

# SPATIAL AND TEMPORAL INTERACTIONS OF SOLAR AND WIND RESOURCES IN THE NEXT GENERATION UTILITY

Bryan Palmintier  
Lena Hansen  
Rocky Mountain Institute  
1820 Folsom St.  
Boulder, CO 80302  
bpalmintier@rmi.org  
lhansen@rmi.org

Jonah Levine  
ECE-Eng-Elect/Comp Admin  
University of Colorado at Boulder  
425 UCB  
Boulder, CO 80309-0425  
jonah.levine@colorado.edu

## Abstract

The “next generation” electric utility must incorporate variable renewable resources, including wind and solar, in much larger quantities than conventionally thought possible. While resource variability presents a challenge, it should be possible to reduce and manage that variability by geographically distributing renewables, combining them with different renewables, and having more dynamic control of electric loads.

This study shows that interconnecting individual solar generation sites into geographically diverse arrays can reduce power output variability, and that including solar generation sites in arrays of geographically diverse wind sites can further reduce the total variability beyond what is possible for either resource type alone. Specifically, optimized portfolios offer an average decrease in variability of 55% below the average of all individual sites. Finally, it was observed that, in the modeled system, only a small subset of the potential sites in an interconnected array need to be included to achieve these variability reductions.

## 1 INTRODUCTION

The ever-growing energy demands of the 21<sup>st</sup> century are dependent upon a power infrastructure designed for the early 20<sup>th</sup> century. Advances in digital communications and renewable energy technologies could facilitate a transition to a “next generation utility” that fully integrates both supply- and demand-side resources in a way that can enable significantly larger penetrations of variable renewable energy technologies than conventionally thought possible.

This paper begins with a brief overview of the “next generation utility” concept, then turns to the ability of the

next generation utility to incorporate solar and wind power on a large scale, driven by geographical dispersion of both solar and wind resources at utility and larger scales, cross-firming of solar and wind resources, and increased grid flexibility to absorb and mitigate variability.

## 2 THE NEXT GENERATION UTILITY

A new electric utility paradigm is needed to meet increasing demands for power quality and reliability and to significantly reduce global greenhouse gas emissions generated by electricity production. A new generation of power technology is developing, however, and can enable the “next generation utility”, which will involve (see Fig. 1):

- Fully capturing the potential of energy efficiency and demand response;
- De-carbonizing electric supply through greatly increased penetration of renewable and distributed supply technologies; and
- Electrifying or substituting clean, renewable fuels for loads that would otherwise depend on fossil fuel, including vehicles.

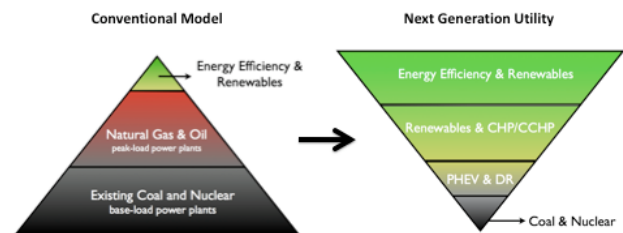


Fig. 1: The next generation utility will turn generation infrastructure on its head, with a mix dominated by efficiency and renewables with minimal coal and nuclear.

A key tenet of the next generation utility concept is that it should be possible to provide the energy services required by our modern society using significantly less “baseload” coal and nuclear power. Doing so requires increased reliance on variable renewable sources and more dynamic control of energy demand, and consequently, more focus on short time scales.

Taken together, the components of the next generation utility can be thought to interact as seen in the load duration curve in Fig. 2 below. Specifically, radical gains in building energy efficiency should reduce the entire demand significantly. Demand is then met largely through an intelligently designed portfolio of variable and “firm” renewable resources. Finally, remaining demand is met through a combination of distributed generation (combined heat & power and combined cooling, heat & power), demand response and plug-in hybrid electric vehicles.

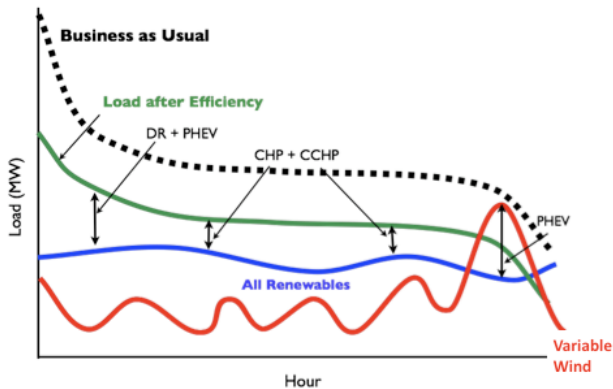


Fig. 2: Conceptual load duration curve for a next generation utility.

The design of the next generation utility concept is currently under development by Rocky Mountain Institute. This paper describes research around new strategies for integration of large-scale variable renewable resources.

### 3 BACKGROUND

One of the primary goals of electric utilities is maintaining the reliability of the electric system—the implication being that the reliability of any individual generator is only important in the larger context of system reliability. This insight also recognizes that all generators, both conventional and variable, have some probability of failure. The forced outages of conventional generators result from unplanned mechanical failures, whereas the effective “forced outages” of variable generators are due to the risk of “fuel” (i.e., wind or sun) availability. These two factors lead to the conclusion that we must evaluate variable renewable generators for their contribution to overall system reliability, rather than the reliability of an individual renewable generator.

Because of the implications for reliability, capacity credit—the amount of capacity that can be counted on to contribute to system reliability—has financial value and can therefore greatly improve the cost-effectiveness of wind power. Conventional wisdom holds that capacity credit is given to an individual site based on the individual site characteristics. (Milligan 2002) This philosophy generally leads to the assumption that wind farms have little or no capacity value because the degree of the resource’s variability is so high at each individual site. (Kirby, et al 2002)

Similarly, while solar is more predictable than wind, it is still variable and therefore given little credit for contributing to system reliability.

However, modern financial portfolio theory offers a different way of looking at the world. A financial portfolio consists of a combination of individual stocks. Developed by Harry Markowitz in 1952, modern portfolio theory enables the creation of minimum-variance portfolios for a given level of expected return. This theory is based on diversification—the lower the correlation between the individual assets that make up the portfolio, the lower the portfolio variance, or risk. (Alexander 1996)

Portfolio theory can be easily applied to energy resources. In this context, a renewable portfolio can comprise a geographically dispersed set of wind farms and solar electric systems. This paper seeks to analyze the reliability value, and therefore capacity value, of a set of wind and solar generators dispersed across the U.S. Midwest.

## 4 DATA AND METHODS

### 4.1 Data Sources

This study attempts to maximize the use of high quality measured wind speed and solar insolation data. All data were recorded at hourly intervals. The wind data was measured at or near a 50-80 meter hub height and the solar data includes separate direct and diffuse radiation values.

This initial analysis is limited to the Midwest Reliability Organization (MRO) for the 2004 calendar year. This region and timeframe were selected from among those previously analyzed by Hansen & Levine (2008) because they provided the highest number of corresponding sites for which measured solar data was available.

The wind data was chosen from the RMI/UC-Boulder wind database compiled by Levine and Hansen (Levine 2007, Hansen & Levine 2008). The original source for the MRO wind data was the University of North Dakota Energy & Environmental Research Center (EERC) hosted Plains

Organization for Wind Energy (POWER) database.<sup>1</sup> Thirty-five (35) wind sites from MRO were included in this analysis.

All solar data was taken from the National Solar Radiation Database (NSRDB) 1991-2005 Update maintained by the National Renewable Energy Lab (NREL).<sup>2</sup> Though this database contains radiation data for 1,454 sites, only 40 of these sites include *measured* data.

For the region and period of interest – MRO in 2004 – three solar insolation sites were selected with measured data for 90% or more of the time. An additional five modeled sites were selected to increase the spatial diversity of the dataset. These modeled sites were carefully selected to be class-I sites with 100% low data uncertainty during 2004. (NREL 2007)

#### 4.2 Data Preparation

Both wind speed and solar insolation data were first cleaned to remove any negative, grossly out of range values, or flagged as invalid points. These removed points were conservatively set to zero. The measurement times were also normalized to coordinated universal time (UTC) to ensure data alignment across time zones.

For wind, the raw wind speed was converted to a consistent 80-meter or greater hub height using the methodology described in detail in Hansen and Levine (2008). In summary, all data gathered at lower than 40m were discarded, data gathered between 40m and 80m were scaled up to 80m, and all data gathered at or above 80m were left at the recorded height. Wind speeds were adjusted for height using the one-seventh-power rule.

For solar, both direct (beam) insolation and diffuse horizontal collector data was included. Where measured solar data was not available on an hour-by-hour or site-by-site basis, modeled data was substituted when possible.

#### 4.3 Wind Power Production Model

As described further in Hansen & Levine (2008), the 2 MW Vestas V80 was chosen to model power production. The turbine's power curve was adjusted for elevation and air density at each site.

#### 4.4 Solar Power Production Model

Solar power production was modeled for an idealized 1-axis polar mount tracking photovoltaic system with a maximum power point (MPP) tracker. Although solar thermal systems

are more common for utility scale solar power, a photovoltaic system was chosen in this analysis because:

- The NSRDB-Update modeled direct insolation data does not adequately capture some frequency components important for solar thermal analysis (Renné, et al 2008); and
- Concentrating solar power production, including solar thermal is less suited for areas, such as MRO, where diffuse radiation comprises a substantial portion of the total insolation.

The model system was tilted at an angle above horizontal equal to the site latitude. The Maximum Power Point (MPP) current was assumed to vary linearly with insolation. Temperature effects and decreased MPP voltage at lower insolation levels were not included. An isotropic sky is assumed and implies equal diffuse radiation intensity in all directions. Reflected radiation is conservatively assumed to be zero. Other losses, including conversion and inverter efficiencies were assumed to be constant. Since the system was scaled to a fixed total AC nameplate power it was not necessary to quantify these other losses. The resulting equations for insolation and power production are:

$$I_{1-axis} = I_B \cos \delta + I_{DH} \left[ \frac{1 + \cos(\zeta + \delta)}{2} \right]$$

$$P_{1-axis} = I_{1-axis} \times P_{nameplate}$$

Where  $I_B$ =direct (beam) insolation,  $I_{DH}$ =horizontal diffuse insolation,  $\delta$ =solar declination, and  $\zeta$ =zenith angle. (adapted from Masters 2004)

Though this model is very simple, it is adequate to capture the time variability of the solar resource, which is the primary concern in this study. Further efforts are underway to refine this model to both include non-idealities and the balance of system hardware and to compare other solar power system designs including fixed photovoltaics and concentrating solar technologies.

#### 4.5 Scaling and Interconnection

As described in section 3, this study combined multiple individual generation sites to create portfolios of geographically and resource (wind vs. solar) diverse generation. This analysis does not consider the constraints and losses associated with an interconnecting transmission system and other infrastructure components.

To facilitate comparisons of results for different scenarios, all individual wind and solar site data was scaled to a nameplate power rating of 100 MW AC. For solar, this scaling was done on the AC power rating at 1-sun (1000

<sup>1</sup> Available on line at: [www.undecr.org/programareas/renewableenergy/wind/default.asp](http://www.undecr.org/programareas/renewableenergy/wind/default.asp)

<sup>2</sup> Available on-line at: [http://trredc.nrel.gov/solar/old\\_data/nsrdb/1991-2005/](http://trredc.nrel.gov/solar/old_data/nsrdb/1991-2005/)

W/m<sup>2</sup>). When multiple sites were interconnected to form a portfolio, individual site output power was scaled such that the total nameplate power for the portfolio was kept at 100 MW. The selection of 100 MW was arbitrary, and the results can be readily scaled up (or down) as needed. The use of 100 MW also affords easy conversions to/from percent of nameplate load.

#### 4.6 Variability and Output Metrics

The variability of site (or portfolio) output was quantified as the standard deviation,  $\sigma$ , of the (combined) hourly power production in MW. The standard deviation also has units of MW. The output was quantified as the arithmetic mean of the hourly power production in MW. If desired, this average output measure can be converted to annual energy production in MWh by multiplying by the number of hours in a year.

In addition to representing important considerations for integrating a variable resource into a utility load, the choice of mean and standard deviation allow for significant computational savings when optimizing large portfolios. This is because, rather than having to recalculate the hour-by-hour power output at each optimization step, it is only necessary to scale the covariance matrix and mean.

The computation of the portfolio mean power output,  $\overline{p_p}$ , for  $n$  sites is straightforward:

$$\overline{p_p} = \sum_{i=1}^n a_i \overline{p_i}$$

where  $a_i$  is the percent share, or weight, of generating capacity for an individual site. And  $\overline{p_i}$  is the mean of the hourly output series,  $P_i$ , of the corresponding site.

The computation of the portfolio standard deviation,  $\sigma_p$ , takes advantage of the fact that the variance ( $\sigma^2$ ) of the sum of a set of random variables,  $X_i$ , is equal to the sum of the elements in their covariance matrix. Namely,

$$\text{Var}(X_1 + X_2 \dots X_n) = \sum_{i=1}^n \sum_{j=1}^n \text{Cov}(X_i, X_j)$$

And the property that the covariance of scaled random variables is equal to the scaled covariance of the original variables:

$$ab \text{Cov}(X, Y) = \text{Cov}(aX, bY)$$

As a result, the portfolio output power standard deviation is given by:

$$\sigma_p^2 = \sum_{i=1}^n \sum_{j=1}^n a_i a_j \text{Cov}(P_i, P_j)$$

or in Matrix form:

$$\sigma_p^2 = \mathbf{a}^T \boldsymbol{\mu} \mathbf{a}$$

where:

$$\mathbf{a} = \begin{bmatrix} a_1 \\ \vdots \\ a_n \end{bmatrix} \quad \boldsymbol{\mu} = \begin{bmatrix} \text{Var}(P_1) & \cdots & \text{Cov}(P_1, P_n) \\ \vdots & \ddots & \vdots \\ \text{Cov}(P_1, P_n) & \cdots & \text{Var}(P_n) \end{bmatrix}$$

since  $\text{Cov}(X, X) = \text{Var}(X)$ .

#### 4.7 Optimization Methodology

The portfolio variability was minimized using Monte Carlo methods subject to a constraint on the average output power:

$$\text{minimize}(\sigma_p) \quad \text{subject to} \quad \overline{p_p} \geq p_{limit}$$

This portfolio power constraint,  $p_{limit}$ , was varied from the minimum to maximum single site output average power,  $p_i$ , for the set of sites in a scenario.

Rather than running a separate optimization for each  $p_{limit}$ , in which any runs that did not meet the constraint must be thrown out, the results of each Monte Carlo trial were binned according to output level. In this way the simulation lets us run multiple constrained optimizations simultaneously.

Also, to more fully explore the potential value of sparse portfolios, at the start of each trial random weights were assigned not to all  $n$  sites, but to a randomized subset,  $\mathbf{N}$ , of the available sites. This was necessary since the probability of multiple zero or near-zero share members existing in a portfolio of randomly weighted sites drops precipitously with increasing  $n$ .

#### 4.8 Treatment of Constrained Number of Sites

During the analysis, it was noticed that the optimal portfolio rarely contained all of the sites. Further investigations were conducted to determine the impacts of restricting the number of sites included in the portfolio.

This introduced an additional constraint to the optimization:

$$\text{length}(\mathbf{N}) \leq n_{\text{limit}}$$

Separate simulations were run for each value of  $n_{\text{limit}}$ .

In these scenarios, the subset of sites with nonzero output shares was randomly selected for each trial from the entire appropriate set of power data (e.g. all wind sites). In this way, the members in the subset of sites was allowed to vary to achieve the optimal results across a spectrum of output levels. The sites represented at low output levels for a given  $n_{\text{limit}}$  would typically be different than those included in a higher output portfolio for the same  $n_{\text{limit}}$ .

## 5 RESULTS AND DISCUSSION

### 5.1 Wind alone

Given the growing body of literature on the subject (Archer & Jacobson 2007, for example) and the results of prior studies by the group using different optimization methods (Hansen & Levine 2008), it was not surprising to find that the power production for an optimized portfolio of wind assets was less variable than that for its sites individually.

Specifically, optimized wind portfolios for MRO in 2004 reduced output variability an average of 45%<sup>3</sup> compared to the individual sites and increased the capacity factor from 0.19 to 0.25<sup>4</sup>. The 80/90/95/99% available output level also increased from an average of 1.5/0/0/0MW to 9/6/4/1MW<sup>5</sup>.

### 5.2 Solar alone

Similar to wind, combining solar generating assets into an optimal portfolio reduced the output variability compared to that of the individual sites. Optimized solar only portfolios for MRO in 2004 reduced output variability an average of 15% compared to the individual sites and increased the capacity factor from 0.23 to 0.25. Because the sun sets, the power output for individual solar sites is zero at least half of the time. When combined into a portfolio, this increased to 8 MW of firm output capacity available 50% of the time.

A major factor in this reduced variability comes from the range of longitudes included in a portfolio. Increasing longitudinal spans makes it possible for the sun to be available to some collector in the portfolio for more hours of

<sup>3</sup> All portfolio averages include the two middle quartiles of the set of optimal portfolios.

<sup>4</sup> CF for portfolio with moderately high output and standard deviations (bin 15/20) vs site average.

<sup>5</sup> Increased guaranteed output levels for portfolio with moderately high output and standard deviations (bin 15/20.)

the day. Spatial diversity of solar also reduces the impact of patchy clouds covering the sun, since it is likely that the sun will be unobscured at one of the other sites.

In this analysis, the variability reduction was less dramatic than for wind, largely because solar radiation is more correlated between sites than wind speed. In fact, the minimum covariance between individual solar sites is 50x higher than that for wind sites.

### 5.3 Solar & Wind Together

When combined, solar and wind resources provide optimal portfolios which offer further decreases in power variability beyond that of either alone.

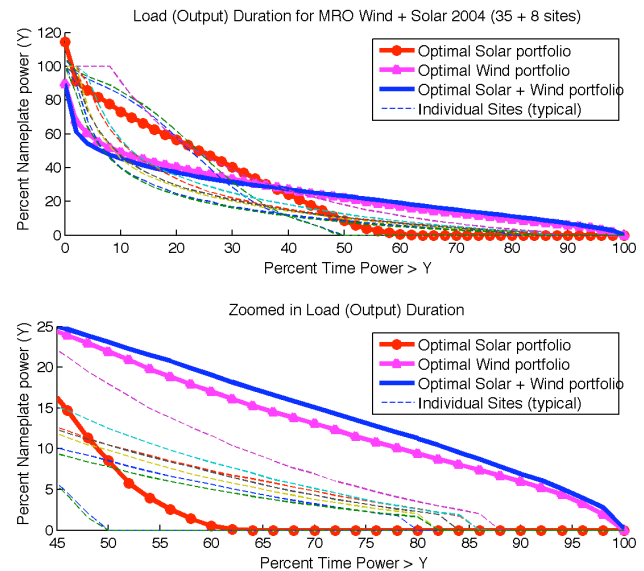


Fig. 3: (top) Load-duration-style output curves for optimal portfolios. A high, flat line that is never at zero is best. (bottom) Zoom in on the lower right showing significantly improved firmness of output for portfolios.<sup>6</sup>

In this analysis, both the wind-only and solar-only covariance matrices were strictly positive, indicating that the resource specific power production was more or less correlated. In the combined solar & wind scenario, negative elements appear corresponding to an anti-correlation between the solar and wind resources which is a powerful indicator for the potential of cross-firming.

Optimized portfolios offer an average decrease in variability of 55% below the average of individual sites. This represents a 13% lower average variability than the optimal for wind only and 60% lower than the optimal solar. The

<sup>6</sup> The portfolios depicted as optimal in these figures are those with moderately high output and standard deviations. (bin 15/20). See section 5.4 for further discussion.

combined optimal capacity factor was 0.25 and the 80/90/95/99% available output increased to 11/7/4/2 MW.

The top chart in Fig. 3 compares the output duration improvements for the optimal combined portfolios with those of the individual technology portfolios and those of an arbitrary subset of the individual sites. The upper plot shows that all of the optimal portfolios and the combined wind+solar and the wind-only profiles in particular, have a relatively flatter profile, illustrating that a narrower range of output levels is produced for a majority of the time. The combined portfolio produces the flattest profile, illustrating its further variability reductions. The flat regions of the curve are also higher than those of the individual sites, indicating an increase in reliable output power during these periods of reduced variability.

The bottom chart in Fig. 3. shows that the optimal combined and wind-only portfolios eliminate the amount of time with zero output. This represents a significant improvement above the roughly 15% of the time the wind sites in this analysis have zero output. The optimal solar-only portfolio also shows a large reduction in zero output from 50% to 40% of the time.

Some of the ways in which the solar and wind resources compliment each other are illustrated in Fig. 4. At night, the wind generators provide power when the sun can't. During the afternoon of May 27<sup>th</sup> and all day on May 28<sup>th</sup> solar output is able to compensate for low wind power output to produce a lower variability output.

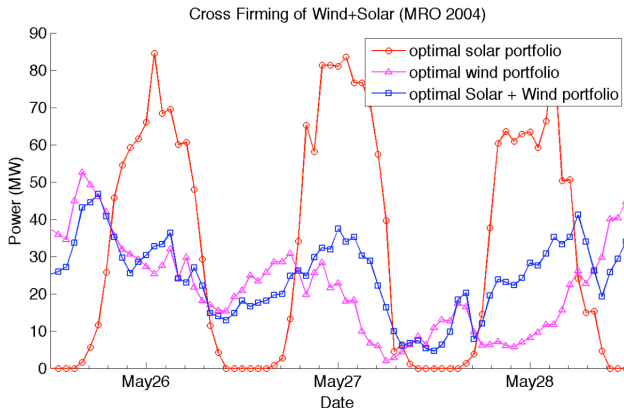


Fig. 4: Generation profile of optimal portfolios.

#### 5.4 Trade-offs

For each scenario there is a set of optimal portfolios that represent a trade-off between variability (standard deviation) and power output ( $p_p$ ).

This concept is represented graphically with the efficient frontier shown in Fig. 5 This plot shows the trade-off between risk (variability) and reward (output). Individual

sites appear as points, while optimal portfolios lie along a curve. Moving toward the left (lower variability) and up (higher output) represent desired trajectories. A utility can pick from along the curves to select the best-suited balance of output and variability.

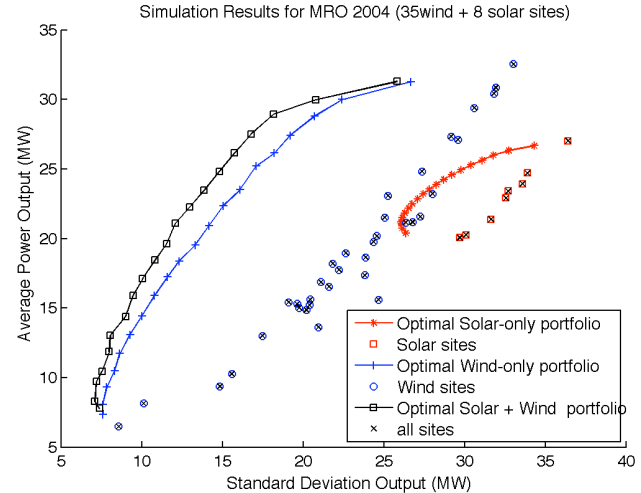


Fig. 5: Tradeoff of output power vs variability. Upper left is best.

In the figure it is clear that in all cases – wind-alone, solar-alone, combined solar and wind – the optimal portfolios offer decreased variability (standard deviation) for a given output level and/or increased average power output for a given variability compared to their associated individual sites alone. This figure also clearly shows the added value of cross-firming wind with solar to allow a few percentage points of increased output or decreased variability.

#### 5.5 Effect of Number of Site Constraints

This study conducted preliminary analysis on the impacts of limiting the number of sites selected for a portfolio. As seen in Fig. 6, including only a few of the available sites can achieve the majority of reductions in variability (or increases in output). A marked improvement in variability is achieved by interconnecting portfolios as small as two sites and portfolios of only six optimally chosen sites are nearly indistinguishable from the unconstrained optimums.

Furthermore, the actual number sites that make up the optimal portfolios for less-constrained simulations is observed to be much lower than  $n_{limit}$  as seen in Table 1. This could plausibly be due to the difficulty of finding optimal solutions from the extremely large number of combinations of sites and weights for high  $n_{limit}$  scenarios. However, increasing the number of trials, which should increase the odds of locating an optimal portfolio with a high number of sites, has instead been observed to further reduce the number of sites in optimal portfolios. This

observation taken together with the trend that increasing  $n_{limit}$  beyond a certain point does not significantly affect the variability, provides support for the theory that the optimal portfolio for a given output level does not contain all of the sites.

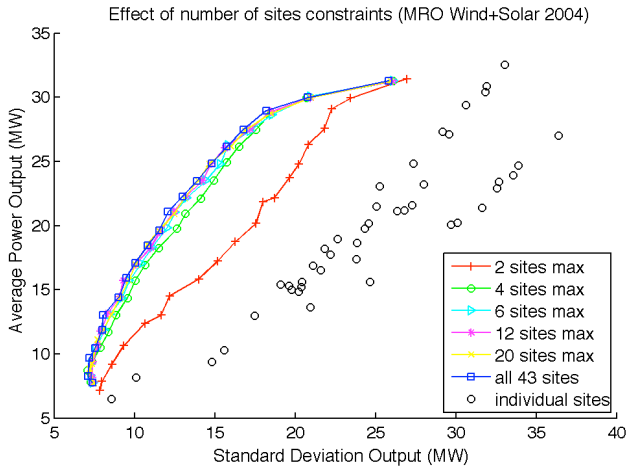


Fig. 6: Improvement in variability for a given output can be had with only a few optimally selected sites.

This analysis shows rapidly diminishing returns for decreasing variability by increasing  $n_{limit}$  for a given geographic region. Others, including Archer and Jacobson (2007), have shown seemingly contradictorily results that the variability of power output tends to decrease monotonically with the number of sites interconnected in an array with only gradually diminishing returns. One possible explanation is that the number of sites available to draw from when creating a portfolio, rather than the actual number of interconnected sites is the key to reducing variability. Further investigation is required to better understand this phenomenon.

**TABLE 1: OPTIMAL PORTFOLIO RESULTS (WIND+SOLAR)**

Max Sites Constraint	Avg # Sites in Best Portfolios	Average Drop in Std. Dev. <sup>7</sup>
2	2.0	9.0 MW
4	4.0	13.0
6	5.5	13.4
12	8.8	13.7
20	9.8	13.8
43 (all)	8.1 <sup>8</sup>	13.8

<sup>7</sup> Relative to the average std. dev. of individual sites of 25MW

<sup>8</sup> The full portfolio is the result of 5-10x as many simulations as the other sites.

## 6 SOLAR AND WIND IN A NEXT GENERATION UTILITY

While geographical dispersion of variable resources and the combination of different variable resources can significantly reduce portfolio variability, as described in this paper, the remaining variability must be managed in order to balance demand and supply on the hourly, minute, and second scales.

This balancing currently happens through the use of automated generation control and ancillary services. However, with greatly increased penetrations of variable renewables, more flexible capacity will be required. Given advances in communications and control technologies, much of this remaining variability could be met effectively through the dynamic use of:

- **Responsive Loads**—demand response has traditionally been used to clip and shift on-peak demand to off-peak periods in order to defer building new generation capacity. Increasing the magnitude and duration of demand response contributes to controlling absolute demand growth. Furthermore, developing demand response techniques that can operate at more than just peak periods should allow demand response to provide ancillary grid services and help manage renewable variability. Previous pilot projects in California and Nevada have shown that automated technologies with two-way digital communications can successfully drive demand response;
- **Energy Storage**—powerful system performance synergies can be derived from the integration of the electric and transportation sectors through the use of plug-in hybrid electric vehicles and full electric vehicles. For the electric utility, PHEVs and EVs (collectively xEVs) offer responsive off-peak load, the potential for dispatchable on-peak capacity from vehicle-to-grid (V2G) connections, and the prospect of economic electric storage, since the high capital costs of batteries would be shared with drivers; and
- **Intelligent Grid Communications**—Increased use of responsive load and xEVs requires advanced grid communications technologies. Utilities must be able to communicate in real-time with loads and xEVs to make most effective use of the firming capabilities of those resources. Such capabilities are being explored in on-going research into “smart grid” technologies.

## 7 CONCLUSIONS

This study shows that, as is the case for wind, interconnecting individual solar generation sites into

geographically diverse arrays can reduce the variability of the power output. It also shows that including solar generation sites into arrays of geographically diverse wind sites can further reduce the total variability beyond what is possible for either resource type alone. Finally, it was observed that, at least in the modeled system, only a small subset of the potential sites in an interconnected array need to be included to achieve these variability reductions.

## 8 NEXT STEPS

To expand and enhance this analysis for incorporation into the next generation utility concept, there are several additional elements of analysis that will be addressed, including:

- **Other geographic areas**—this analysis covers only the Midwest Reliability Organization (MRO). As with the wind-only analysis conducted by Hansen & Levine in 2008, this analysis will be expanded into the Southwest Power Pool (SPP) and the Electric Reliability Council of Texas (ERCOT). Additionally, both the wind-only analysis and the wind and solar analysis will be expanded into the Western Electric Coordinating Council (WECC). Once these regions have been analyzed, the majority of good wind and solar sites within the continental United States will have been addressed.
- **Longer time periods**—this analysis comprises only the year 2004. To more accurately capture the variability over time of both wind and solar power, hourly data over at least three years should be analyzed. This expanded analysis will be conducted as possible given the availability of hourly data in a consecutive three-year period.
- **Match to load shape**—as discussed at the beginning of this paper, renewable resource variability is only important in the context of system load. Therefore, a complete analysis includes the covariance of renewables with load over the same time period. This type of analysis, frequently referred to as the effective load carrying capability (ELCC) of a renewable resource, is dependent in part on the ability to acquire accurate hourly load data.
- **Integration with demand-side resources**—finally, the next generation utility project will analyze the interactions between variable renewable resources and demand-side resources, including responsive load and xEVs. The ability of these resources to manage renewable variability largely depends on the duration and possible rate of change of each resource.

- **Economic drivers**—the viability of the next generation utility concept is dependent on the cost-effectiveness of the system and its components. The theory put forward in this paper is that the intelligent combination of resources can reduce the cost of the portfolio. However, this and other economic drivers, including the cost of various technologies and of the transmission capacity needed to connect them, must be explicitly addressed.

## 9 ACKNOWLEDGEMENTS

The authors would like to thank Joel Swisher, Ph.D., P.E., and the Energy & Resources Team of the Rocky Mountain Institute for their collective work on the next generation utility concept. This research is funded through the generous support of the William and Flora Hewlett Foundation.

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