Costs of Solar and Wind Power Variability for Reducing CO₂ Emissions

Colleen Lueken,*† Gilbert E. Cohen,‡ and Jay Apt§

†Carnegie Mellon University Electricity Industry Center, Department of Engineering and Public Policy, Carnegie Mellon University
5000 Forbes Avenue, Pittsburgh, Pennsylvania 15213, United States
‡Eliasol Energy, 11010 Lake Grove Boulevard, Suite 100, PMB 342, Morrisville, North Carolina 27560, United States
§Carnegie Mellon University Electricity Industry Center, Department of Engineering and Public Policy and Tepper School of Business, Carnegie Mellon University, 5000 Forbes Avenue, Pittsburgh, Pennsylvania 15213, United States

Support Information

ABSTRACT: We compare the power output from a year of electricity generation data from one solar thermal plant, two solar photovoltaic (PV) arrays, and twenty Electric Reliability Council of Texas (ERCOT) wind farms. The analysis shows that solar PV 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 that of 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 CO₂ 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 CO₂ 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 CO₂ to the cost of abatement for solar thermal power, $25 for wind, and $33−$40 for PV.

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 and other ancillary services. As these sources begin to provide a larger fraction of the electricity supply, the relative costs of their variability and the cost of variability for CO₂ emissions reduction may become important considerations in selection of technologies to meet renewables portfolio standards (RPSs).

We quantify the differences in variability among three types of renewable electricity generation: solar thermal, solar photovoltaic (PV), and wind, using power spectrum analysis. The power spectrum analysis in this paper follows the method used by Apt.1 Katzenstein et al. have examined wind variability using power spectra, and have shown that variability of a single wind farm can be reduced by 87% by interconnecting four wind farms, but additional interconnections have diminishing returns.2 In addition, we demonstrate how these differences in power spectra translate into different costs of variability. Katzenstein and Apt calculate the cost of wind power variability, and our analysis of the cost of variability of all three technologies uses a similar method.3 We focus on subhourly variability to calculate the cost of variability to a scheduling entity. Solar variability at subhourly time scales is caused by the movement of clouds across the sky; wind variability on this time scale is caused by turbulence and weather patterns.

Lavania et al. 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.4 Gowrisankaran et al. present an economic model to calculate the cost of solar power intermittency in a grid with high levels of solar penetration.5 They scale the power output of a 1.5 kW test solar facility in Tucson to simulate the solar power output. Researchers at LBNL compare the variability and variability costs of solar PV and wind using solar insolation and wind speed data.6

Reducing CO₂ emissions is a motivating factor behind integrating renewables into the electricity grid. Dobesova et al. calculated the cost of reducing CO₂ emissions through the Texas RPS, taking into account the added costs of transmission, wind curtailments, production tax credits, and RPS administration.7 Our calculation adds to their work by including only...
the cost of obtaining balancing and ancillary services for subhourly variability of the renewable resource per tonne of CO₂ abatement.

Our research differs from earlier solar PV studies because we use real power output data from operational utility-scale plants to calculate the variability and cost of variability. To our knowledge this is the first work to examine the variability and cost of variability of solar thermal power using real power output data. We also show how variability affects CO₂ emissions abatement. Comparing the costs of the three technologies can inform policy discussions about requiring technology set-asides for RPSs.

We find that at frequencies greater than ~10⁻³ Hz (corresponding to times shorter than ~15 min) solar thermal generation is less variable than generation from wind and considerably less variable than 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 ancillary service prices from California, the cost of variability considerably less variable than solar PV. Using energy and generation is less variable than generation from wind and ERCOT wind farms was $4 per MWh. Variability adds to the cost of abatement for solar thermal power, $25 for wind, and $33–$40 for PV.

2. METHODS AND DATA

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

We obtained data from EPA’s Clean Air Markets Data and Maps Web site on hourly emissions and electricity production for each thermal generating unit greater than 25 MW capacity in California for 2010.⁸ Using these data we calculate the cost of variability per unit of displaced CO₂ emissions.

