New Frontiers in Utility Valuation of Renewable Resources

by
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Executive Summary

Over the next few years, significantly higher penetration rates of renewable energy will be necessary to address climate change and to hedge fossil fuel costs and volatility. As penetration of renewable energy grows, the industry will increasingly have to address both the integration and valuation of these resources that, taken together, can provide electric power services with higher quality and reliability, at lower cost, and with less environmental impact than conventional generation resources. The correct valuation of renewable resources is challenging for several reasons:

- Risk mitigation, including fossil-fuel risk, reliability risk and the risk of over (or under) estimating demand growth, must be quantitatively evaluated for renewables to be properly valued. Techniques for quantitatively evaluating risk mitigation can be found in financial theory, and must now be applied to the planning of electric power systems;
- Intermittent renewable power often imposes operational costs at each time scale (regulation, load-following, and unit commitment);
- The reliability benefit of intermittent renewable resources must be explicitly recognized as the amount of conventional generation capacity that can be displaced due to the addition of a particular portfolio of renewable assets;
- The portfolio benefits of combinations of renewable and distributed resources need to be defined that account for the covariance between resources. The combination of renewable and distributed resources often creates synergies that are unseen if each is looked at in isolation;
- The impact of renewable resources to the risk-reward tradeoffs of the utilities' entire power supply portfolio must be incorporated;
- The benefits and costs are dynamic, not static. They change with penetration rate. There are often diminishing returns to the addition of increasing amount of intermittent renewable resources.

The implications of correctly valuing these resources are profound. The incorporation of the appropriate capacity credit for intermittent resources will often provide the economic justification for building additional resources, particularly wind. Conversely, failure to

incorporate capacity credit for these resources may mean overbuilding conventional generation capacity at a rate of roughly 10–20% the amount of renewable resources on the system—a $320 million loss within the United States alone.

To be conservative, we are not including the valuation of the carbon emissions, as the U.S. is not a member of the Kyoto Protocol. Nonetheless, state public utility commissions are starting to value displaced CO_{2e} emissions at between $8-17/ton CO_{2e}.[1] Similarly, due to the wide variation in rules among U.S. states, Renewable Energy Credits (RECs) are not discussed in this paper. Nevertheless, both CO_2 emissions displacement and RECs are economic values that should be incorporated into proper utility valuation of renewable power.

In this report, Rocky Mountain Institute explores the underlying theory and practical methodologies for the valuation of renewable resources. This paper draws heavily from our previous study on distributed resources, "*Small is Profitable: The hidden benefits of making electrical resources the right size (2002)*". We present the theoretical basis first to acquaint the reader with the underlying rationale for the approach to valuing these resources. We then present the practical methodologies that can be used to estimate these benefits on real utility systems.

Fundamentals of Renewable Reliability

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 intermittent, have some probability of failure. The forced outages of conventional generators result from unplanned mechanical failures, whereas the effective "forced outages" of intermittent generators are due to the risk of "fuel" (i.e., wind or sun) availability. These two factors lead to the conclusion that, when evaluating the reliability of intermittent renewable generators, we must evaluate them for the contribution they make to overall system reliability rather than the reliability of an individual renewable generator.

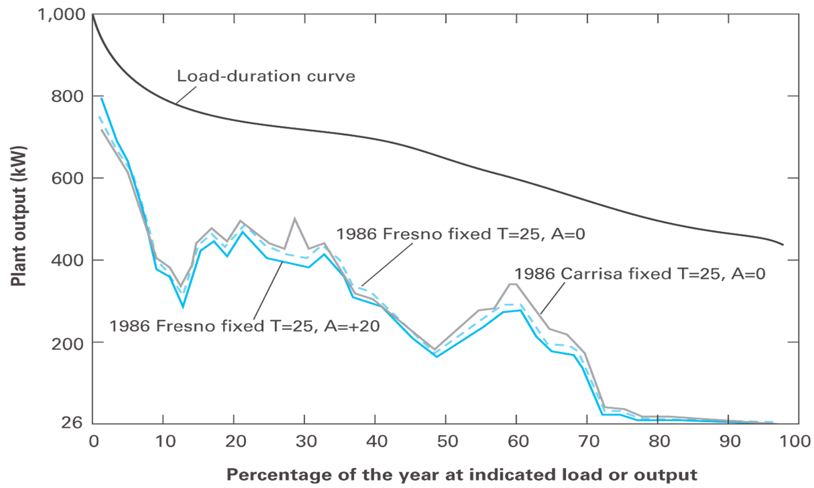
To properly understand the value of intermittent generators in terms of system reliability, though, it is critical to return to first principles and understand how intermittent generators can contribute to system reliability. This knowledge is, in turn, based on an understanding of how both system demand and renewable power output are impacted by the weather. In some systems, load and renewable output are frequently driven by the same underlying cause. For example, in many warm regions where cooling loads peak in the early afternoon, a solar generator's output is generally at its highest level. Thus, if load and intermittent output peak at the same times, the intermittent generator likely contributes substantially to system reliability.

