Assumptions and the Levelized Cost of Energy for Photovoltaics

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Photovoltaic electricity is a rapidly growing renewable energy source and will ultimately assume a major role in global energy production. The cost of solar generated electricity is typically compared to electricity produced by traditional sources with a levelized cost of energy (LCOE) calculation. Generally, LCOE is treated as a definite number and the assumptions lying beneath
10 that result are rarely reported or even understood. Here we shed light on some of the key assumptions and offer a new approach to calculating LCOE for photovoltaics based on input parameter distributions feeding a Monte Carlo simulation. In this framework, the influence of assumptions and confidence intervals becomes clear.

Introduction

15 Solar energy is the most abundant and therefore one of the most promising renewable energy option for large-scale global electricity production. The photovoltaics (PV) industry is expanding at a phenomenal pace, with grid-tied installations in the U.S. growing from about 50 MW in 2004 to a projected
20 1 GW this year; globally installations may exceed 14 GW. Despite this growth, PV still represents only a tiny fraction of the overall worldwide electricity production, and the reason for this is that the cost of generation from PV is typically higher than that from traditional sources such as coal and
25 natural gas power plants. For PV to attain deep market penetration, its costs must be comparable to those from fossil fuels, though it should be noted that there are substantial hidden costs associated with fossil fuels that are generally not accounted for such as pollution and climate change.[1]

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The cost of conventional electricity is rising while the cost of solar electricity is dropping, so wide-scale grid parity is likely at some point in the future. Improvements to existing solar technologies and the development and commercialization of
35 second- and third-generation technologies are the source of much of the cost savings, though decreases in the balance of systems and power electronics costs are also contributing. There are numerous groups of stakeholders interested in tracking these developments, with quantitative accuracy
40 carrying enormous value. Investors need to know their expected return on investment, regulators and policy makers help define the economics of energy production and require reliable information, funding agents need a means to analyze proposed technology development,[2] and technology
45 developers want to understand how they will compete relative to other technologies. One needs a method to fairly compare energy costs produced by different means, and the levelized cost of energy (LCOE) is intended to be just this.

Levelized Cost of Energy

50 LCOE can be thought of as the price at which energy must be sold to break even over the lifetime of the technology. It yields a net present value in terms of, cents per kilowatt-hour.

This is an assessment of the economic lifetime energy cost and lifetime energy production (Eq. 1) and can be applied to
55 essentially any energy technology. For computing the financial costs the equations can be embellished to take into account not only system costs, but also factors such as financing, insurance, maintenance, and different types of depreciation schedules.

60 $$LCOE = \frac{\text{Lifecycle cost}}{\text{Lifetime energy production}}$$

[1]

SunPower Corporation recently produced a whitepaper that details a simplified LCOE equation for utility-scale PV.[3] It can be represented as:

$$LCOE = \frac{\text{Project cost} + \sum_{n=1}^{N} \frac{AO}{(1+DR)^n} - \frac{RV}{(1+DR)^n}}{\sum_{n=1}^{N} \frac{\text{Initial kWh} \times (1-SDR)^n}{(1+DR)^n}}$$ [2]

65 where AO is the annual operations cost, DR is the discount rate, RV is the residual value, SDR is the system degradation rate, and N is the number of years the system is in operation. Equation 2 computes the economic LCOE. This formulation can be modified to include financial considerations such as
70 taxes, subsidies, and other complexities. An equation taking some of these additional factors into account was recently reported[4]:

$$LCOE = \frac{PCI - \sum_{n=1}^{N} \frac{DEP+INT}{(1+DR)^n} TR + \sum_{n=1}^{N} \frac{LP}{(1+DR)^n} + \sum_{n=1}^{N} \frac{AO}{(1+DR)^n} (1-TR) - \frac{RV}{(1+DR)^n}}{\sum_{n=1}^{N} \frac{\text{Initial kWh} \times (1-SDR)^n}{(1+DR)^n}}$$ [3]

where PCI is the project cost minus any investment tax credit
75 or grant, DEP is depreciation, INT is interest paid, LP is loan payment, and TR is the tax rate.

