The Costs of Solar and Wind Power Variability for Reducing CO_2 Emissions

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Abstract

We compare the power output from a year of electricity generation data from a solar thermal plant, two solar PV arrays, and 20 ERCOT wind farms. The analysis shows that solar photovoltaic electricity generation is approximately one hundred times more variable at frequencies on the order of 10^{-3} Hz than solar thermal electricity generation, and the variability of wind generation lies between solar PV and solar thermal. We calculate the cost of variability of the different solar power sources and wind by using the costs of ancillary services and the energy required to compensate for its variability and intermittency, and the cost of variability per unit of displaced CO_2 emissions. We show the costs of variability are highly dependent on both technology type and capacity factor. California emissions data were used to calculate the cost of variability per unit of displaced CO_2 emissions. Variability cost is greatest for solar PV generation at \$8-11 per MWh. The cost of variability for solar thermal generation is \$5 per MWh, while that of wind generation in ERCOT was found to be on average \$4 per MWh. Variability adds ~\$15/tonne CO_2 to the cost of abatement for solar thermal power, and \$33-\$40 for PV.

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1. Introduction

The variability and intermittency of wind and solar electricity generators add to the cost of energy by creating greater demand for balancing energy services and other ancillary services. As these sources begin to provide a large percent of the electricity supply, the relative costs of their variability may become important considerations in selection of technologies to meet renewables portfolio standards, in addition to their capital costs and environmental benefits.

We quantify the differences in variability among three types of renewable electricity generation: solar thermal, solar photovoltaic (PV), and wind. The power spectrum analysis in this paper follows the method used in Apt (2007) (*1*). In addition, we demonstrate how these differences in power spectra translate into different costs of intermittency. The analysis of the cost of variability uses a similar methodology to that of Katzenstein and Apt (2010) (*2*).

Lavania et al. (2011) have examined solar variability in the frequency domain, and propose a method to reduce variability by interconnecting solar plants, but they use solar insolation data to estimate power output rather than actual solar array power output data (*3*). Gowrisankaran et al. (2011) present an economic model to calculate the cost of solar power intermittency in a grid with high levels of solar penetration (*4*). They scale the power output of a 1.5 kW test solar facility in Tucson to simulate the solar power output. Our research differs from previous work because we use real power output and price data from operational utility-scale plants to calculate the actual cost of variability of different energy technologies.

We find that at frequencies greater than ~10^{-3} Hz (corresponding to times shorter than ~ 15 minutes), solar thermal generation is less variable than generation from wind and solar PV. Using energy and ancillary service prices from California, the cost of variability of a solar thermal facility would be $5 per MWh. This compares to a cost of variability at a solar PV facility of $8-11 per MWh. Using the same 2010 California energy and ancillary service prices, we calculate the average cost of variability at 20 Electric Reliability Council of Texas (ERCOT) wind farms was $4 per MWh. Variability adds ~$15/tonne CO_2 to the cost of abatement for solar thermal power, and $33-$40 for PV.

1.1 Description of Technologies

Solar photovoltaic technology uses energy from sunlight to create electricity by exciting electrons on a photovoltaic material such as silicon (*5*). Solar thermal generation also uses the energy of the sun to create electricity, but instead of exciting electrons, reflecting mirrors focus sunlight on rows of tubes containing a working fluid. The heated working fluid runs through a heat exchanger, creating steam to generate electricity. In contrast to solar PV arrays, solar thermal facilities can ride through short periods of reduced insolation due to the inertia of the heat stored in the working fluid.

2. Methodology and Data

2.1 Data

We obtained 1-minute energy data gathered over a full year from a 4.5 MW solar photovoltaic (PV) array near Springerville, Arizona (in 2005), and 5-minute energy data from Nevada Solar One (NSO), a 75 MW solar thermal generation facility near Boulder City, Nevada (in 2010). We also use 1-minute energy data from a 20 MW+ class solar PV array, provided on the condition of anonymity. We use 15-minute wind data from 20 ERCOT wind farms from 2008.

We use data from the California Independent Service Operator (CAISO) for up and down regulation (in the day-ahead, DAH, market) and energy prices. The 2010 CAISO energy prices represent the Southern California Edison (SCE) utility area real time hourly averages. We use the same price data for all simulations to eliminate the effects of price variations in different years and in different geographic regions. The SCE data (Table 1) were chosen to represent a geographical area as close as possible to the solar generation facilities in the Southwest. Figure 1 is a time series representation of the Springerville solar PV and NSO solar thermal data sets.