Renewable generators are, by definition, driven by the weather. The question is simply whether the weather patterns driving renewable resources are the same patterns driving load. Tidal and solar power are perhaps most obviously correlated to distinct weather patterns. The tides are driven by perhaps the most reliable weather pattern known, and the fluctuations in the tides can be predicted well into the future. Insolation is also driven by a well-known and regular weather pattern—the sun. Insolation is only less reliable than the tidal action because of the interference from clouds. Because solar-power production is driven by the sun, which also typically drives

[1] California, Oregon directly value CO_2 emissions in the utility procurement process.

temperature, and thus load, in many systems, there is reason to believe in a significant correlation between solar output and load. This concept is depicted in the following figure, which shows the general correlation between solar output and load in the California system.

Figure 1. PVs closely match PG&E's annual load-duration curve.[2]



While this idea of weather-driven peak coincidence is relatively easy to comprehend for renewables such as tidal, solar, and even hydropower, wind is significantly more complicated. There are many wind regimes that affect most systems, including trade, convection, and frontal.[3] Trade winds are seasonal and highly reliable, but they are primarily driven by pressure, not temperature (which, as discussed above, is a significant driver of power demand in many systems). However, since the trades are very reliable, wind power from the trades has the potential to contribute to system reliability. Convection winds follow a daily cycle governed by land and sea temperature differentials. This combination of daily trends and temperature relations means there is a significant possibility of coincidence with daily patterns in power demand. Finally, frontal winds are driven by storms and are therefore erratic and unlikely to be able to support reliable wind output in most places.

A major consideration for investing in wind generation is whether the power will be there when we need it. Thus the goal becomes identifying sites with good wind speeds that are temporally coincident with peak power demand, such as the one shown in the graph below.

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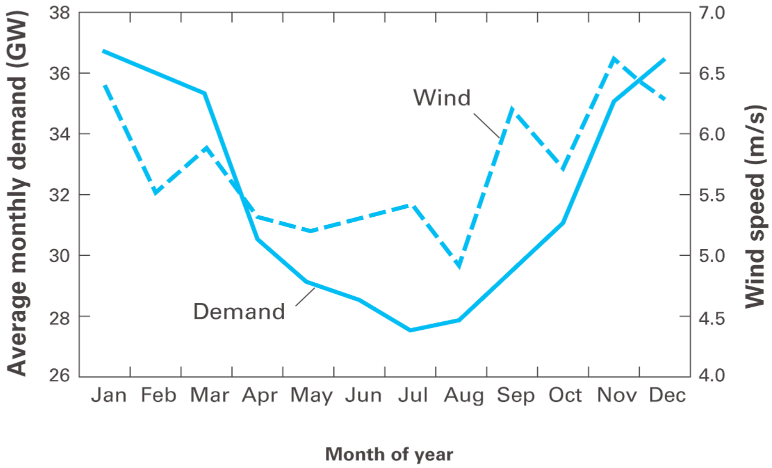
[2] D. Shugar *et al.,* "Benefits of Distributed Generation in PG&E's Transmission and Distribution System: A Case Study of Photovoltaics Serving Kerman Substation," (PG&E, November 1992), p. 3-4.

[3] Cite UH professor.

Figure 2. Correlation of wind and electricity demand in England.[4]



Studies from both the United States and Europe support the conclusion that renewables have non-zero capacity benefits to a power system. As an example of the value of weather-driven peak coincidence, California's 2004 *RPS (Renewable Portfolio Standard) Integration Study* found solar provided a significant reliability contribution in the form of an expected load carrying capacity (ELCC) greater than 80%.[5] Again, this is because the sun ultimately drives both solar output and peak load in Calfornia. Geothermal also has a high capacity credit, not due to any coincidence with load, but because geothermal is essentially a fuel-based renewable that behaves much like a conventional resource (i.e., geothermal is not intermittent). Three wind farms—Altamont, San Gorgonio, and Tehachapi—have capacity credits on the order of 22%. This lower number represents the fact that wind is not directly linked to load, but still shows some correlation. Additional U.S. studies consistently show a positive reliability value for intermittent renewables such as wind.[6]

Since it is reasonable to assume that variability will increase as the total rated wind capacity increases, it is also important to understand how capacity credit changes as the penetration of intermittent generation within a system increases. Combining the results of several U.S. and European studies, including discrete analyses of strictly parameterized scenarios and analyses across a range of penetration rates, reveals notable trends in both the benefits and costs of renewable resources. As shown in Figure 3, many studies found that the marginal reliability contribution of intermittent renewables decreases as the penetration rate rises.