2.2. Power Spectral Analysis. As described in Apt,¹ we examined the frequency domain behavior of the time series of power output data from the generation plants by estimating the power spectrum (the power spectral density, PSD). We compute the discrete Fourier transform of the time series. The highest frequency that can be examined in this manner, f_{max} is given by the Nyquist sampling theorem as half the sampling frequency of the data (i.e., 8.3 × 10⁻³ Hz for 1-min data). One of the attributes of power spectrum estimation through periodograms is that increasing the number of time samples does not decrease the standard deviation of the periodogram at any given frequency f_k. To take advantage of a large number of data points in a data set to reduce the variance at f_k, the data set may be partitioned into several time segments. The Fourier transform of each segment is then taken and a periodogram estimate is constructed. The periodograms are then averaged at each frequency, reducing the variance of the final estimate by the number of segments (and reducing the standard deviation by the reciprocal of the square root of the number of segments). Here we use 16 segments. This has no effect on f_{max} but increases the lowest nonzero frequency by a factor equal to the number of segments (i.e., for data sampled for a year, the lowest frequency is increased from 3.2 × 10⁻⁶ to 5.1 × 10⁻⁷ Hz for 16 segment averaging).

The PSD gives a quantitative measure of the ratio of fluctuations at high frequency to those at low. It is fortunate that the PSDs of wind, PV, and solar thermal are not flat (white noise). If that were true, large amounts of very fast-ramping sources would be required to buffer the fluctuations of wind and solar power. The observed spectra show that the power fluctuations at frequencies corresponding to 10 min, for example, is at least a factor of a thousand smaller than those at periods of 12 h. Thus, slow-ramping generators (e.g., coal or combined-cycle gas) can compensate for the majority of variability.

2.3. 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 or wind resource.³ 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 expected production. We use the absolute value of deviation because any deviation from the expected production obligates the ISO to pay a premium to traditional generators to either ramp down, to accommodate the must-take energy from the variable generator, or ramp up to make up for underproduction. 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 s) effects of variability, but that is outside the scope of this research because our data sets contain generation information down to only 1-, 5- or 15-min granularity. Calculation of the cost of variability is per eqs 1 and 2.

<table>
<thead>
<tr>
<th>type of charge</th>
<th>average hourly price ($) per MWh</th>
</tr>
</thead>
<tbody>
<tr>
<td>CAISO SCE energy (2010)</td>
<td>42</td>
</tr>
<tr>
<td>CAISO SP-15 energy (2005)</td>
<td>56</td>
</tr>
<tr>
<td>CAISO DAH up regulation (2010)</td>
<td>5.6</td>
</tr>
<tr>
<td>CAISO DAH down regulation (2010)</td>
<td>5.0</td>
</tr>
</tbody>
</table>
Figure 1. Solar thermal and solar PV data: (a) 2005 Springerville PV data; (b) one week of 2005 Springerville 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; (e) 2008 single ERCOT wind farm data; (f) one week of 2008 single ERCOT wind farm data.

Figure 2. Utilities use load following and regulation services to compensate for variability in solar and wind 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).
Variability Cost \((h)\)
\[
= \sum_{k=1}^{n} |\varepsilon_k| \frac{P_h}{n} + P_{up,h} \min(\varepsilon_k) + P_{down,h} \max(\varepsilon_k)
\]

Annual Average Variability Cost
\[
= \frac{\sum_{h=1.8760}^{1.8760} \text{Variability Cost} \,(h)}{\sum_{h=1.8760}^{1.8760} \sum_{k=1}^{n} S_{k,h}/n}
\]

where
- \(P_h\) is the hourly price of energy
- \(P_{up,h}\) is the hourly price of up regulation
- \(P_{down,h}\) is the hourly price of down regulation
- \(q_h\) is the amount of firm hourly energy scheduled in hour \(h\) (calculated as the mean of all \(S_{k,h}\) in hour \(h\)
- \(S_{k,h}\) is the actual subhourly production of energy in hour \(h\)
- \(\varepsilon_k = S_{k,h} - q_h\) is the difference between energy scheduled and produced in segment \(k\) of hour \(h\)
- \(n\) is the number of energy production records per hour
- \(60\) for Springerville PV, \(12\) for NSO, \(4\) for ERCOT wind, and \(60\) for the 20 MW+ PV array

The scheduled hourly energy production, \(q_h\), is the mean of all \(S_{k,h}\) for hour \(h\). In reality, an ISO would schedule \(q_h\) according to forecast data. By using actual energy production data instead, we calculate a lower bound estimate of actual variability costs. The second two terms in eq 1 represent the cost of up and down regulation for the hour.