More importantly, though, one must recognize that each of these parameters is associated with a set of assumptions. In many cases, there is sufficient uncertainty revolving around these assumptions to render the output only a very crude estimate. Quantification of that uncertainty is currently absent from essentially all LCOE calculations.

Solar Advisor Model

In an effort to overcome some of the challenges associated with performing a reliable LCOE calculation, the National Renewable Energy Laboratory, Sandia National Laboratory and the U.S. Department of Energy have developed a system performance model incorporating financing options ranging from residential to utility scale named the Solar Advisor Model (SAM).[5] This software is among the most broadly used to analyze solar technologies for specific locations and provides users with the capability to probe the relative influence of input parameters on both the energy production and financial aspects. It represents the best tool publically available today for the industry to examine the financial feasibility of a solar project.

In the SAM analysis, utility-scale LCOE is calculated based on the required revenues over the project life and is described as "real" or "nominal" according to:

$$\text{real } LCOE = \frac{\sum_{n=1}^{N} \dfrac{R_n}{\left(1 + DR_{nominal}\right)^n}}{\sum_{n=1}^{N} \dfrac{Q_n}{\left(1 + DR_{real}\right)^n}} \qquad [4]$$

$$\text{nominal } LCOE = \frac{\sum_{n=1}^{N} \dfrac{R_n}{\left(1 + DR_{nominal}\right)^n}}{\sum_{n=1}^{N} \dfrac{Q_n}{\left(1 + DR_{nominal}\right)^n}} \qquad [5]$$

where Q_n is the electricity generated in year n, R_n is the required revenue from electricity sales in year n, DR_{real} is the real discount rate (no inflation), and $DR_{nominal}$ is the nominal discount rate (with inflation). Hidden within Q and R are numerous factors such as degradation rate, weather data, price escalation rate, etc.

As with all calculations built around LCOE, however, SAM results in a specific number and is calculated in such a way that it inherently incorporates a set of assumptions. (The most recent releases of SAM have incorporated the ability to provide a sensitivity analysis of one or more parametric variables, which begins to address this issue.) Without a detailed understanding of these underlying assumptions, their distribution profiles, and a sensitivity analysis of them, a single resulting number may give an unfounded confidence in the certainty of the result.

In this article, we will shed light on the assumptions that go into an LCOE calculation for utility-scale PV. When the dramatic effect of assumptions is revealed, it becomes clear that a single number from an LCOE calculation does not capture the uncertainty associated with the economic and financial implications of a PV project.
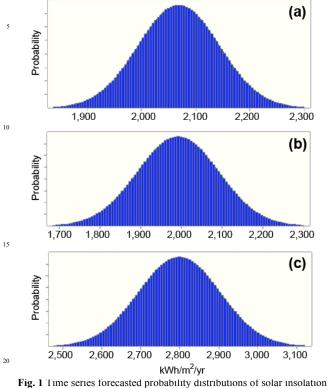
Assumptions associated with energy production

Accurately predicting the energy output of a PV system over its lifetime is enormously challenging. It is apparent that simply using the vendor's reported conversion efficiency under standard test conditions and the average annual solar insolation at a given location is dreadfully insufficient. Below we describe an improved approach to estimating energy production based on input distributions rather than single numbers. In each case we outline the rationale behind our distributions, which again relies on a series of assumptions. The key is to use the best available data, but more importantly to understand the source of the data and the uncertainty associated with it.