Figure 3. Reliability Credit as a Function of Wind Penetration.[7]

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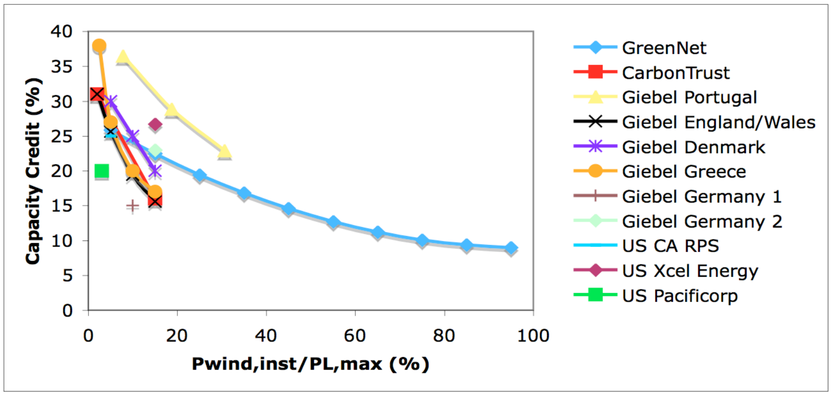
[4] R. W. Thresher, "Wind as a Distributed Resource," (EPRI 2nd DR Conference, 6 November 1996).

[5] M. Milligan and K. Porter, "Determining the Capacity Value of Wind: A Survey of Methods and Implementation,". (Windpower 2005 Conference, 24 May 2005).

[6] M. Milligan and K. Porter, "Determining the Capacity Value of Wind: A Survey of Methods and Implementation," (Windpower 2005 Conference, 24 May 2005),

[7] Hans Auer, et al. *The GreenNet Project: Costs and Technical Constraints of RES-E Grid Integration*, (August 2004), www.GreenNet.at; The Carbon Trust & DTI. *Renewables Network Impact Study: Annex 4,* (November 2003); Commission of the European Communities, "Wind Power Penetration Study (Case Studies for Portugal, the UK CEGB System, Denmark, Greece, and Germany)," EUR 14245 EN, EUR 14247 EN, EUR



Additionally, there is evidence to support rising marginal costs of system integration as the renewable penetration rate increases. The combination of these two trends—decreasing reliability contribution and increasing marginal costs—suggests that some optimum renewable penetration rate exists where the marginal reliability benefit equals the marginal integration cost. This implies that the importance of forecasting and storage rises with increasing intermittent renewable penetration rates. Since forecasting addresses the predictability of intermittent generation, more accurate forecasting can lead to significant economic value.

Both the theory and empirical results discussed above suggest that intermittent renewables do contribute to the reliability of a power system. While this contribution depends on the correlation of weather to both load and power output, the inherent variability of weather—and therefore renewable power output—does not preclude its consideration as a reliable power generator. After all, conventional power generators also suffer from variability in that there is always a non-zero probability of failure for any given unit.

<u>Renewable portfolio approach</u>

After analyzing an intermittent generator's covariance with load and correlation to peak, the next step is to analyze whether intermittent generators exhibit any covariance with *each other*. That is, what are the impacts to reliability of considering several intermittent generators together as a portfolio? Conventional wisdom holds that capacity credit is given to an individual site based on the individual site characteristics.[8] This philosophy generally leads to the assumption that wind farms have little or no capacity value because the degree of variability of the resource is so high at each individual site.[9]

14248 EN, EUR 14252 EN, EUR 14249 EN, (Brussels/Luxembourg 1992); L. Jarass, "Strom aus Wind: Integration einer regenerativen Energiequelle," ISBN 3-540-10436 (1981); California Wind Energy Collaborative, *California Renewables Portfolio Standard Renewable Generation Integration Cost Analysis: Phase III*, (July 2004); California Energy Commission website: www.energy.ca.gov; EnerNex Corporation and WindLogics, *Xcel Energy and Minnesota Department of Commerce: Wind Integration Study* (28 September 2004); Pacificorp, *Integrated Resource Plan,* (2004).