Simulating the cost of variability using energy forecast data would give more information about the realistic costs of intermittency of wind, solar thermal, and PV. Actual forecast data for the RE generators in our analysis are unavailable, so we simulated solar 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 (SI).

Katzenstein and Apt’s method is similar, but instead of using the average hourly power production to set \(q_h\), they create an objective function to minimize the intermittency cost with the \(q_h\) as the decision variable. Comparing their method to ours, we find similar results and have chosen to use the average energy method to reduce computation times.

It would be possible instead to calculate the variability cost of net load (load minus output from one RE generator). However, the cost of net load variability is highly dependent on the magnitude of the load relative to the capacity of the variable generator under consideration. The variability signals of small generators, such as the 4.5 MW Springerville PV array, are dominated by the variability signals of much larger load regions, such as CAISO. Our calculation is meant to indicate of variability cost of an RE generator independently of its size and of the magnitude and variability of demand in its region.

We assume that all plants considered are price takers, 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.

2.4. Cost of Variability and Emissions Displacement.

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

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

\[
E_{\text{avoided}} = E_{\text{displaced}} - E_{\text{ancillary}}
\]

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

\[
cost_{\text{avoided emissions}} = \text{Variability cost} / E_{\text{avoided}}
\]

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, so we disregard the term \(E_{\text{ancillary}}\) in our calculation. This calculation is meant to be a lower-bound estimate of variability cost per emissions avoided, but one that treats solar thermal, PV, and wind in the same way.

We calculate \(E_{\text{displaced}}\) for each hour of the year based on the emissions of the marginal generating units and the quantity of power being supplied by the RE 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. 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 first, second, etc. marginal units are defined.

The marginal emissions factor in any given hour is

\[
M_{E} \,(h) = \sum_{i=1}^{U} \frac{M_{U_{\text{emission}}}(i, h)}{\sum_{i=1}^{U} M_{U_{\text{power}}}(i, h)}
\]

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.
where

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

\( i \) is a marginal power plant unit operating in hour \( h \)

\( U \) is the number of relevant marginal units operating in

hour \( h \)

\( MU_{\text{emission}}(i,h) \) is the \( CO_2 \) emissions rate of marginal unit

\( i \) in hour \( h \)

\( MU_{\text{power}}(i,h) \) is the power output of marginal unit \( i \) in

hour \( h \)

3. RESULTS

3.1. Power Spectral Analysis. We follow the method of

Apt to calculate the power spectra of a solar thermal plant, a

solar PV array, and a wind plant. Graphing multiple power

sources together and normalizing the spectra at a frequency

corresponding to a range near 24 h 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 \( \sim 15 \) min). Electricity from wind farms is intermediate

between solar PV and solar thermal in terms of variability in

this frequency range. High variability at frequencies corre-

sponding to less than 1 h 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-h 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 U.S., 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 \( \sim 4 \times 10^{-5} \) Hz (corresponding to

periods greater than 6 h).

3.2. Cost of Variability of Solar Thermal, PV, and

Wind. The average cost of variability of the Springerville PV

plant using average energy production levels to schedule

\( q_h \) and 2010 CAISO prices is $11.0/MWh. For the 20 MW+ class PV

array, the average cost of variability is $7.9/MWh. 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 smooths 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 \( q_h \)). This 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, with a range between $3.5/MWh and $6.2/

MWh. Variability costs of wind were on average lower than that

of solar thermal, despite the opposite trend appearing in Figure

4, because solar energy incurs all variability costs during the day

when electricity prices are highest. Wind turbines continue to

produce energy at night, when electricity prices are lower

(Figure S3 in the SI).

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) is consistent with the observed variability

characteristics (Figure 4).

The majority of the variability cost consists of charges for

balancing energy for all plants considered (Table 3). The

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average energy costs in 2010 were higher than the average regulation costs by nearly a factor of 8 (Table 1).

### Table 3. Cost of Variability Breakdown between Energy and Regulation Charges

<table>
<thead>
<tr>
<th>facility</th>
<th>energy costs</th>
<th>regulation costs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sprinerville solar PV</td>
<td>69%</td>
<td>31%</td>
</tr>
<tr>
<td>20 MW+ solar PV</td>
<td>65%</td>
<td>35%</td>
</tr>
<tr>
<td>NSO solar thermal</td>
<td>69%</td>
<td>31%</td>
</tr>
<tr>
<td>wind (average)</td>
<td>73%</td>
<td>27%</td>
</tr>
</tbody>
</table>

3.3. Cost of Variability and CO2 Displacement. One of the goals of an RPS is to reduce CO2 emissions by replacing fossil fuel generation with renewable energy. By calculating the hourly marginal emissions factors 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 4 contains the average MEF and average cost of variability per ton CO2 displaced for each generating unit.