In this study we consider a 20 MW utility-scale PV system at three diverse domestic locations; namely, Sacramento, CA, Chicago, IL, and Boston, MA. Although other types of systems are readily analyzed by our model, here we specifically consider a 1-axis tracking PV system with flat-plate collector and an axis tilt equal to the latitute of the location. Using the total stated system capacity and an assumed performance of 197 peak watts per square meter, the effective area of this PV system is 103,627 m^2. Based on current cost trends for the year 2012, the total capital cost of this system is estimated at $54 million. Subsidies provided by the federal government represent as much as 30% of the total installation cost. The annual insurance cost, which is conservatively assumed to be 0.5% of the installation cost, equals $270,000. In this analysis, we assume a 2.5% inflation rate, 30% federal tax rate, and 8% state tax rate. A 30-year project lifetime is considered in this analysis. Even considering only these initial parameters, it becomes clear how many assumptions go into such a calculation.

Solar insolation

As the modeled PV system will be operating beginning today, we use the time series method to forecast the annual solar insolation in the coming 30 years based on the historial montly solar insolation data (1960–1990) of the three cities. As the annual solar insolation is nonseasonal, we use four time series methods (single moving average, double moving average, single exponential smooth, and double exponential smooth) for the data set of each city and select the one with the best forecast as defined by the one having the minimum mean square error with respect to the historical data. It turns out that the single moving average provides the best forecast for Boston and Sacramento, whereas a single exponential smooth works best for the forecast of Chicago. The initial forecasted annual solar insolations of the three cities are presented in Figure 1. The projections are assumed to follow a normal distribution, which is actually somewhat broader than the historical data due to the small sample size. As one looks

further into the future with the forecast, the outyears in the trend toward greater uncertainty, as would be expected.

Fig. 1 Time series forecasted probability distributions of solar insolation in (a) Boston, (b) Chicago, and (c) Sacramento.

Power conversion efficiency

The power conversion efficiency can be affected by many factors. In this analysis, we assume it follows a normal distribution with a mean of 16% and a standard deviation of 1% (see Figure 2).
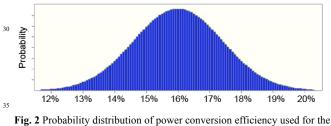

Fig. 2 Probability distribution of power conversion efficiency used for the PV system in this model.

Most analyses of LCOE treat conversion efficiency as a constant using the value reported by the module vendor using standard conditions of illumination and temperature. In reality, this value only provides an approximation of the actual performance in the real world. Overall efficiency actually has many parameters rolled up in it. For example, not only will a PV panel produce less power when there is less sunlight, in many cases it will also do so less efficiently. Moreover, the dependence of efficiency on insolation is not necessarily linear. Ideally, one would use real illumination-dependent performance data time synched with forecasted insolation. Other factors can also affect actual efficiency such

as temperature, partial shadowing from clouds or debris, and so on. Using a distribution of values takes a step toward capturing these uncertainties, though even greater accuracy is surely achievable.

System degradation rate

The rate at which solar cell performance degrades may depend on the type of solar cell, quality of manufacturing, power production level, and local weather/climate. As with the previous parameters, system degradation rate is generally treated as a single value in LCOE calculations despite the fact that it is known that even within a single PV installation individual panels will degrade with substantially different rates. In this analysis, we assume the system degradation rate has the probability distribution shown in Figure 3, which accounts for a small number of unusually poor performers as is often observed in real systems.
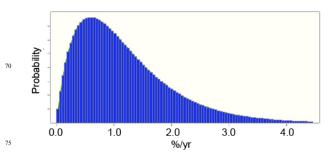

Fig. 3 Probability distribution of system degradation rate used in this model.

Other production assumptions

In this analysis, we are making a number of additional assumptions regarding electricity production. (Note that grid integration costs are yet another factor that can be incorporated into an LCOE calculation, and that distributed power systems will have a markedly different behavior than centralized systems.) A few of these include (1) the fact that conversion efficiency and solar insolation are independent parameters (not actually the case) and (2) weather patterns over the past 30 years provide a reasonable foundation for forecasting sunlight over the next 30 years.

