to determine which factors have the greatest influence on PV module cost. The advantages of this method are:

- Monte Carlo models can incorporate information about known statistical correlations in the inputs, which can skew the final result. Such distortions in the output were not visible in earlier studies.
- Sensitivity to particular inputs can be easily ranked to determine the most effective means to cost reduction.
- Synergistic influences caused by interactions between input variables can be discovered using statistical methods for discovering such interactions.

It accomplishes this by directly linking PV cell and module design to manufacturing cost. Solar cell design changes propagate through the model to yield estimates of the impact on both cost and performance.

Preliminary testing of this framework indicates that it shows promise as a tool for uncertainty and sensitivity analysis, as well as estimating changes in electrical and economic performance resulting from design modifications. The detailed linkage of economics to engineering suggests that the proposed framework may eventually be useful as an optimization tool.

2 DEVELOPMENT OF THE FRAMEWORK

2.1 Overview

The basis for the framework described in this work is a pair of deterministic models manipulated so as to produce stochastic outputs in response to uncertainties in their inputs. The outputs of these models are linked to produce a probabilistic estimate of PV module manufacturing cost and an assessment of the factors to which it is most sensitive. One of the models is related to solar cell design and produces a distribution of performance indicators as a result of uncertainties in design parameters (e.g., cell thickness, base resistivity, or bulk lifetime). The other model is economic, producing a distribution of PV module manufacturing cost as a result of uncertainties in the costs of fabrication materials. While changes in solar cell design may lead to changes in the fabrication process, these two models are otherwise independent.

Following Monte Carlo simulation using the two deterministic models, one is left with distributions of solar cell performance and manufacturing cost. In order to estimate manufacturing cost per peak watt, the solar cell performance data must first be transformed into a distribution of module power outputs and combined with manufacturing cost data. In this manner, the framework establishes a link between module cost and design parameters. By analyzing the manufacturing process in this way, it is hoped that PV manufacturers may better be able to target research efforts to more rapidly reduce the cost of PV modules.

2.2 Electrical performance modeling

PV module performance for a given solar cell design is estimated by modeling a module as a network of interconnected non-ideal (i.e., electrically mismatched) solar cells. Solar cell performance is modeled using the commercially available PV device simulator PC1D [5] in conjunction with Monte Carlo methods to produce a probability density function (pdf) representing the variability in solar cell performance that is typical of commercial devices. This quantifies the impact of the manufacturing sequence on the solar cell design, a method that could be useful in optimizing commercial solar cell designs and production processes.

Module power output is estimated by sampling the pdf of solar cell efficiency and summing the power outputs of the cells in the sample, neglecting mismatch losses. In the next section, these module power output estimates are used to determine the expected value and uncertainty of the module cost per peak watt.

2.3 Module cost estimation

PV module manufacturing cost is estimated using PVCost, a prototype model under development by the authors. It models each step of the manufacturing process independently. Each step takes a quantity of objects, such as silicon bricks, as inputs and produces a quantity of output objects, such as silicon wafers, and a list of resources required to complete the step. By daisy-chaining these models together, one can model an entire production facility. This step-by-step independence gives the user great flexibility in configuring the production line model, which can be useful when comparing different fabrication processes or modifying an existing process.

PVCost models the costs incurred during module production as levelized cash flows over the lifetime of the production line. The estimated module manufacturing cost is the annual levelized cash flow divided by annual module production.

Any or all of the inputs to PVCost may be modeled as stochastic variables in order to represent the uncertainty inherent in forecasting material or equipment prices. PVCost translates this information into an estimate of the uncertainty in the module cost prediction and uses the statistical relationship between the input and output data to gauge the sensitivity of the output to a given input. This technique is particularly useful in the presence of correlated input variables, which can significantly alter sensitivity relationships from those observed when considering only a single variable at a time.

As with the electrical performance modeling, module cost is modeled as a pdf representing both the expected value for the module cost and the uncertainty in the cost estimate. With discrete values for the outputs, finding the module cost per unit per peak watt is as simple as dividing the manufacturing cost of the module by its peak power output. However, in this case the manufacturing cost and solar cell efficiency are each represented as pdfs. As a result, the module cost per peak watt will also be a pdf. To generate it, PVCost samples a value from the module manufacturing cost pdf and divides it by the module power estimated in the previous section. It repeats this process until enough values have been sampled to generate an approximate pdf for the module cost per watt. Finally, the expected value, uncertainty, and sensitivity for the module cost per watt are computed.