As a comparison, Dobesova et al. report the cost of abatement using wind power for the 2002 Texas RPS to be $56 per ton CO2 ($70 per ton CO2 in 2011 dollars), not including any costs of intermittency or variability. Our result suggests that variability may increase the cost of CO2 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 3 h (frequencies greater than $10^{-4}$ Hz). The low variability of solar thermal power compared to wind and PV is caused by the thermal inertia: solar thermal can continue producing electricity from the heat in its working fluid during cloudy periods while solar PV cannot. Variability in wind power output is caused primarily by changes in wind velocity, which are more gradual than changes in cloud cover, but traditional wind turbines do not have the inertial capability to continue producing electricity during any but the briefest calm periods. We find that the cost of variability is greatest for solar PV generation at $7.9−11.0 per MWh, less for solar thermal generation at $5.2 per MWh, and lowest on average for wind at $4.3 per MWh. Variability adds $15/tonne CO2 to the cost of abatement for solar thermal power, $25 for wind, and $33−$40 for PV. These methods can be applied to any variable energy source to calculate the costs of variability and CO2 abatement.

Our results suggest that not all RE technologies should be treated equally in terms of variability charges. 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. The Docket states that ISOs may use the same rate they charge utilities for load variability in Schedule 3. 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". 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. 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. To avoid creating market biases, utilities can use methods like ours to determine how each variable generator contributes to total variability cost in its service area. Adopting proposals for intrahourly scheduling would also help ISOs reduce the cost of RE 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 NOx, a criteria air pollutant. 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.

### Table 4. Average Marginal Emissions Factors and Cost of Variability Per Unit Emissions

<table>
<thead>
<tr>
<th>facility</th>
<th>average marginal emissions factor (tons CO2/MWh)</th>
<th>average cost of variability per ton CO2</th>
</tr>
</thead>
<tbody>
<tr>
<td>20 MW+ solar PV</td>
<td>0.56</td>
<td>$33</td>
</tr>
<tr>
<td>Sprinerville solar PV</td>
<td>0.47</td>
<td>$40</td>
</tr>
<tr>
<td>wind (average)</td>
<td>0.51</td>
<td>$25</td>
</tr>
<tr>
<td>NSO solar thermal</td>
<td>0.48</td>
<td>$15</td>
</tr>
</tbody>
</table>
output measurements and the effect of increasing the frequency of scheduling power on cost of variability in Sections 3 and 4, respectively; Section 5 information about solar technologies; Section 6 hourly costs of variability of solar thermal and wind. This material is available free of charge via the Internet at http://pubs.acs.org.

■ AUTHOR INFORMATION

Corresponding Author
*Phone: +01 240 413 4685; e-mail: chorin@andrew.cmu.edu; mail: Instituto Superior Técnico, DEEC, AC Energia; Av. Rovisco Pais; 1049-001 Lisbon, Portugal.

Notes
The authors declare no competing financial interest.

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■ REFERENCES

The Cost of Solar and Wind Power Variability for Reducing CO₂ Emissions
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S1. Forecasts

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.

We have made the following alterations to Equation 1 to accommodate using forecast data for hourly energy scheduling:

\[
\text{Variability Cost}(h) = \sum_{k=1}^{n} \varepsilon_k \left[ P_{h,k} / n + P_{up,h} \right] \min \left\{ \begin{array}{c} 0 \\ \min(\varepsilon_k) \end{array} \right\} + P_{dn,h} \max \left\{ \begin{array}{c} 0 \\ \max(\varepsilon_k) \end{array} \right\}
\]

In case the observed minimum power output is greater than the scheduled hourly energy, \( q_h \), Equation 1 would have calculated a negative cost for up regulation, and vice versa if the observed maximum power output for the hour is less than \( q_h \). Equation S1 would make the cost of up or down regulation in those cases zero.