Assumptions associated with costs

The two core pieces of an LCOE calculation are energy production and cost. There are fundamental assumptions associated with each of these, and below we outline some of the considerations that enter into the costs. Again, we will use input distributions to quantitatively capture the uncertainties associated with some of these assumptions.

Real discount rate

In addition to risks associated with solar insolation levels and the performance of PV technologies at a specific location, there is also financial uncertainty in terms of the time value of money. On the down-side, borrowing money now is disadvantagous if one locks into an interest rate that in the future falls percipitously relative to inflation. On the other

hand, if future lending rates increase significantly faster than inflation, the apperant cost of borrowing may be significantly less expensive than anticipated at the time of the load. This uncertainity is characterized in Figure 4. The shape of the curve is based on projections made by the Financial Forecast Center (http://www.forecasts.org/ffund.htm) for the Fed Funds interest rate. The general shape was then scaled such that the most probable real discount rate reflects currrent rates for borrowing money for constructing new PV projects. In the LCOE calculation described below, the real discount rate is converted to a nominal discount rate using the assumed inflation factor.
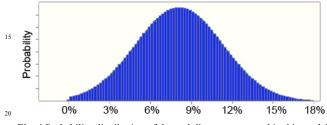

Fig. 4 Probability distribution of the real discount rate used in this model.

Operations and maintenance

Upkeep of a utility-scale PV system will vary widely depending on the local conditions. For example, in dusty regions or regions with substantial snowfall, panels will have to be cleaned more frequently. This cost can shift from year to year depending on the weather and other factors. We assume that fixed O&M costs may vary from $8/kW/yr to $20/kW/yr, with the most likely case being approximately $10/kW/year. Therefore, here we assign a triangular distribution to this parameter, as depicted in Figure 5. Lacking good local data, this distribution is used for all three modeled locations, though it will certainly vary for different environments.
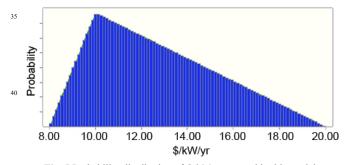

Fig. 5 Probability distribution of O&M costs used in this model

Carbon market or tax

Emissions trading ("cap and trade") is an approach to controlling pollution via economic incentives. Market forces are enlisted to achieve reductions of carbon emissions by capping the total permissible amount, allocating carbon credits to firms, and enabling the trading of permits. The European Union has put a greenhouse gas trading scheme into place. A carbon tax is an alternative maket-based approach that directly taxes emissions and thereby provides an incentive to reduce pollution. As neither system has yet been implemented in the United States, we have not included them

into our calculation, but these systems can have a dramatic effect on comparative fincancial LCOE by either raising the cost of competing technologies based on fossil fuels or by adding value to renewable energy production. Furthermore, incorporating carbon taxes or emission trading will introduce yet another uncertainty that must be properly accounted.

Tax rates and subsidies

As with inputs such as solar insolation, taxes and incentives for promoting solar energy also vary widely by location. In our model we have used a consistent federal tax rate of 30% and state tax rate of 8%. Future policy changes regarding solar subsidies is yet another uncertainty that is not quantified in this paper. However, it can greatly influence project financial viablity. For the United States, there is a valuable online database that compiles the various state, local, utility, and federal incentives and policies.[6]

Analysis of the influence of assumptions

As any solar LCOE calculation must be performed for a specific location due to local conditions, we selected three geographically dispersed locations in the United States: Sacramento, CA, Chicago, IL, and Boston, MA. While there are other factors that vary between locations, we have taken the assumption that only solar insolation will be different between these three cities. Surely this overlooks important factors such a increased module degradation in regions with greater temperature and humidity fluctuations, different O&M costs (e.g., snowfall amounts in Chicago and Boston as compared to Sacramento) and non-linearities between insolation and conversion efficiency. Time series forecasting using three decades of historical insolation at these locations provides an estimation of the expected sunlight conditions over the lifetime of the modeled PV system.

To calculate the LCOE for each of these locations (using Eq. 3), we have used the parameter probability distributions outlined above in a Monte Carlo simulation. This approach provides a more complete projection of the expected LCOE than can be offered by a simple calculation using singular inputs.

Monte Carlo simulation is a computational mathematical technique that allows one to account for risk in quantitative analysis and decision making. Monte Carlo simulation performs uncertainty analysis by building models of possible results through the substitution of a range of values—a probability distribution—for any factor that has inherent uncertainty. By using probability distributions, variables can have different probabilities of different outcomes occurring. Probability distributions are an informative method for describing uncertainty. During a Monte Carlo simulation, values are sampled at random from the input probability distributions. Each set of samples is called an iteration, and the resulting outcome from that sample is recorded. Depending upon the number of uncertainties and the ranges specified for them, a Monte Carlo simulation could involve thousands or millions of iterations. The resulting range of all

calculation results form a distribution from which uncertainty information can be derived with basic statistical methods. In this way, Monte Carlo simulation provides a much more comprehensive view of what may happen. *It tells you not only what could happen, but also how likely it is to happen*.

Monte Carlo simulation provides a number of advantages over deterministic, or "single-point estimate" analysis:

1. Probabilistic results: Results show not only what could happen, but also how likely each outcome is.
2. Sensitivity analysis: With just a few cases, deterministic analysis makes it difficult to see which variables impact the outcome the most. In Monte Carlo simulation, it is easy to see which inputs had the biggest effect on bottom-line results.
3. Correlation of inputs. In Monte Carlo simulation, it is possible to model interdependent relationships between input variables. It is important for accuracy to represent how, in reality, when some factors goes up, others go up or down accordingly. (Here we have assumed independent inputs for simplicity.)

In this work, we use 1,000,000 iterations for the uncertainty anlaysis of LCOE for each of the three cities. The Monte Carlo simulations produce not only the probability distribution of the LCOE, but also sensitivity charts and correlation charts.

Figure 6 shows the LCOE output distributions for each of the three locations, and Table 1 includes relevant numbers from these output statistics. Note that these outputs are based on the relatively rudimentary input distributions and assumptions outlined above and are presented here simply as a demonstration of the methodology. It is striking how broad these distributions are, which emphasizes the shortcomings of calculations that use singular input parameters.
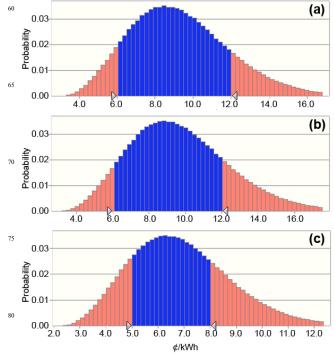

Fig. 6 LCOE output distributions for (a) Boston, (b) Chicago, and (c) Sacramento simulated using the input parameter distributions outlined in Figures 1-5. The blue shaded area represents one standard deviation.

Table 1 Statistics from LCOE output calculations (all units are ¢/kWh)

Parameter	Boston	Chicago	Sacramento
Mean	9.34	9.71	6.89
Median	9.07	9.42	6.70
Std Dev	2.66	2.79	1.95
Variance	7.09	7.78	3.79

It is no surprise that the LCOE for the system in comparatively sunny Sacramento is centered around a lower value (6.89 ¢/kWh) than that in Chicago or Boston (9.71 and 9.34 ¢/kWh, respectively), but these mean values only provide part of the overall picture. For example, there is also a marked difference in the standard deviation among these locations. In this simple model, these differences arise solely from the different insolation distribution as the remaining inputs are treated as being independent of location. That is, the predicted LCOE result is known with better certainty for Sacramento. This sort of information is of tremendous potential value to investors, utility companies, insurers, and other stakeholders who need to ascertain the risk associated with a new installation.