Table 1. Average price information for CAISO price data used in analysis

Type of charge	Average hourly price per MWh
CAISO SCE Energy (2010)	$42
CAISO DAH Up Regulation (2010)	$5.6
CAISO DAH Down Regulation (2010)	$5.0

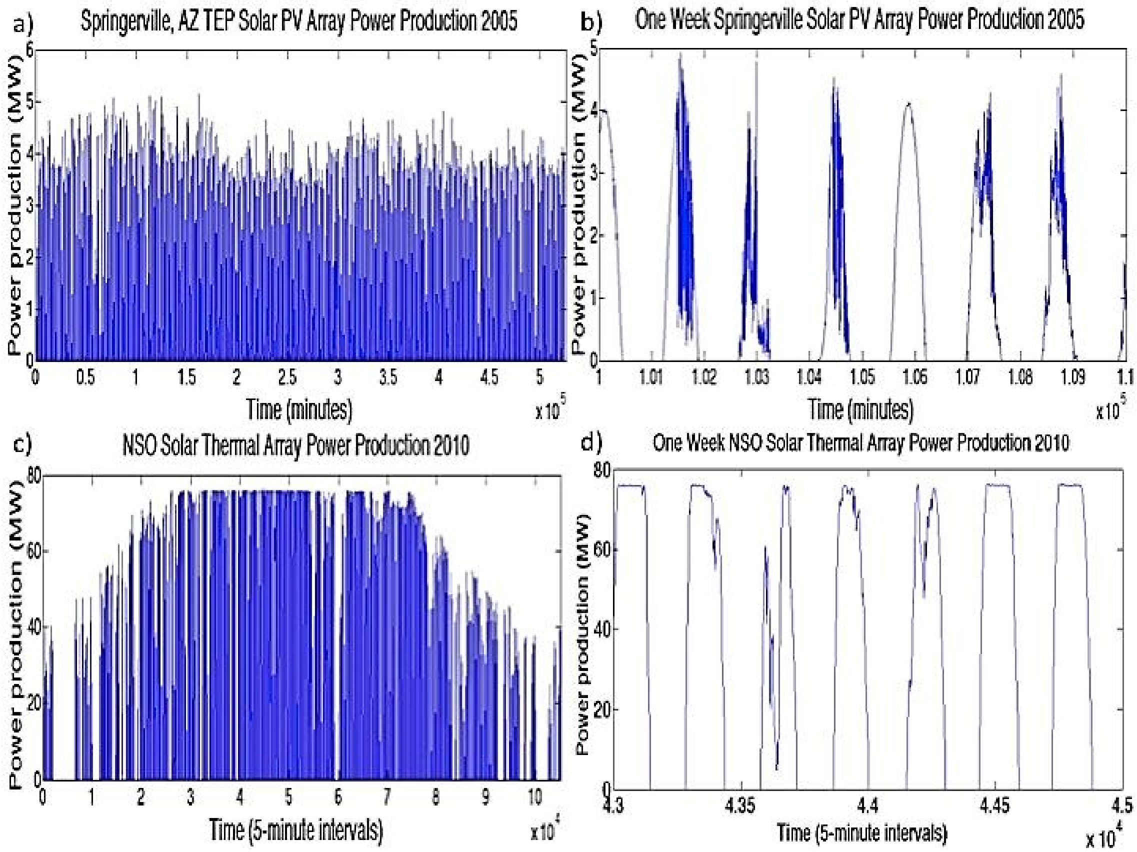

Figure 1. Solar thermal and solar PV data: (a) 2005 Tucson Electric Power (TEP) solar PV data; (b) One week of 2005 TEP solar PV data; (c) 2010 NSO solar thermal data (the data gaps near the beginning and end of the year represent times the plant was out of service); (d) One week of NSO solar thermal data.

We obtained data from EPA's Clean Air Markets Data and Maps website on hourly emissions and electricity production for each thermal generating unit greater than 25 MW capacity in California for 2010 (*6*). These data allowed us to calculate the cost of variability per unit of displaced CO_2 emissions.

2.2 Cost of variability

We calculate the cost of mitigating variability in the generation output by adding the costs of ancillary services and the energy costs required for the ISO to handle variability of the solar resource (*2*). The ancillary service cost includes the cost of providing up and down regulation for each hour of operation. The energy term is the absolute value of deviation from the hourly prediction to reflect the cost to the ISO when the generator deviates from its forecasted production. We average cost of variability in each hour of the year and normalize the average by the total annual energy produced by the generator. Figure 2 is a graphical representation of the calculation; the ISO uses load following energy and up and down regulation to mitigate the effects of variability of the renewable generation. An ISO would also use frequency response ancillary services to mitigate the very short-term (1-10 second) effects of variability, but that is outside the scope of this research because our datasets contain generation information down to only 1-minute or 5-minute granularity. Calculation of the cost of variability is per equations (1) and (2).