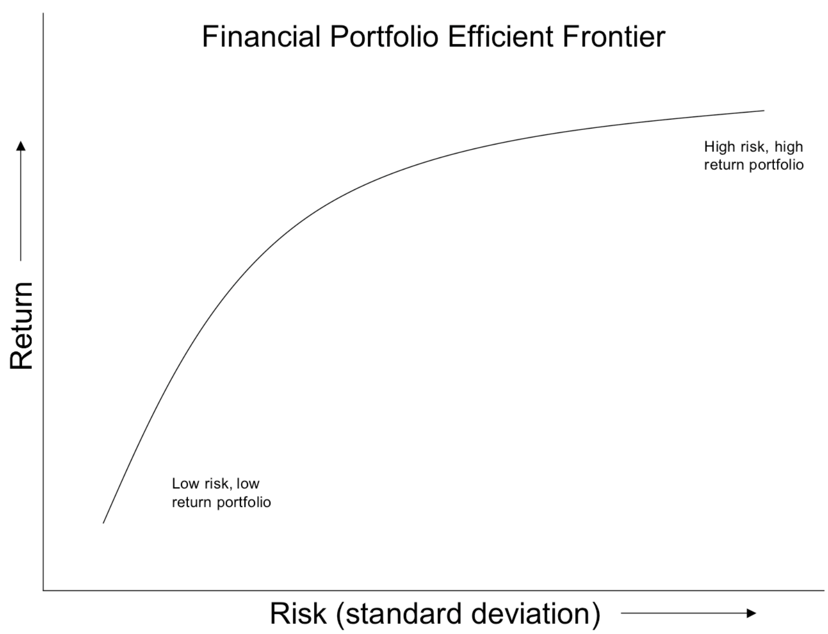
[8] Michael Milligan. Modeling Utility-Scale Wind Power Plants Part 2: Capacity Credit. (National Renewable Energy Laboratory 2002). NREL/TP-500-29701, at 12.

[9] Brendan Kirby, et al. California Renewables Portfolio Standard Renewable Generation Integration Cost Analysis, Phase III: Recommendations for Implementation. (California Energy Commission 2004), at 17.

Modern financial portfolio theory, though, offers a different way of looking at the world. A financial portfolio consists of a combination of individual stocks.[10] Developed by Harry Markowitz in 1952, modern portfolio theory enables the creation of minimum-variance portfolios for a given level of expected return.[11] This theory is based on diversification—the lower the correlation between the individual assets that make up the portfolio,[12] the lower the portfolio variance (risk).

In Figure 4 below, the curved line illustrates how expected return and standard deviation change as you hold different combinations of two stocks. This is known as the portfolio efficient frontier, and was also developed in the 1950s by Markowitz. Portfolios below the curve are not efficient, because a greater return could be achieved for the same risk. Portfolios above the line are impossible. Portfolios on the line represent the portfolio with the highest return for a given risk level, and involve different quantities of each stock.

Figure 4. Portfolio Efficient Frontier.



Financial portfolio theory can be easily applied to energy resources. In this context, a renewable portfolio could comprise either multiple renewable resources (e.g., wind, solar, etc.) or a single renewable resource that is geographically dispersed. When using portfolio theory to analyze the reliability impacts of renewables, there are two time frames of interest. If using this type of analysis by itself, it is helpful to look at portfolio impacts during the utility's annual peak period. However, if using this type of analysis as part of a larger reliability analysis (e.g., ELCC), the portfolio should be analyzed for the entire year in order to provide appropriate input data for further analysis. Finally, it is important to recognize that portfolio analysis can be used not only as a tool to value *existing* resources but also as a tool to plan for *future* resource additions.

[10] Carol Alexander. Handbook of Risk Management and Analysis. (John Wiley & Sons 1996).
[11] *Id.*
[12] *Id.*

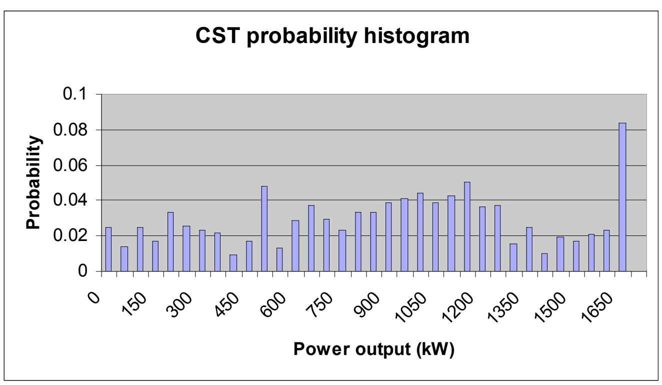
Portfolio diversification is discussed here as applied to wind power. Due to topography and meteorology, winds in different geographic locations are often not correlated while sometimes they are negatively correlated.[13] By blending individual sites together into a portfolio, the overall risk, or variability, of portfolio power production should be reduced. Take, for example, three geographically dispersed wind farms as described in Table 1. It shows each wind farm's average power output and the total site variability (defined here as the variance of the data) for each 1.65-MW turbine at that site for the utility's annual peak period.

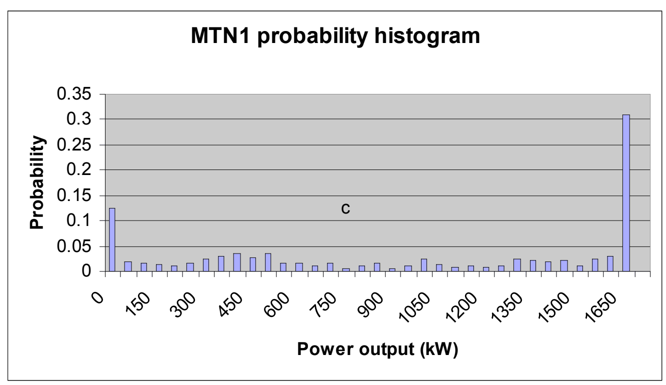
Table 1. Annual average power output and variability at three wind sites

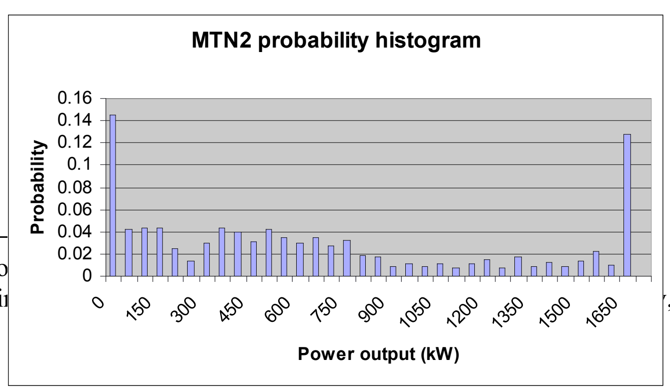
Site	Mean (kW)	Total variability
Site 1	870	220,000
Site 2	950	400,000
Site 3	650	320,000

As can be seen in the following site probability distributions (Figure 5),[14] power outputs do not have a clear distribution pattern because the power conversion function is non linear. So while wind speeds might appear to follow a Weibull distribution, we should not expect power outputs to. Because wind turbines have a cut-in wind speed of about 4 m/s, all speeds below that produce zero power output, and there can therefore be a higher probability of getting zero power. Likewise, once the wind speed reaches roughly 13 m/s, the turbine produces a constant power output of 1650 kW, and thus there is a higher probability of producing the maximum power output.

Figure 5. Site probability distributions.







[13] Milligan 2002, *supra* no

[14] L. M. Hansen, "Can Wi … , 2004).

As expected, the power outputs of turbines at these three sites during the annual peak period exhibit extremely high variability. At each of the three sites, there is generally less than a 5% probability of getting any particular power output other than zero or the maximum.

Because the power distributions are not normally distributed, the standard deviations reported here for each site are not equivalent to standard deviations in normally distributed functions. However, the standard deviation still serves as a valuable indicator of variability.

High variability, as seen here, is often the primary concern cited by electric utilities. The question here is whether geographically distributing wind generation effectively raises the capacity value of the system by decreasing this variability. Geographical distributions of wind resources have been considered in other studies, although not, as yet, in great detail. In 2002, Eric Hirst, a consultant for the Bonneville Power Administration (BPA), suggested that the variability of the output of wind generation at dispersed locations would be less than the variability of co-located wind generation.[15] Hirst found that the standard deviation of the total output of five dispersed wind farms would have been 30% lower than the standard deviation had they been co-located.[16]

The first step in determining the value of geographical dispersion for this portfolio is to determine whether the three sites exhibit any covariance. That is, are large power output values at one site associated with simultaneous large power output values at another site (positive covariance), are the power output values unrelated (covariance near zero), or are large power output values at one site associated with small power output values at another site (negative covariance)?

A covariance matrix was generated for the annual peak period (see Figure 6), according to the formula:

$$\mathrm{cov}(x,y) = 1/n^*\Sigma\ (x_i - \mu_x)(y_i - \mu_y)$$

x, y = data series
n = number of data points
μ = data series average
i = data point

Figure 6. Annual Peak Covariance Matrix.

[15] Eric Hirst. Integrating Wind Energy with the BPA Power System: Preliminary Study. (Power Business Line, Bonneville Power Administration 2002).
[16] *Id.*

	Site 1	Site 2	Site 3
Site 1		-	-
Site 2	-		+
Site 3	-	+	

As can be seen in the above matrix, there is some degree of negative covariance between the three sites. Specifically, Sites 1 and 2 and Sites 1 and 3 exhibit negative covariance during the annual peak, while Sites 2 and 3 exhibit positive covariance. Positive covariance between Sites 2 and 3 is not particularly surprising, since they are geographically closer to one another than to Site 1 and therefore likely share some topographical and meteorological characteristics.