Additional information can be gleaned from an examination of the sensitivity of the LCOE to the various input parameters. There are myriad ways in which one can begin deciphering these relative influences; here we report the results of a sensitivity analysis in which the inputs were varied according to their defined probability distributions rather than, for example, artificially shifting specific parameters by a set percentage. Figure 7 shows the rank correlation analysis

results for each location, which quantify the agreement between each input parameter and the LCOE output on a scale of -1 to +1. A negative correlation means a lower value for the input parameter tends to result in a higher value for the LCOE, and a positive correlation means a higher value for the input parameter tends to result in a higher LCOE. The magnitude of the correlation indicates how strong this relationship is across the numerous simulated cases.
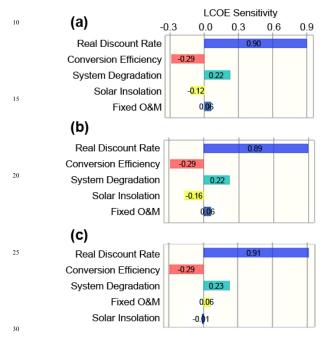

Fig. 7 Rank correlation sensitivity analyses for (a) Boston, (b) Chicago, and (c) Sacramento obtained by varying inputs according to defined probability distributions.

Clearly, adjustments to the input parameter distributions will have a direct effect on the LCOE and sensitivity results, but taking the distributions proposed here, there are some surprising findings that emerge. For one, the financial uncertainties represent by far the biggest correlation with LCOE. For example, a higher real discount rate almost always resulted in a higher LCOE. As with most of the inputs, the actual financial values for a given real-world project are essentially out of one's control; however, knowing that this factor is a major contributor to risk, this is an area where stakeholders such as governments interested in facilitating the utilization of solar energy can step in to provide greater certainty through creative approaches that lessen the impact of overall capital markets.

System performance, represented by conversion efficiency and system degradation, is also a significant contributor to the uncertainty in LCOE. One cannot simply use a vendor-supplied power conversion efficiency when predicting the lifetime production for a system. As real-world performance databases become deeper (note that these data must be obtained from the specific location of interest to be truly relevant), they will provide an invaluable resource for developing reliable input distributions.

Uncertainties in system degradation rate can be minimized as manufacturers improve their processes to eliminate the number of modules that fail prematurely. Developments in this direction will have a direct impact on the projected uncertainty and will therefore reduce risk for photovoltaic projects.

Interestingly, despite the substantial variation in solar insolation seen both historically and in the time series forecasts presented in Figure 1, insolation appears to have a relatively small correlation with LCOE when compared with the discount rate and performance inputs. Variation should not be ignored, but this analysis implies that one may focus more on the uncertainty revolving around other factors when estimating LCOE distributions. That said, the fact that insolation and conversion efficiency are actually coupled can introduce unforeseen complexity to this situation.

Conclusions

We are venturing into the era of renewable energy, and photovoltaics will represent an increasing share of this sector. Countless decisions associated with solar energy technologies rely on financial calculations, ranging from investors to regulators to technologists, yet the established method of comparing costs between electricity-generating technologies—LCOE—is being misused in virtually all cases in the context of photovoltaics. There are many assumptions that underlie an LCOE calculation, and anyone performing such a calculation or utilizing the results must fully appreciate the influence of these assumptions.

It is unadvisable to input single numbers into the calculation and receive a single LCOE number as a result. This carries with it an unfounded and potentially misleading sense of certainty. Rather, input parameter distributions based on the best available data should be employed, resulting in a LCOE *distribution* that far more accurately reflects cost uncertainty associated with a solar project.

Here we have used Monte Carlo simulations to produce such a distribution, and we have focused on assumptions revolving around (decoupled) sunlight variation, panel performance, operating costs, and inflation. The distributions used here are relatively crude approximations with no interdependence used to demonstrate the Monte Carlo approach to LCOE. Even within this limited scope, it is clear that the LCOE output can vary substantially from a single value, giving enhanced guidance to all stakeholders in the solar energy arena.

Notes and references

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