Table I: Differences between base and thin cell designs.

	Base	Thin
Thickness	300 μm	200 μm
Back contact	Ohmic	Passivated reflector
Contact firing	Co-fired	Two-step
Nominal efficiency	14.2%	16.2%

3 EXPERIMENTAL METHOD

3.1 Module design and simulation

In order to illustrate the advantages of this modeling framework, two different module designs were simulated. Each design incorporates 36 screen-printed multicrystalline silicon solar cells with dimensions 125 × 125 mm square. Both designs were assumed to have standard commercial solar cell fabrication processes with silicon nitride antireflection coatings. The two designs differed only in substrate thickness and rear contact technology; these differences are summarized in Table I.

In order to accommodate the screen-printed back reflector in the thin design, the fabrication process was altered slightly from that of the base case. Following antireflection coating deposition, the wafers undergo an additional silicon nitride deposition step on their rear sides. Application of the back side reflector involves an additional screen printing step as well as an additional firing step. These additional steps and the equipment they require are accounted for in PVCost.

3.2 Selection of input variables

Between the device model and the cost model there are an enormous number of input variables. To investigate all of them simultaneously would require an excessive amount of computational effort. In order to minimize the number of stochastic inputs, only those with the most significant impacts on the outputs were selected. The remaining inputs were fixed at some nominal value. Space constraints prohibit a complete listing of all of the inputs and their nominal values.

The inputs to be treated as random variables were selected by varying each input individually ±10% from their nominal values. The variables were then ranked in order of magnitude of the change these variations induced in the output. The results for the device model appear in Figure 1. From this, the most influential variables were selected for Monte Carlo modeling. In addition, any

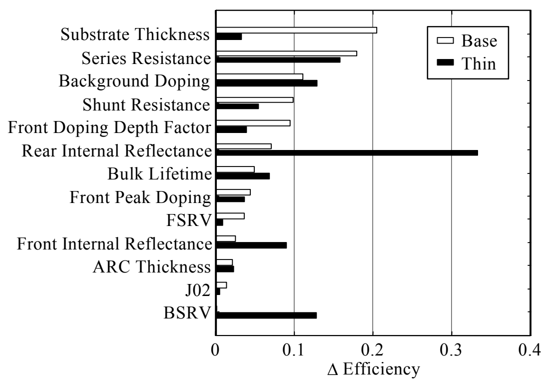

Figure 1: Single-factor sensitivity analysis for two solar cell designs.

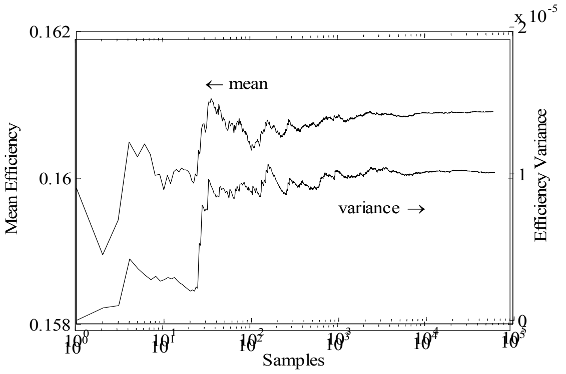

Figure 2: Convergence of mean and variance of solar cell efficiency for Monte Carlo simulation with PC1D.

inputs that influential variables might be correlated with were selected. The complete list of inputs treated stochastically is shown in Table II.

It must be noted that a more thorough statistical study of the input variables is needed before this framework can generate results with potential for practical application. The values used to complete the examples in this work are assumptions with no empirical backing, and the case studies that follow are intended only to illustrate a promising approach to PV cost analysis and forecasting.

3.3 Probability distributions of random variables

The results of Monte Carlo simulation can be highly dependent upon the probability distributions assumed for the stochastic inputs. The closer the assumed distribution is to the real distribution, the greater the predictive value of the output. By the same token, if the distribution is unknown the modeler must be wary of making too many assumptions about it. Frequently, the only available data are expert opinions indicating a range of values or a "likely" value. In the case of the former, it is prudent to use a uniform distribution to model the range; in the latter, a triangular distribution with its peak at the likely value is appropriate. If uncertainties in a value are thought to be a result of random processes, a normal distribution (or a similar, but bounded, distribution such as the beta or Weibull) may be appropriate [6].

Table II: Stochastic input variables and their ranges. Unless noted, all variables uniformly distributed. A "—" indicates the value was held constant for that simulation.