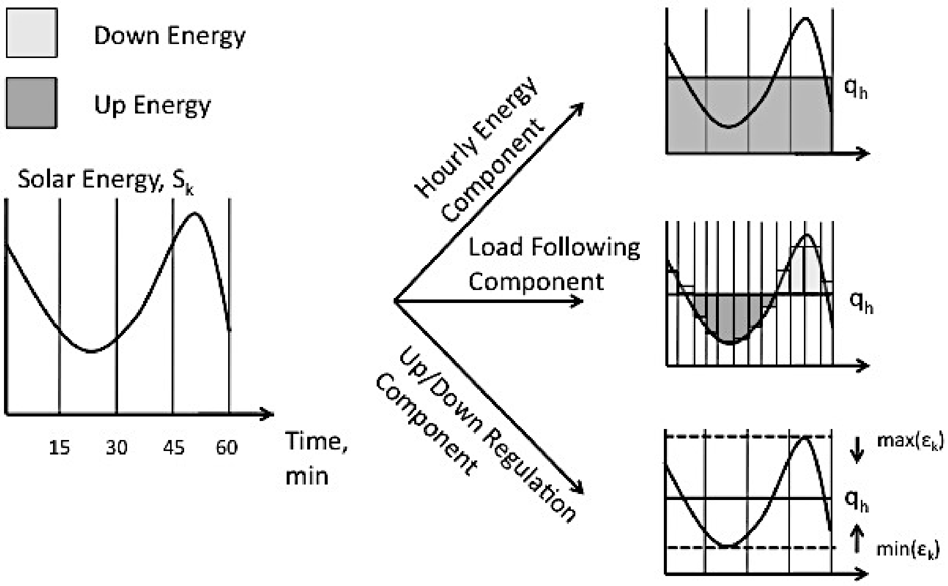

Figure 2. Utilities use load following and regulation services to compensate for variability in solar energy. When the energy production, S_k, deviates from the hourly energy set point, q_h, the ISO uses load following regulation to ramp down or supplement the system-wide generation (middle-right graph). In addition, the ISO utilizes up and down regulation equivalent to the minimum and maximum deviation from q_h, respectively (lower right graph).

(1) $$\text{Variability Cost}(h) = \sum_{k=1:n} |\varepsilon_k| P_h / n + P_{up,h} \left| \min\begin{Bmatrix} 0 \\ \min(\varepsilon) \end{Bmatrix} \right| + P_{dn,h} \left| \max\begin{Bmatrix} 0 \\ \max(\varepsilon) \end{Bmatrix} \right|$$

(2) $$\text{Normalized Cost} = \frac{\sum_{h=1:8760} \text{Variability Cost}(h)}{\sum_{h=1:8760} \sum_{k=1:n} S_{k,h} / n}$$

Where:

P_h	is the hourly price of energy
$P_{up,h}$	is the hourly price of up regulation
$P_{dn,h}$	is the hourly price of down regulation
q_h	is the amount of firm hourly energy forecasted
$S_{k,h}$	is the actual subhourly production of energy in hour *h*
$\varepsilon_k = S_k - q_h$	is the difference between energy forecasted and produced

n is the number of energy production records per hour (60 for TEP, 12 for NSO, 4 for ERCOT wind, and 60 for the 20 MW+ PV array)

We arrive at q_h, the hourly energy forecast, by taking the mean of n energy records for an hour, h. The second two terms in equation (1) represent the cost of up and down regulation for the hour. The minimum and maximum terms directly inside the absolute value symbols are only active if the hourly energy forecast lies outside of the actual upper and lower bound of energy production for the hour. That situation can occur only when using imperfect forecast data, since the perfect forecast q_h always falls between the maximum and minimum energy level for the hour.

Simulating the cost of variability using energy forecast data would give more information about the realistic costs of intermittency of solar thermal and PV. We were unable to obtain actual forecast data for the two solar generators in our analysis, so we simulated forecast data using National Renewable Energy Laboratory's System Advisor Model (SAM) in order to more closely simulate utility operations. We include the analysis of SAM forecast data in the supporting information.

Katzenstein and Apt's method is similar, but instead of using the average for the hourly energy set point, they create an objective function to minimize the intermittency cost with the energy set point as a variable. Comparing their method to ours, we find similar results and have chosen to use the average energy method to reduce computation times.

We assume that the solar plants are price takers, in that they are not large enough to influence the market price for electricity. We also assume that the balancing energy price is equivalent to the market average hourly energy price.