The simplest application of modern portfolio theory is to an existing portfolio of resources. In this case, simply calculate the combined output and variation, according to the following equations:

$$P_{total} = \overline{p_1}s_1 + \overline{p_2}s_2$$
$$V_{total} = v_1 s_1 + v_2 s_2 + 2\operatorname{cov}(v_1, v_2)$$

where P_{total} is the portfolio output, V_{total} is the portfolio variance, p_i is the individual site output, v_i is the individual site variance, and s_i is the share (percentage of wind) at each site.

With more than two sites, simply add terms for the covariance between all combinations of sites.

The more complex, but potentially more useful, application is in designing a new portfolio or new additions to an existing portfolio. In this case, new additions can be optimally sited to minimize portfolio variability. The value of this negative covariance in reducing system variability is determined by running an optimization model to determine the mix of generation at each site that would yield the collective minimum variability. This optimization problem minimizes the portfolio variability by changing the share of wind at each site, subject to several constraints, according to the following form:

minimize: $s'\Omega s$
by changing: s
subject to: $0 \leq s \leq 1$
$s'i = 1$

$$s'\mu \geq \mu_{min}$$

where:

$$\Omega = \text{covariance matrix} = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{13} \\ \sigma_{21} & \sigma_2^2 & \sigma_{23} \\ \sigma_{31} & \sigma_{32} & \sigma_3^2 \end{bmatrix}$$

$$s = \text{shares vector} = \begin{bmatrix} s_1 \\ s_2 \\ s_3 \end{bmatrix}$$

$$i = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

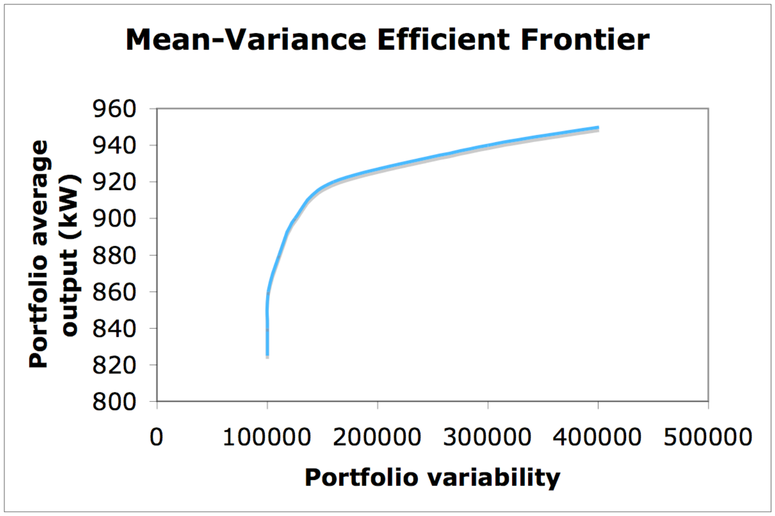
$$\mu = \text{mean output vector} = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \end{bmatrix}$$

μ_{min} = specified minimum portfolio weighted power output

Variance is not independent of the mean—as portfolio mean power output increases, variance increases. While minimal variability in power output is desirable, some higher level of variability might be acceptable in order to achieve a higher average output. The decision to accept a higher level of variability is based on the individual risk preferences of the wind developer and utility, and the comparative value of energy and capacity payments. If capacity is more valuable, a developer may choose a portfolio with a lower output and correspondingly lower variance. However, if energy is more valuable, a developer may choose a portfolio with a higher mean output and variance, thereby giving up possible capacity payments.

The following graph describes the mean-variance efficient frontier for the annual peak period (see Figure 7). Different mean portfolio outputs are associated with different portfolios of wind (i.e., a different percentage of the total wind capacity at each site).

Figure 7. Annual peak mean-variance efficient frontier.



During this period, Site 2 has the highest mean output of the three sites. Therefore, the point (952, 387000) represents the portfolio with 100% of the wind turbines at Site 2. As wind is added at the other two sites, portfolio variance decreases, but so does mean portfolio output, according to the above mean-variance frontier. This analysis is focused on the potential for capacity credit, so the portfolio that has the absolute lowest variability is shown below in Table 2.

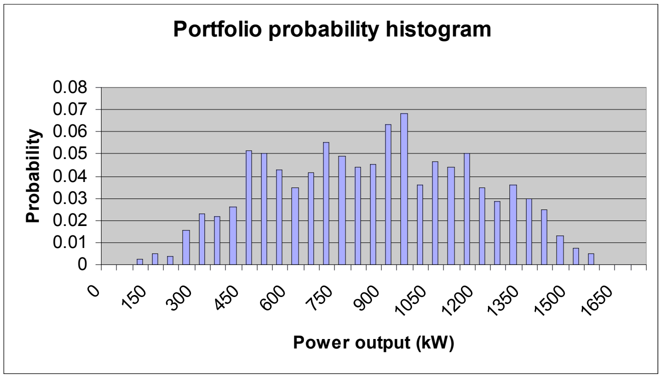
Table 2. Annual peak portfolio

Site 1 share	Site 2 share	Site 3 share	Mean power output (kW)	Standard deviation (kW)
52%	21%	27%	830	315

Shares at each site are given here as percentages of the total number of turbines to be installed. For example, if a developer wanted to install a total of ten wind turbines, this portfolio would require five be installed at Site 1, two at Site 2, and three at Site 3. If twenty wind turbines were desired, ten would be installed at Site 1, four at Site 2, and six at Site 3.

Figure 8 depicts the probability histogram for this lowest variance portfolio during the annual peak period. It represents the weighted average of the probabilities of the three individual sites during this time period. Aggregation of the three individual sites results in a distribution substantially closer to normal.

Figure 8. Portfolio probability histogram.



As can be seen in Table 3, the standard deviation of the combined output is substantially less than any of the three individual sites. This result occurs because geographic distribution results in some degree of negative covariance. The variation at one site to some degree cancels the variation at another site.

Table 3. Site and Portfolio average output and standard deviation.

Site	Average output (kW)	Standard deviation (kW)
Site 1	870	470
Site 2	950	630
Site 3	650	570
Portfolio	830	310

While this smaller variability is good, the absolute magnitude of the variability is still quite large. The capacity credit given to fossil-fuel power plants is less than rated capacity, because there is always some probability, no matter how small, that the plant will fail and therefore not be available when needed.[17] Therefore, wind should be given capacity credit for the power output generated with 95% confidence. In a normal distribution, this level is represented by the mean power output minus 1.645 standard deviations.[18]

Because the lowest variability portfolio distributions for the annual peak period are not precisely normally distributed, the 95%-level was calculated by using a histogram of power output, and then determining the capacity value that resulted in a 0.95 cumulative probability. Based on this methodology, this portfolio contributes 340 kW of capacity credit during the annual peak period.

The mean-variance frontier for the annual peak period (Figure 7 above) increases sharply until roughly 900 kW mean portfolio output, at which point variance begins to increase quickly in comparison to output. It is likely that a developer would prefer a portfolio at this point because while the mean portfolio output is substantially higher than the minimum, variance is only slightly higher. The results from this analysis are echoed by analyses of geographical dispersion in Europe.

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[17] M. Milligan. Modeling Utility-Scale Wind Power Plants Part 2: Capacity Credit. (National Renewable Energy Laboratory 2002). NREL/TP-500-29701, at 12.
[18] E.S. Pearson and H.O. Hartley (eds.). The Biometrika Tables for Statisticians, Vol. 1, 3d ed. (Biometrika, 1966).

The benefits of developing a portfolio of different renewable resources or of geographically dispersed renewable resources are clear, and should be taken into consideration when analyzing the reliability impacts of renewables on an electric system.

Power Supply Portfolios

Financial portfolio theory can also be used to combine different mixes of resources along an efficient frontier with respect to fuel price risk.[19] In essence, renewable resources and energy efficiency act a hedge against fossil fuel resources in the same way that treasury bonds reduce risk in a financial portfolio.[20] As in financial theory, combining low-risk assets with high-risk assets improves portfolio performance by raising expected returns without increasing overall risk. By combining different mixes of renewable resources with fossil resources, we will create an efficient frontier, defined as the mix of resources that provide the minimum expected cost for the desired risk level. Portfolio combinations that do not lie along the efficient frontier can be eliminated. Utility management can then define its preferred risk tolerance along this efficient frontier, and decide what degree of price volatility it is willing to accept against its risk aversion criteria.

Measuring Capacity Credit

In addition to properly valuing the portfolio benefits of wind farms, the wind farms actual impact to the reliability of the electric system must be quantitatively valued. Evaluating the reliability value of intermittent generators is more complicated than evaluating the reliability for conventional generators—but not impossible. There are analytical methods for correctly accounting for the value that intermittent generators provide to system reliability—because after all, *system* reliability should be the goal, not individual plant reliability. Many utilities and researchers, most notably by the National Renewable Energy Laboratory (NREL),[21] have rigorously analyzed these methods. For that reason, we will not address them in depth here.

In general, a positive impact to system reliability results in a capacity credit for wind, which, as discussed here, is the capacity a given generator adds to the electrical system as compared to a fossil-fuel-based conventional generator that would add the same level of system reliability. In other words, for intermittent generators, capacity credit is equal to the amount of conventional generation that could be displaced by the intermittent generator. There are several methods currently being used by utilities to measure capacity credit, but the most common is effective load carrying capability (ELCC). ELCC is a way to measure a power plant's capacity contributions based on its influence on overall system reliability, and is based on traditional utility reliability analysis in conjunction with statistical methods drawn from a large established literature in both the United States and Europe. More detailed information on these methods is available from NREL.