	Base	Thin
Thickness (μm)[1]	250.5–349.5	—
R_{series} (Ω-cm^2)	0.99–1.21	0.72–0.88
R_{shunt} (Ω-cm^2)	100–900	—
Resistivity (Ω-cm)	0.5–2.0	0.5–2.0
Lifetime (μs)	20–60	30–90
Emitter depth factor	0.0928–0.1134	—
BSRV (cm/s)	—	100–3000
Front internal ref.	—	69.3–84.7%
Rear internal ref.	58.5–71.5%	81–99%
Si feedstock (\$/kg)[2]	15–30	
Silicon carbide (\$/kg)	4.05–4.95	
Glycol (\$/L)	3.24–3.96	
Aluminum paste (\$/g)	0.072–0.088	
EVA (\$/module)	7.35–8.99	
Tedlar (\$/module)	4.50–5.50	
Glass (\$/module)	6.84–8.36	
Frame (\$/module)	6.03–7.37	
Junction box (\$/module)	4.50–5.50	

[1] Normally distributed with mean 300 and standard deviation 15, limited to a range of 3.3 standard deviations from the mean.
[2] Triangularly distributed between 15 and 30, peaking at 25.

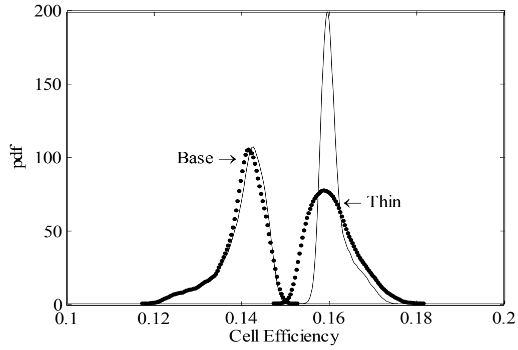

Figure 3: Calculated probability density functions for solar cell efficiency. Solid curves calculated using correlations of Section 3.3, dotted curves without correlations.

A second set of simulations was performed to investigate the effects of input correlations. In these simulations, selected pairs of inputs were assigned rank correlation coefficients. In the base case, the coefficients were set to 0.3 between junction depth and shunt resistance, and 0.7 between bulk lifetime and bulk resistivity. In the thin case, they were set to 0.7 between bulk lifetime and bulk resistivity, and –0.9 between back surface recombination velocity (BSRV) and bulk resistivity; for computational reasons, this necessitated setting the coefficient between bulk lifetime and BSRV to –0.4. It should be noted that, while correlations may exist between these parameters in reality, the correlation coefficients given here are intended only to be illustrative.

4 RESULTS AND DISCUSSION

4.1 Model stability

Monte Carlo simulations are not likely to converge until a sufficient number of samples have been taken to reach an estimate for the mean and variance of a function. Figure 2 shows how the mean and variance of cell efficiency change as the number of samples increases to 60,000. The data shown are for the thin cell design with correlated input variables, which stabilizes after approximately 10,000 samples. The performance data for the other cell designs show similar trends, as do the manufacturing cost simulations, though the required number of samples is generally case-dependent and can vary with both the model and its inputs.

4.2 Results of modeling

Figure 3 shows the probability distribution functions (pdfs) for solar cell performance in each case. Note that introducing correlations between input variables had little effect on the base case, but a very significant effect on the thin case. Particularly of note is that the correlations narrow the distribution of cell efficiencies, which may translate to a reduction in mismatch losses when they are connected into series strings.

The distribution of module cost per watt is shown in Figure 4 for both the correlated and uncorrelated simulations in each case. Because the correlations had no effect on the mean cell efficiency, the central limit theorem prevents their influence on the thin cells from being seen here. However, the difference between the correlated and uncorrelated simulations of the thin case would likely

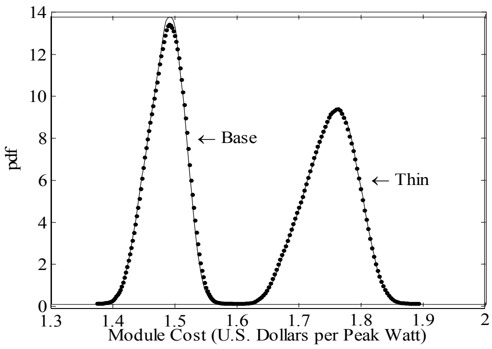

Figure 4: Calculated probability density functions for PV module cost per peak watt. Solid curves calculated using correlations of Section 3.3, dotted curves without correlations.

produce differences in mismatch losses, which are sensitive to distributions [7]. Thus, accounting for mismatch losses might ultimately affect the module cost per watt.

4.3 Uncertainty and sensitivity analysis

Uncertainty in the module cost per watt is expressed in two ways. A 95% confidence interval about the mean indicates uncertainty on the predicted mean, and a table of percentiles indicates the likely range of the module cost per watt along with a probability that a given price within that range will be attained. Table III shows these percentiles for each case, along with the mean cost per watt and the associated 95% confidence interval.

Table III: Module manufacturing cost (U.S. dollars per peak watt).

Percentile	Base	Base Correlated	Thin	Thin Correlated
100	1.88	1.88	1.58	1.58
90	1.80	1.80	1.52	1.52
80	1.79	1.79	1.51	1.51
70	1.77	1.77	1.50	1.50
60	1.76	1.76	1.49	1.49
50	1.75	1.75	1.49	1.49
40	1.74	1.74	1.48	1.48
30	1.73	1.73	1.47	1.47
20	1.71	1.71	1.46	1.46
10	1.69	1.69	1.45	1.44
0	1.61	1.61	1.38	1.38
Mean	1.7487	1.7487	1.4852	1.4833
Interval	0.0003	0.0003	0.0002	0.0002

From these data it appears the mean is very accurately determined. The correlations between solar cell design inputs appear to have had little effect on the module cost; however, it is possible that an accurate accounting of mismatch losses would lead to greater differences in module outputs in the thin correlated case, which would certainly affect the calculated cost per watt.

Sensitivity analysis proceeded by shifting the mean of each input variable by ±10% independently and recomputing the output with 10,000 samples. This method superficially resembles the single-input method used to screen variables in Section 3.2; however, because the outputs are stochastically recomputed, it accounts for correlations between inputs. The results are shown in Figure 5 for the sensitivity of module cost to cell design parameters for the thin design with correlated inputs. By comparison to Figure 1, the correlations appear to have increased sensitivity to BSRV and bulk resistivity.

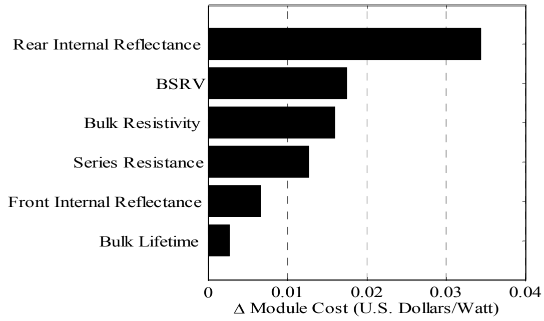

Figure 5: Sensitivity of thin design with correlated inputs to uncertainty in solar cell design parameters.

More sophisticated methods for sensitivity analysis exist [8], but because the inputs become convoluted during computation of the final output they are difficult or impossible to apply. The authors continue to investigate improved methods for this task.

5 CONCLUSIONS

The synthesis of solar cell performance modeling, manufacturing cost estimation, and stochastic simulation offers great potential for statistical forecasting and optimization. However, the flexibility of the Monte Carlo approach can only be exploited if a concentrated effort is made to statistically quantify real inputs. The preliminary analysis presented here was carried out primarily for illustrative purposes; while in this case the resulting data may have no practical application, the results are nonetheless very interesting and indicative of the potential of the proposed methodology. Improvements in input qualification and the model itself will follow in future work.

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REFERENCES

[1] B. G. Carbajal, Proc. 13th IEEE Photovoltaic Specialists Conf. (1978), 252.
[2] G. Darkazalli, S. Hogan, and M. Nowlan, Proc. 22nd IEEE Photovoltaic Specialists Conf. (1991), 818.
[3] L. A. Grenon and M. G. Coleman, Proc. 13th IEEE Photovoltaic Specialists Conf. (1978), 246.
[4] R. G. Little and M. J. Nowlan, Prog. Photovolt. Res. App. 5, 309 (1997).
[5] P. A. Basore and D. A. Clugston, Proc. 25th IEEE Photovoltaic Specialists Conf. (1996), 377.
[6] P. R. Garvey, *Probability Methods for Cost Uncertainty Analysis*. New York: Marcel Dekker, Inc., 2000.
[7] L. L. Bucciarelli, Solar Energy 23, 277 (1979).
[8] A. Saltelli, K. Chan, and E. M. Scott, ed., *Sensitivity Analysis*. West Sussex, UK: John Wiley & Sons, Ltd., 2000.