2.3 Cost of Variability and Emissions Displacement

One goal of utilizing solar energy for electricity is reducing carbon dioxide emissions. We first calculate the cost of solar variability on a per megawatt-hour basis. We also calculate the cost of solar variability per unit of avoided emissions.

We define avoided emissions, $E_{avoided}$, as the difference between the emissions displaced by using solar, $E_{displaced}$, and the emissions created, $E_{ancillary}$, from ancillary services that support the solar power provider. $E_{displaced}$ represents the avoided emissions due to displacing marginal generating units with must-take solar electricity generation. $E_{ancillary}$ represents the additional emissions created because of reserve, balancing, and frequency support for the solar resource.

(3) $$E_{avoided} = E_{displaced} - E_{ancillary}$$

In any given hour, the cost of avoided emissions is equivalent to the cost of variability divided by the mass of avoided emissions.

(4) $$Cost_{avoided\_emissions} = Variability\ Cost/E_{avoided}$$

For this calculation we assume perfect forecasts of solar energy, so the up and down balancing energy component of $E_{ancillary}$ cancels out. CAISO also pays for spinning reserve, generating units that are running and emitting CO_2 but not providing power to the grid, to balance intermittent resources. However, calculating the emissions due to ancillary services is outside the scope of this research. This calculation is meant to be a best-case scenario of variability cost per emissions avoided, but one that treats solar thermal, PV, and wind in the same way.

We calculate $E_{displaced}$ for each hour of the year based on the emissions of the marginal generating units and the quantity of power being supplied by the solar generating facility. For each hour, we assume that the most recently switched on unit or units will be displaced by power from a solar or wind generator. If more than one unit is dispatched in the same hour, we calculate the average emissions factor of these units. We do not construct a dispatch model, but rather use the observed hourly plant dispatch for California in 2010 per EPA's Clean Air Markets data (*6*). If the solar or wind power generation for that hour surpasses the power production of the marginal unit(s), we identify the next most recently turned on unit until the sum of marginal power surpasses the solar power generated. Figure 3 illustrates how the 1st, 2nd, etc. marginal units are defined.

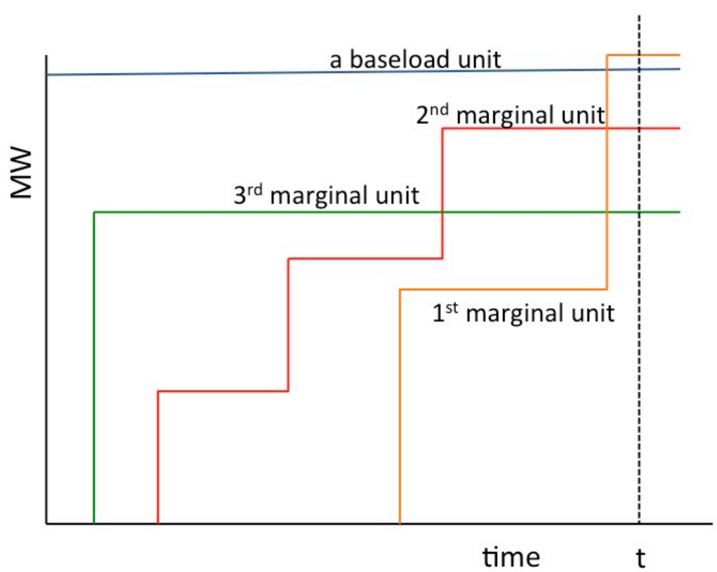

Figure 3. Power output of individual generating units over time. Our notation of "1st marginal unit" indicates the last unit to be dispatched; the 2nd marginal unit is the next-to-last, and so forth.

Equation 5 below calculates the marginal emissions factor in any given hour.

(5) $MEF(h) = \Sigma_i MU_{emissions}(i) / \Sigma_i MU_{power}(i)$

Where:

$MEF(h)$ is the marginal emissions factor in hour h

i is the number of relevant marginal units operating in hour h

$MU_{emissions}$ is the CO_2 emissions rate of marginal unit i in hour h

MU_{power} is the power output of marginal unit i in hour h

3. Results

3.1 Power Spectral Analysis

We follow the method of Apt (2007) to calculate the power spectra of a solar thermal plant, a solar PV array, and a wind plant (*1*). Graphing multiple power sources together and normalizing the spectra at a frequency corresponding to a range near 24 hours reveals a difference in the variability of each source at high frequencies (Figure 4).

The power spectral analysis shows that solar photovoltaic electricity generation has approximately one hundred times larger amplitude of variations at frequencies near 10^{-3} Hz than solar thermal electricity generation (this frequency corresponds to ~ 15 minutes). Electricity from wind farms is intermediate between solar PV and solar thermal in terms of variability in this frequency range. High variability at high frequencies creates the need for more ancillary energy services to avoid quality problems or interruptions in electricity service to customers.

Both types of solar generation exhibit strong peaks corresponding to a 24-hour period and its higher harmonics, as expected from the cessation of generation each night. Wind power exhibits this property to a lesser extent (in the continental US, wind tends to have a diurnal variation, blowing more strongly at night).

The power spectra are similar for the three generation types at frequencies lower than ~$4\text{x}10^{-5}$ Hz (corresponding to periods greater than six hours).

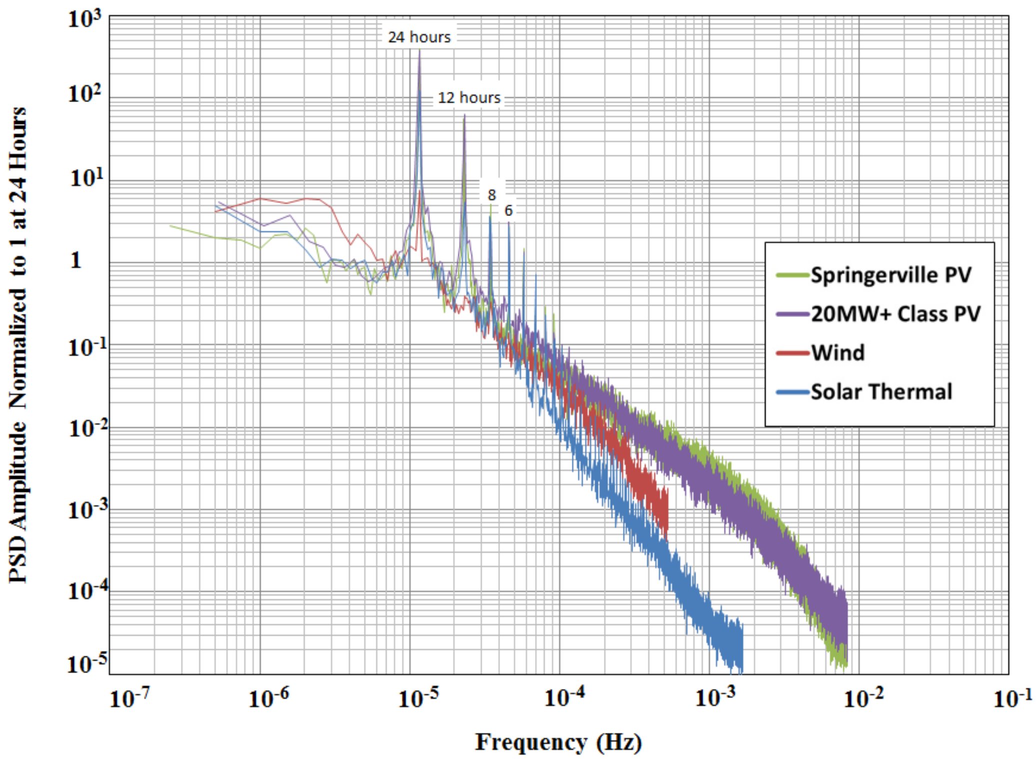

Figure 4. Power spectra of solar PV, wind, and solar thermal generation facilities. The spectra have been normalized to one at a frequency corresponding to approximately 24 hours. All spectra are computed using 16-segment averaging. The strong diurnal peaks of solar power, and weaker one for wind power (along with their higher harmonics) are evident. There is very little difference between the 5 MW Springerville PV spectrum and that of the much larger PV array. The highest frequency in the spectra is governed by the Nyquist frequency for the temporal resolution of each data set (1 minute for the PV data, 5 for the solar thermal data, and 15 for the wind data).

3.2 Cost of Variability of Solar Thermal and PV

The average cost of variability of the Springerville PV plant using hypothetical perfect forecasts and 2010 CAISO prices is \$11.0/MWh. For the 20 MW+ class PV array, the average cost of variability is \$7.9/MWh. The difference in the variability cost of the two PV plants may be due to their capacity factors: 19% for Springerville and 25% for the larger array. For the Nevada Solar One (NSO) thermal plant, the average cost of variability is \$5.2/MWh (23% capacity factor, but as noted previously, solar thermal plants have a significant thermal inertia that smoothes their power output). Using Katzenstein and Apt's optimization method the cost of variability for the NSO plant is \$4.7/MWh (within 6% of our method using the average q_h). The perfect forecast result confirms the hypothesis that the cost of variability for the solar thermal plant ought to be less than that of the solar PV plant since the solar thermal plant's thermal inertia allows it to continue to produce electricity during cloudy periods. As a comparison, the average cost of variability of 20 ERCOT wind farms using the same price data is $4.3/MWh. The highest cost of variability of an individual wind farm was $6.2/MWh and the lowest was $3.5/MWh. While most wind farms had lower variability costs than the solar thermal plant, the wind farms had consistently higher capacity factors, which we found to be a predictor of lower variability cost.

The average price of power in the southern CAISO region in 2010 was $42/MWh. Variability cost as a percentage of the price of power varies significantly across power sources (Table 2). The average cost of variability per megawatt of installed capacity (Table 2) follows from the variability characteristics observed in Figure 4. We think the disparities between costs of variability per megawatt and the observed variability characteristics in Figure 4 result from differences in the capacity factors among different plants.

Table 2. Cost of variability of solar PV and solar thermal and the average price of electricity in the CAISO zone or region

Average price per MWh power=$42	Solar thermal (NSO)	ERCOT wind	Solar PV (Springerville, AZ)	Solar PV (20 MW+ class)
Cost of variability per MWh	$5.2	$4.3	$11.0	$7.9
Cost of variability per MW capacity	$1.2	$1.4	$2.2	$2.0
Variability cost as a percent of total cost of power	11.9%	10.2%	26.5%	18.9%
Capacity factor (or average capacity factor)	23%	34%	19%	25%

The majority of the cost of variability consists of charges for balancing energy for both the solar thermal and solar PV plants (Table 3). The average energy costs in 2010 were higher than the average regulation costs by nearly a factor of ten (Table 1).

Table 3. Cost of variability breakdown between energy and regulation charges

	Energy costs	Regulation costs
TEP Solar PV	69%	31%
20 MW+ Solar PV	65%	35%
NSO Solar Thermal	69%	31%
Wind (average)	73%	27%

Based on sub-array data from the 20 MW+ class PV array, we conclude that the size of an array does not have a major influence on its cost of variability per unit of energy delivered.

To illustrate, the average cost of variability of a sub-array with one-sixth the capacity of the full sized array was $8.2/MWh, compared to $7.9/MWh for the full sized array.

If the power output data from the renewable plants is averaged over long time intervals, the apparent variability and resulting computed ancillary service cost will be reduced. We find that interval between power measurements has some effect on the measured cost of variability, but does not change conclusions drawn from the results using 5 and 15 minute averages compared to 1 minute data (Table 4). We also note that the measured cost of variability can vary significantly year-to-year (Table 5).

Table 4. TEP Solar PV cost of variability using 1-, 5-, and 15-minute intervals

	TEP Solar PV $/MWh
1-minute	11.0
5-minute	9.7
15-minute	7.8

Table 5. Cost of variability is sensitive to the price differences over multiple years

$/MWh	CA 2005 prices	CA 2010 prices
20 MW+ PV	9.8	7.9
TEP Solar PV	12.6	11.0
NSO Solar Thermal	5.9	5.2
Wind (average)	5.0	4.3

3.3 Cost of Variability and CO_2 Displacement

One of the goals of an RPS is to reduce CO_2 emissions by replacing fossil fuel generation with renewable energy. By calculating the marginal emissions factors during each hour using the method described in Section 2.3, we can calculate the cost of variability in terms of emissions avoided. We note that this measurement is only part of the total cost of emissions avoided when considering renewable energy. Table 6 contains the average MEF and average cost of variability per ton CO_2 displaced for each generating unit.

Table 6. Average marginal emissions factors and cost of variability per unit emissions

Facility	Average marginal emissions factor (tons CO_2/MWh)	Average cost of variability per ton CO_2
20 MW+ Solar PV	0.56	$33
TEP Solar PV	0.47	$40
Wind (average)	0.51	$25
NSO Solar Thermal	0.48	$15

As a comparison, Dobesova et al. report the cost of abatement using wind power for the 2002 Texas RPS to be $56 per ton CO_2 ($70 per ton CO_2 in 2011 dollars), not including any costs of intermittency or variability (*7*). Our result suggests that variability may increase the true cost of CO_2 abatement using wind power by a third.

3.4. Policy Implications and Discussion

We show through a power spectral analysis of observed data that solar thermal generation is less variable than either wind or solar PV at periods of less than approximately three hours (frequencies greater than ~10^{-4} Hz). We also use time-domain data for PV, wind, and solar thermal to estimate the cost of variability. All calculations of the cost of variability used the same data for energy and ancillary service prices. We find that the cost of variability is greatest for solar PV generation at $11.0 per MWh. The cost of variability for solar thermal generation is $5.2 per MWh, while that of wind generation in ERCOT was found to be $4.3 per MWh. Variability adds $15/tonne CO_2 to the cost of abatement for solar thermal power, and $33-$40 for PV.

The Federal Energy Regulatory Commission (FERC) proposes in its Docket "Integration of Variable Energy Resources" to charge renewable energy resources a per-unit rate for regulation services related to the variability of generation (*8*). If the Docket is adopted, the rate would be the same across all types of generation, and utilities could use the common rate structure already in place under Schedule 3, which contains the rules governing variability of load in a service area. FERC envisions that individual transmission utilities can apply to charge different rates as long as they "demonstrate that the per-unit cost of regulation reserve capacity is somehow different when such capacity is utilized to address system variability associated with generator resources" (*8*).

Based on our results, we note that a flat rate under the Docket's Schedule 10 would advantage certain variable generators at the expense of others. However, since we have shown that cost of variability depends on both the type of generation and the capacity factor of the individual generating unit, FERC does well not to mandate specific rates for different technologies. One principle that the Docket mentions is "cost causation," or fairly determining a rate based on evidence that the rate is based on real costs. Using our methods and data from individual variable energy resources, utilities should work with generators to determine a fair rate for variability. We conclude that FERC Schedule 10 allows for this type of calculation and utilities can avoid creating market biases by calculating real costs of variability.

Renewable energy generators with lower variability costs require fewer ancillary services for support. Ancillary services often are supplied by gas-fired plants that can ramp up and down quickly. However the quick ramping of the current generation of these plants can increase emissions of NO_x, a criteria air pollutant (*9*). ISOs and those implementing solar power generation mandates can use the method described here to compare unpriced costs of variable and intermittent electricity generating technologies. FERC acknowledged the extra costs created by variable generation in Schedule 10, and advises utilities to charge generators a per-unit rate according to Schedule 3 (*8*). We suggest that utilities and generators examine the actual costs of variability before settling on a single per-unit rate.

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Supporting Information

Running the simulation with forecast data illustrates how the cost of variability can change without a perfect forecast. Here we present a method by which forecast data could be used to develop a likely range for the cost of variability. Because commercial forecast data were not available, we use NREL's System Advisor Model (SAM) as a proxy.

We simulate a forecast of the two data sets using NREL's SAM. SAM takes inputs from different types of renewable energy facilities and climate data, and uses that to simulate the outputs of a typical year of operation. However, SAM is meant to give developers and researchers a general idea of typical outputs of a prospective power plant, and not to make precise forecasts of actual annual output. Because of that, the hourly energy output data from the SAM tool was much less accurate than data that could be produced by today's forecasting techniques. The climate input data, including typical meteorological year (TMY) files or individual year files from 1998-2005, comes from NREL's Solar Prospector (*1*). We used individual year data from 1998-2005 to simulate a forecast for each location, and then averaged the forecasted electricity outputs.

The figures below show a comparison of the SAM output and the actual output for NSO and Springerville. The SAM outputs were normalized so that the total energy produced in the year is equivalent for the actual output and the SAM forecast. The SAM forecast for NSO was shifted one hour behind to match the actual NSO output. The mean error between the SAM forecast and the actual production of NSO is 8.2 MW, or 10.9% of its capacity. For TEP, it is 0.32 MW, or 6.4% of its capacity.

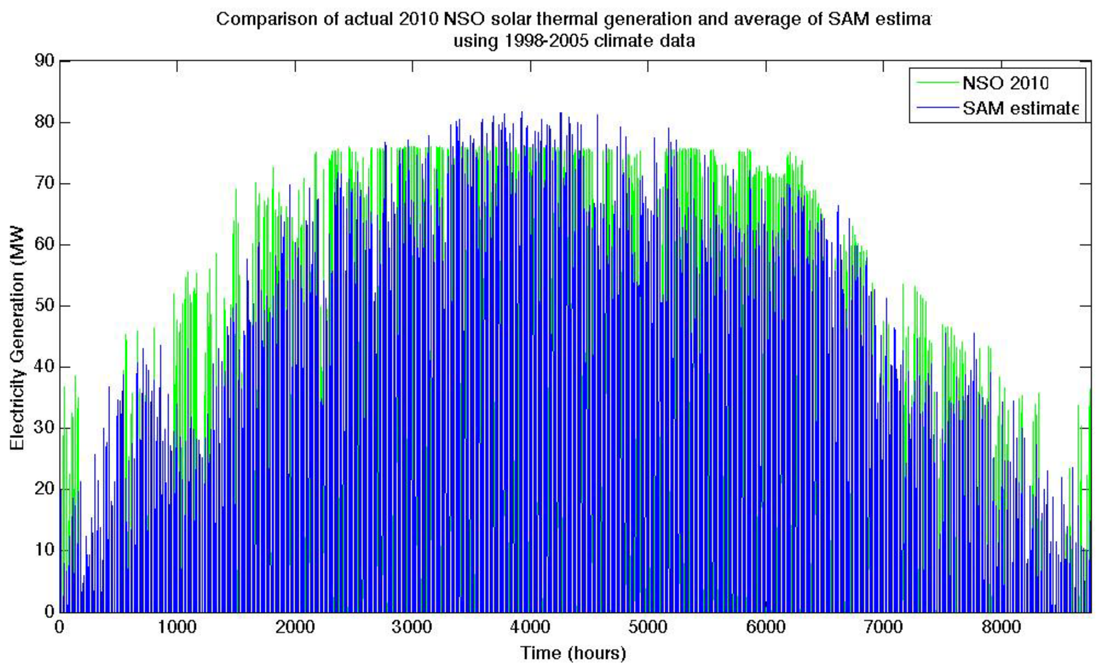

Figure S5. Comparison of actual and forecast NSO hourly electricity generation data

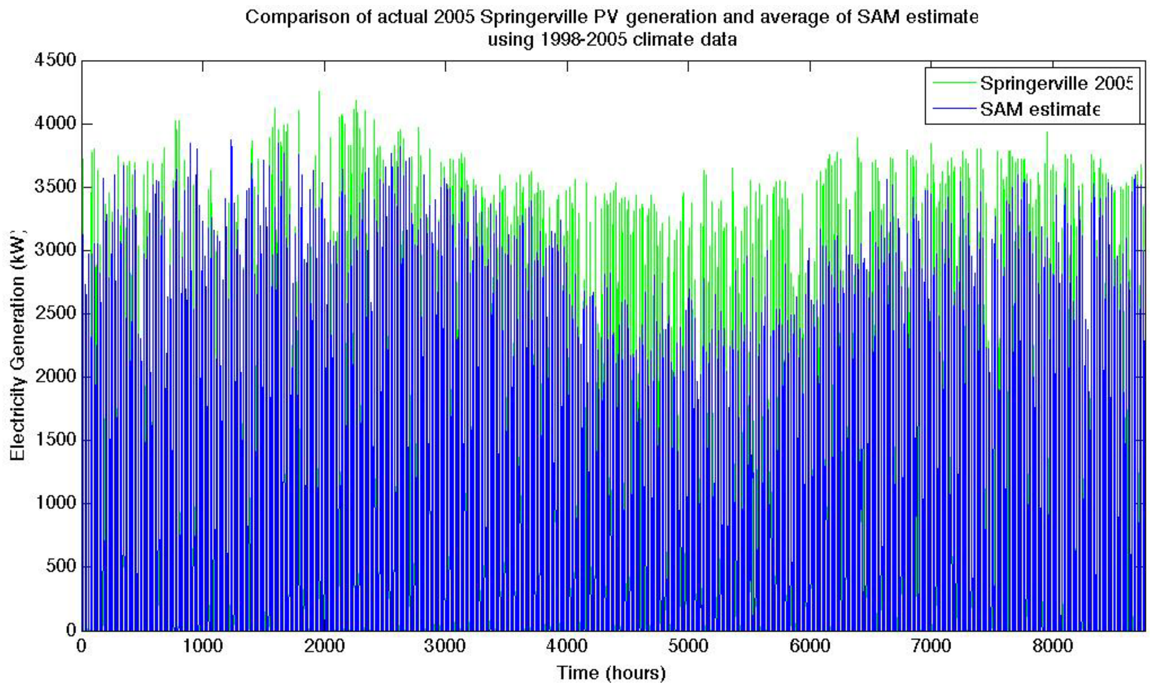

Figure S6. Comparison of actual and forecast TEP hourly electricity generation data

Using SAM to simulate an average year of operation, the cost of variability for the thermal and PV plants were $24/MWh and $23/MWh, respectively (Table S1).

Table S7. Cost of variability of solar PV and solar thermal and the average price of electricity in the CAISO zone or region

	Nevada Solar One Solar thermal	Springerville, AZ Solar PV
Cost per MWh	$5.2	$11.0
Cost per MWh using forecast simulation (normalized)	$24.0	$23.0

We note that the large difference between the perfect information cost of variability and forecast cost of variability, especially for solar thermal, is likely larger than it would be using actual forecast data. Real forecast data of solar PV and solar thermal facilities will be necessary to determine the real cost of variability of each technology. We think that the solar thermal variability and intermittency costs are likely to be lower than those of PV when real forecast data are used, and that SAM energy output estimates are less accurate for solar thermal than they are for PV.

(1) NREL Solar Prospector Map. http://maps.nrel.gov/prospector (accessed August 6, 2011).