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 S1. Comparison of actual and forecast NSO 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 S1. Cost of variability of solar PV and solar thermal and the average price of electricity in the CAISO zone or region

<table>
<thead>
<tr>
<th></th>
<th>Nevada Solar One</th>
<th>Springerville, AZ</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Solar thermal</td>
<td>Solar PV</td>
</tr>
<tr>
<td>Cost per MWh</td>
<td>$5.2</td>
<td>$11.0</td>
</tr>
<tr>
<td>Cost per MWh using forecast simulation (normalized)</td>
<td>$24.0</td>
<td>$23.0</td>
</tr>
</tbody>
</table>

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.

S2. Seasonality of the Cost of Variability

Wind and solar power availability varies on seasonal frequencies in addition to the shorter frequencies analyzed in this paper. We have calculated two seasonal costs of variability for each plant, one for winter (defined as January 1-March 21) and one for summer (defined as June 21- September 21). Table S2 summarizes the results.

Table S2. Summer and winter costs of variability

<table>
<thead>
<tr>
<th></th>
<th>Summer</th>
<th>Winter</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average cost of variability per MWh</td>
<td>Standard deviation of cost of variability per MWh</td>
</tr>
<tr>
<td>NSO</td>
<td>$3.9</td>
<td>$8.3</td>
</tr>
<tr>
<td>Wind</td>
<td>$4.9</td>
<td>$8.4</td>
</tr>
<tr>
<td>Springerville PV</td>
<td>$12.6</td>
<td>$37.4</td>
</tr>
<tr>
<td>20 MW+ PV</td>
<td>$7.2</td>
<td>$11.4</td>
</tr>
</tbody>
</table>

There is a marked difference in the cost of variability of the solar thermal (NSO) plant between summer and winter. On average, the cost of variability in winter is 60% higher than it is in the summer. The cost of variability of the two solar PV plants is also higher in winter than in summer, but not by as much as the solar thermal plant: 25% for the 20 MW+ PV plant and 8%
for the Springerville PV plant. The cost of variability of the wind farms in summer is 9.5% higher than in winter.

S3. Effect of Period Between Power Measurements on Cost of Variability

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 slightly reduces 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 S3). We also note that the measured cost of variability can vary significantly year-to-year (Table 2).

Table S3. Average cost of variability using 1-, 5-, and 15-minute intervals

<table>
<thead>
<tr>
<th>Interval</th>
<th>NSO</th>
<th>Wind</th>
<th>Springerville PV</th>
<th>20 MW+ PV</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-minute</td>
<td>-</td>
<td>-</td>
<td>$11.0</td>
<td>$7.9</td>
</tr>
<tr>
<td>5-minute</td>
<td>$5.2</td>
<td>-</td>
<td>$9.7</td>
<td>$7.1</td>
</tr>
<tr>
<td>15-minute</td>
<td>$4.6</td>
<td>$4.3</td>
<td>$7.8</td>
<td>$6.0</td>
</tr>
</tbody>
</table>

S4. Effect of Intra-hourly Scheduling on Cost of Variability

Many ISOs are considering implementing intra-hourly scheduling to take advantage of updated forecasts for variable generation and load. We calculate new costs of variability for the different technologies if they were able to schedule their generation twice each hour.

Table S4. Intra-hourly Scheduling Cost of Variability

<table>
<thead>
<tr>
<th>Plant</th>
<th>Average cost of variability ($/MWh) with intra-hourly scheduling</th>
<th>Average cost of variability ($/MWh) with hourly scheduling</th>
</tr>
</thead>
<tbody>
<tr>
<td>NSO</td>
<td>$2.5</td>
<td>$5.2</td>
</tr>
<tr>
<td>Wind</td>
<td>$2.2</td>
<td>$4.3</td>
</tr>
<tr>
<td>Springerville PV</td>
<td>$7.8</td>
<td>$11.0</td>
</tr>
<tr>
<td>20 MW+ PV</td>
<td>$5.2</td>
<td>$7.9</td>
</tr>
</tbody>
</table>

S5. Description of Solar Technologies

Solar photovoltaic technology uses energy from sunlight to create electricity by exciting electrons on a photovoltaic material such as silicon. 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.
S6. Hourly Cost of Variability for Solar Thermal and Wind

The annual average cost of wind variability is lower than that of solar thermal, despite its higher variability (as seen on the power spectral density graph) because wind displays a significant amount of variability at night, when electricity prices are generally lower.

Figure S3. Average hourly cost of variability for wind and solar thermal power

References: