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

Presented at WINDPOWER 2008 Conference & Exhibition
June 3, 2008

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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 analysis expands previous studies on reducing the variability of renewable resources through optimized geographic distribution. In this study, the period of analysis was lengthened from one year to three years, and the study area was enlarged to include all states within the Great Plains "wind belt." Lengthening the period of analysis produced no significant difference in either power output or variability. However, enlarging the geographic area to three reliability regions (MRO, SPP, ERCOT) reduced system variability by 28% relative to the average individual region.

1 INTRODUCTION

The ever-growing energy demands of the 21st century are dependent upon a power infrastructure designed for the early 20th 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. To this end, a new generation of power technology is developing that can enable the "next generation utility", which will involve:

- 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.

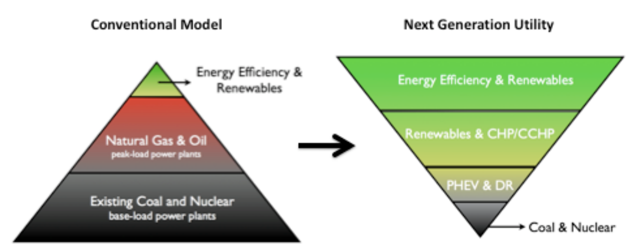


Fig. 1: The next generation utility will turn generation infrastructure on its head, with a mix dominated by efficiency and renewables with minimal coal and nuclear.

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 the figure 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.

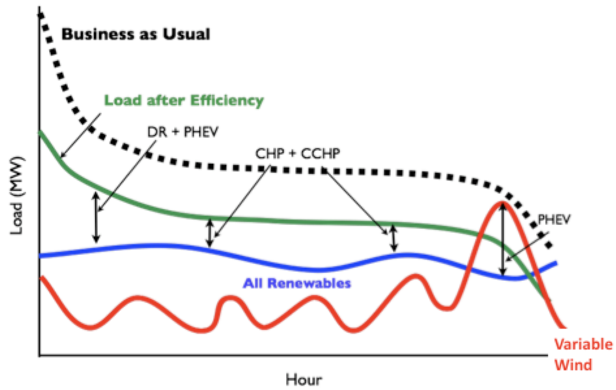


Fig 2: Conceptual load duration curve for a next generation utility.

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. (Milligan 2002)

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 and Texas.

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 recorded at hourly intervals. The wind data were measured at or above a 40-meter hub height and the solar data includes separate direct and diffuse radiation values.

The 3-year analysis was conducted with data from years 2002-2004 for 26 wind sites and 8 solar sites within the Midwest Reliability Organization (MRO). This region and timeframe were selected because they provided the highest number of sites for which three years of data were available. The expanded geographic analysis was conducted for sites within MRO, Southwest Power Pool (SPP), and Electric Reliability Council of Texas (ERCOT), with data from year 2004. The 63 wind sites for this analysis were identical to those used by Hansen and Levine (2008), plus 8 solar sites in MRO used by Palmintier, Hansen, and Levine (2008), 3 additional solar sites in SPP, and 5 additional solar sites in ERCOT.

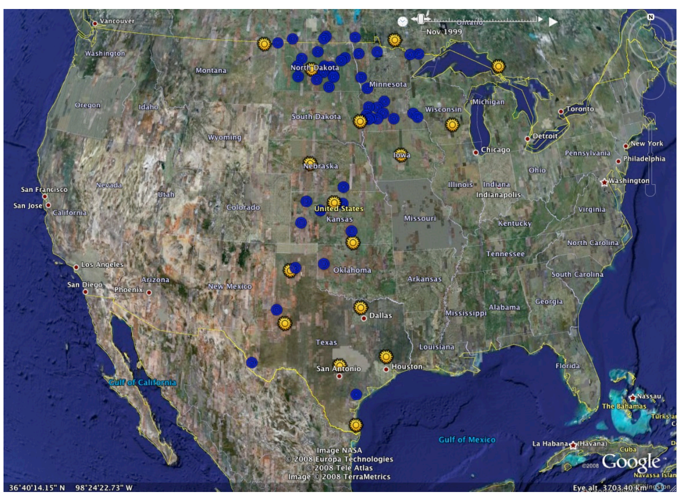
All wind data was chosen from the RMI/UC-Boulder wind database compiled by Levine and Hansen (Levine 2007, Hansen & Levine 2008). The original source for the MRO and SPP wind data was the University of North Dakota Energy & Environmental Research Center (EERC) hosted

Plains Organization for Wind Energy (POWER) database.[1] The original source for the ERCOT data was the Alternative Energy Institute (AEI) hosted by the West Texas A&M University (WTAMU).[2]

All solar data was taken from the National Solar Radiation Database (NSRDB) 1991-2005 Update, maintained by the National Renewable Energy Lab (NREL).[3] Though this database contains radiation data for 1,454 sites, only 40 of these sites include *measured* data. This measured data was used wherever possible, but modeled data was supplemented where necessary to increase the spatial diversity of the dataset.

The 3-year analysis included solar insolation data from 3 measured sites and 5 modeled sites within MRO. The expanded geographic analysis included data from 2 measured sites and 1 modeled site in SPP, and from 5 modeled sites in ERCOT. All modeled sites were carefully selected to be class-I sites with 100% low data uncertainty during the periods of analysis. (NREL 2007)

All sites considered in this analysis are shown in the graphic below, with wind sites shown in blue and solar sites shown in yellow.



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 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 and SPP, where diffuse radiation comprises a substantial portion of the total insolation.

More information about the solar power production model can be found in Palmintier, Hansen, and Levine (2008).

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 megawatts (MW) AC. For solar, this scaling was done on the AC power rating at 1-sun (1000 W/m^2). When multiple sites were interconnected to

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[1] Available on line at: www.undeerc.org/programareas/renewableenergy/wind/default.asp
[2] Monthly average data available on line at: www.windenergy.org
Hourly data available upon request
[3] Available on-line at: http://rredc.nrel.gov/solar/old_data/nsrdb/1991-2005/

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, σ, 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 megawatt-hours 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, σ_p, takes advantage of the fact that the variance (σ^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,

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

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

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

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

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

or in Matrix form:

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

where:

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

since Cov(X,X) = Var(X).

4.7 Optimization Methodology

Portfolios of wind and solar resources were developed by siting resources at those sites that would minimize overall portfolio variability for a given average portfolio power output. Therefore, not all available sites were included in every portfolio, and a number of different portfolios were created given different average portfolio power outputs. The portfolio variability was minimized using Monte Carlo methods subject to a constraint on the average output power:

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

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, **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.

5 RESULTS AND DISCUSSION

The following sections present results for the analysis of portfolio development based on 1 year versus 3 years of hourly data, as well as the analysis of variability reduction across MRO, SPP, and ERCOT.

For each scenario there is a set of optimal portfolios that represent a trade-off between variability (standard deviation) and power output ($\overline{p}_p$).

This concept is represented graphically with the efficient frontier shown in figure 3. 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.

The output versus variability curve illustrates the tradeoff between higher output and lower variability of renewable resources. Because all renewable sites will occasionally produce zero power, the power output of sites with large quantities of sun or wind tends to vary more greatly than the power output of sites with smaller quantities. This trend is illustrated by the upward sloping nature of the output vs. variability graph. Therefore, in order to fairly compare the variability of two renewable portfolios, the average power output of both portfolios must be equal. Variability reduction can always be accomplished at the price of capacity factor; the purpose of this study is to prove that variability reduction can be accomplished through intelligent geographical distribution without reducing capacity factor.

Therefore, when we compare the variability of an optimized wind portfolio to that of an optimized wind/solar portfolio, we must choose portfolios with the same capacity factor. Likewise, when we compare the variability of a portfolio to the variability of the average individual site, we must choose a portfolio with capacity factor equal to the capacity factor of the average individual site.

5.1 3-year analysis

Expanding the analysis from 1 year to 3 years produced no significant difference in either portfolio power output or portfolio variability. Over 3 years, the portfolio chosen based on 1 year of data produced 0.7% less energy with 0.2% more variability than the portfolio chosen based on 3 years of data. This is illustrated graphically in figure 3, which shows both an efficient frontier and load-duration style curve for the 1-year analysis vs. the 3-year analysis.

For this example, then, the conclusion is that optimal sites for low-variability portfolios can be selected based on 1 year of data, so long as the weather for the year in question is fairly typical, as was 2004.

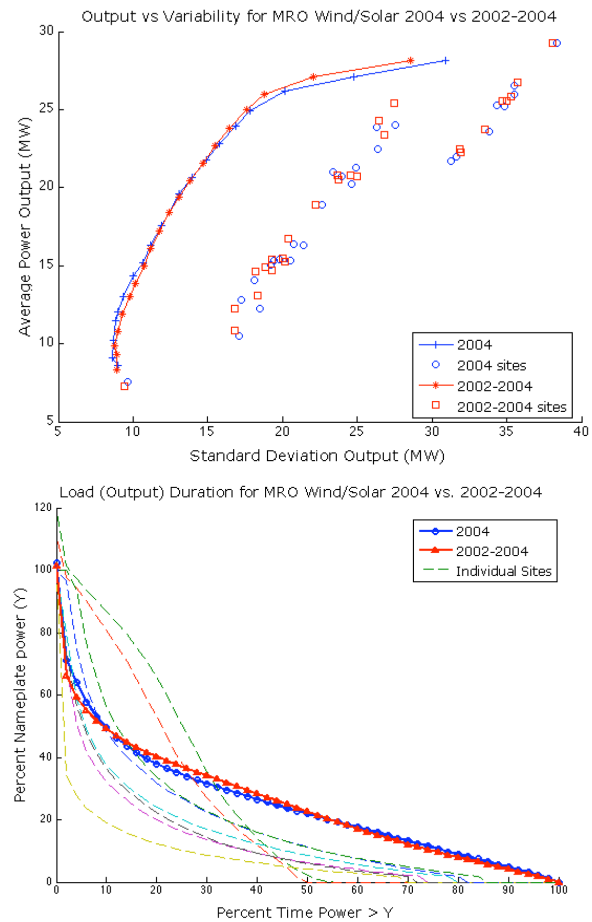

Fig. 3: Efficient frontier and load (output) duration[4] for the 3-year MRO analysis vs. a 1-year analysis with the same sites.

5.2 Expanded geographic area

This section analyzes the variability reduction potential in MRO, SPP, and ERCOT individually, and in all three regions combined. Integrating wind resources across all three reliability regions would require grid ties between ERCOT and the Eastern Interconnect.

The charts below show average power output versus variability for individual sites within a particular region, and for the set of portfolios with minimum variability for a given level of output. In each chart, the optimized portfolio with power output equal to the average of the individual sites is circled. The sites that compose that portfolio are also circled, and the variability reduction between the portfolio and the average individual site is given.

[4] The load (output) duration curve must be calculated for a specific "bin" along the output vs. variability curve. In this paper, all load (output) duration curves are calculated for the "bin of greatest return", which is the bin with the highest power output before the curve bends sharply to the right, introducing significantly more variability. In this case, the "bin of greatest return" is bin 17.

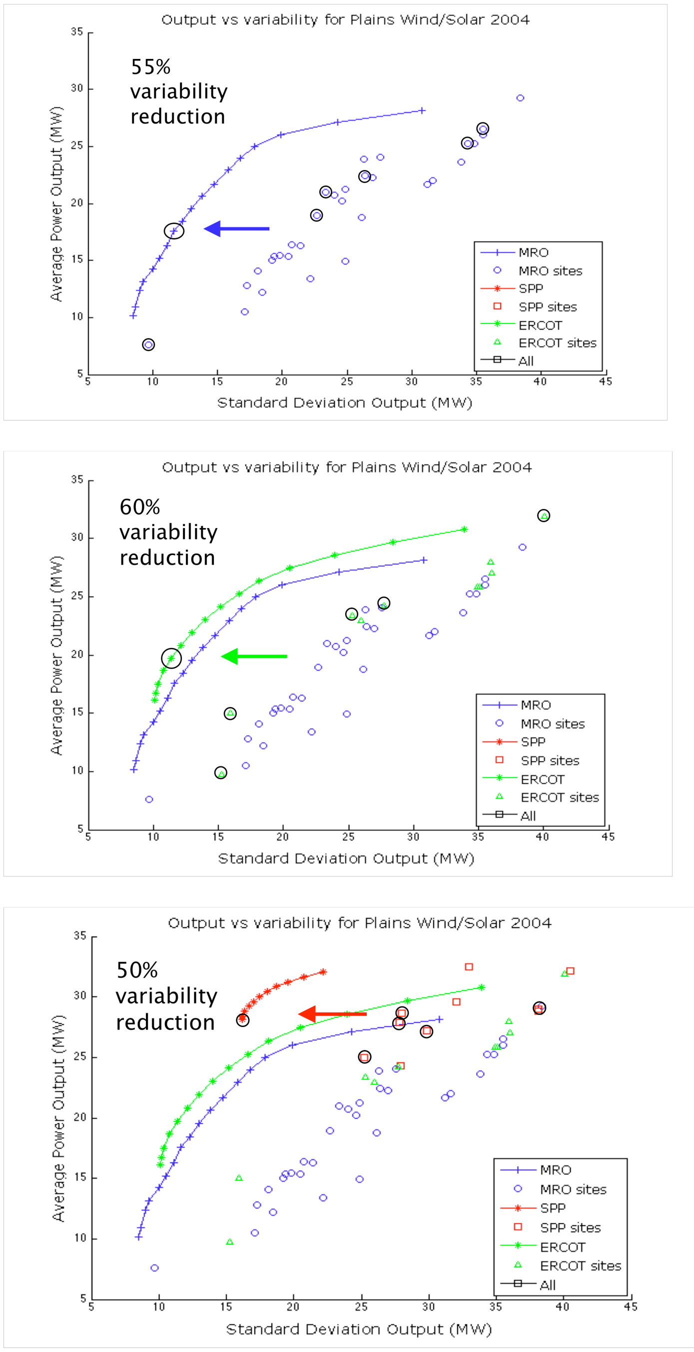

Fig. 4: Output vs. variability for MRO, ERCOT, and SPP, respectively. The graphs show that portfolios can achieve equal power output with less variability than any individual site.

Of particular note is that a large variability reduction can be gained without spreading the resource to all available sites. That is, a few carefully chosen sites can provide the same benefit.

Given the results of Palmintier, Hansen, and Levine (2008), it was not surprising to find that expanding the analysis to three reliability regions produced an optimized portfolio with lower variability than any individual region alone. Specifically, the optimized portfolio for the expanded region was 28% less variable than the least variable individual region (ERCOT). In addition, the 80/90/95/99% available output rose from 13/8/6/2 MW (out of 100 MW total) in the best individual system (SPP) to 15/11/8/4 MW for the three combined systems.

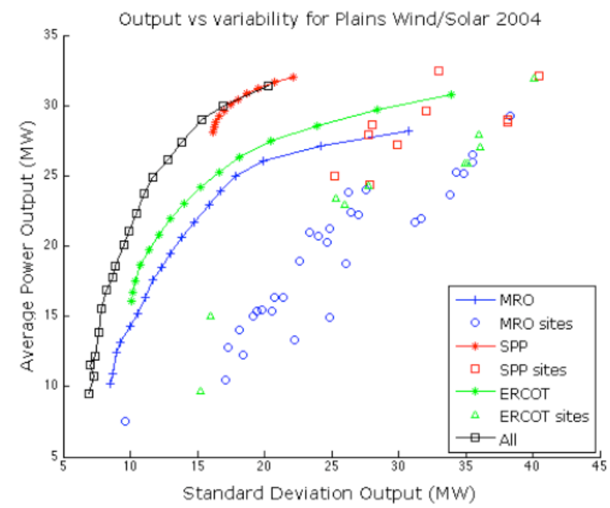

Fig. 5: Output vs. variability for the combined system vs. individual regions. The optimum portfolio composed from sites within the whole system is 28% less variable than the optimum portfolio from the least variable individual region (ERCOT).

Figure 6 also illustrates that the amount of time in which the expanded region portfolio produces no power is significantly less than all individual regions. Specifically, the expanded region produces no power for only 6 hours out of the whole year (0.068% of the time), whereas the best individual region (ERCOT) produces no power for 16 hours out of the year, and the average individual region produces no power for 90 hours out of the year. This represents a 62% and 93% improvement, respectively.

Furthermore, the expanded region has a lower chance of producing less than 12 MW or more than 47 MW than any individual region. For utilities, this represents a lower risk of power shortages or spikes, and therefore a lower cost of integrating wind on a large scale. In the expanded region, the maximum power output for 2004 was 76 MW, vs. 93 MW for the best individual region (ERCOT) and 98 MW for the average individual region. Intelligent geographic distribution therefore facilitates higher wind penetration rates by reducing the risk and intensity of supply spikes.

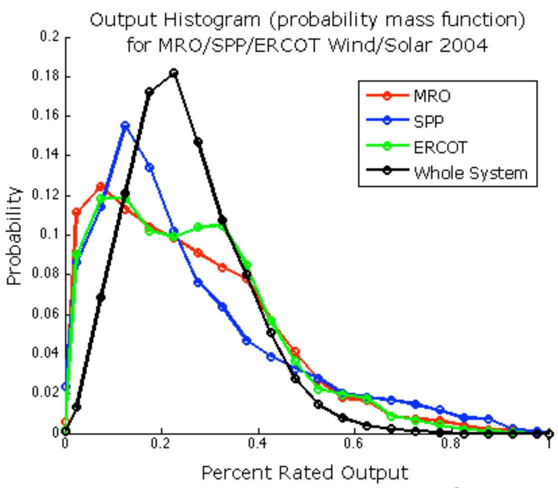

Fig. 5: Output histogram for the expanded system[5]. A curve that is narrower and shifted more to the right has less variability and higher power output, respectively.

5.3 Relative Contribution of Wind vs. Solar

Combining 16 solar sites with the wind sites from Hansen & Levine (2008) produced a wind/solar optimized portfolio with 18% lower variability than the optimized wind portfolio alone. The added resource diversity also raised 80/90/95/99% availability from 12/8/6/3 MW to 15/11/8/4 MW. In the "bin of greatest return" (bin 15) of the expanded region optimized portfolio, approximately 80% of capacity was apportioned to wind and 20% to solar. In general, solar is more prominent in portfolios with higher power output and greater variability. This is due to the fact that solar sites tend to have higher average power outputs than wind sites, but also higher variability because they produce no power at night.

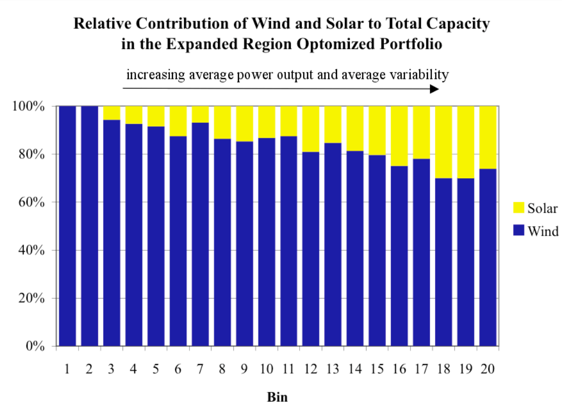

Fig. 6: Relative contribution of wind and solar to total capacity in the expanded region optimized portfolio. Solar sites have higher power output but greater variability than wind sites, and therefore tend to be favored in higher bins.

[5] Like the output duration curve, the output histogram must be calculated for a specific "bin" along the output vs. variability curve. In this graph, the whole system histogram is calculated for bin 15, and the individual system histograms are calculated for bins with an equivalent power output. In addition, these are discrete histogram functions divided into 20 bins between .0001 and .9999, with 2 additional bins for 0 and 1– the dots are connected for better readability.

6 CONCLUSIONS

This study has two conclusions: (1) for this example, extending the period of study from 1 year to 3 years has no significant impact on the variability or power output of a geographically distributed wind-solar portfolio, so long as the 1-year analysis is conducted for a year with relatively normal weather. (2) Expanding the geographic area of the study from 1 reliability region to 3 produces significant decreases in variability, thereby facilitating higher penetrations of wind and solar power in utility portfolios.

7 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, the remaining variability must be managed in order to balance demand and supply on the hourly, minute, and second scales.

This balancing currently occurs 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.

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), Southwest Power Pool (SPP), and Electric Reliability Council of Texas (ERCOT). Future studies will conduct an independent analysis of the Western Electric Coordinating Council (WECC), so long as an adequate quantity of wind data can be obtained. Once this region has been analyzed, the majority of good wind and solar sites within the continental United States will have been addressed.

- **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 and more information on the loss of load probability (LLP) of current utility systems.

- **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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