Operational Impacts

[19] Awerbuch, Shimon. Applying Portfolio Theory to EU Electricity Planning and Policy-Making. IEA/EET Working Paper, 2003.
[20] *Ibid.*
[21] M. Milligan and K. Porter, "Determining the Capacity Factor of Wind: A Survey of Methods and Implementation," (Windpower 2005 Conference, 24 May 2005).

Intermittency in renewable generation is a combination of two factors: variability and predictability. Using wind power as an example, variability refers to the fact that the wind does not always blow at a constant speed, and therefore the quantity of power being produced changes frequently. Predictability, on the other hand, refers to our inability to know the pattern of variability beforehand.

Predictability is important because if we could perfectly predict the quantity of power a wind turbine would produce, and when, there would be no direct system penalty incurred by wind power generation (unless, of course, the variability of the wind exceeded the total underlying flexibility of other generating units in the system). With perfect predictability, the system operator would commit the required other generating resources on the system, and intermittent renewable power would be the functional equivalent of a reduction in load. We do not, however, live in that perfect world.

In practice, the moment-to-moment operation of a power system with high levels of intermittent renewable generation is challenging because the system operator must balance generation and demand while maintaining power quality and low costs and without violating system constraints. The additional variability occurs at all timescales, from seconds to hours. This additional variability produced by intermittent resources must be evaluated within the context of the random behavior of consumers that create variations in power demand.

Studies from the United States and Europe have shown that on the time scale of seconds and minutes, the output of intermittent renewables does not significantly change from its prior state, except during storms and other wind-related events. Thus the prediction error in these time scales is far less than the prediction error in load forecasts. However, as the time scale increases to hours and days, the forecast error can increase to be significantly greater than the load forecast error. When this occurs, costs resulting from additional unit commitment or energy needed to balance the system can be expected. Not surprisingly, energy-balancing costs are primarily due to forecasting errors.[22]

In general, variability and unpredictability lead to several operational issues that are specific to intermittent resources. These operational considerations include impacts at each time scale.[23] Transient stability, or fault ride-through, means that the intermittent resource must be able to continue to operate during and after a fault on the electrical system itself. It can take between a few hundred milliseconds to two seconds to clear the faults. The renewable resources should be equipped with under-voltage ride-through capability for their expected output to avoid either turbine acceleration or over-speed, which could damage the equipment. Also, when equipped with under-voltage ride-through capability, the renewable resources can avoid having their generator tripping off line, which can force the utility to either bring on new generation or shed load. This issue is generally addressed by the interconnection requirements of the utility and the equipment upgrades from the renewable generation manufacturers.

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[22] E.ON, Presentation for Meeting with Tohoku Electric Power Co., Inc. (25 October 2004).

[23] Y. Wan and B. K. Parsons, "Factors Relevant to Utility Integration of Intermittent Renewable Technologies" (National Renewable Energy Laboratory, August 1993), p. 3

From a system perspective, the operational considerations of primary concern are those in a time scale of greater than one second. Frequency regulation is the most important operation issue given the increase and decrease of generation output over seconds or minutes. In interconnected systems, the imbalance between load and generation results in energy balancing costs between systems. Conventional generators include governor droop control so that they can decrease power output in the event of an increase in system frequency. Generation output can be increased (ramped up) in the event of a decrease in system frequency. Clearly, intermittent renewable generators, such as river hydro, wind, and photovoltaic power, do not have the ability to change their output as system frequency changes. In fact, their fluctuating output can be the cause of imbalances that push the system frequency outside the control limits.

This issue can be addressed through a combination of two mitigation approaches. The first is for the utility to create limits on the allowable change in output during specified periods for the renewable power plant (typically related to increases in power production). In this instance, excess power would have to be spilled. The second is to provide the adequate reserves on the appropriate time scale to address the problem, and account for the costs of doing so. We address the second approach in this paper.

Different types of reserves are appropriate for different time scales. These types of reserves include:

- **Regulation:** Fluctuations in the seconds-to-minutes time frame are addressed by automated generation control;
- **Load Following/Energy Imbalance:** Variability in the minutes-to-hours time frame is addressed by ramping the capabilities of the generation mix. A combination of spinning reserves, quick-ramping units, and quick-start units are typically used; and
- **Unit Commitment:** Day-ahead commitment of generation units from secondary reserves.

In general, additional reserves will be needed to cover these operational issues when (1) the system would be unable to meet its loss of load probability (LOLP) reliability targets given the variability increase due to the intermittent resource, (2) ramping requirements for intermittent resources exceed system ramping capabilities, or (3) regulation requirements exceed available automated generation control (AGC). The economic implications include not only the direct cost to conventional generators but also the cost of additional operating reserves or storage to address these operational issues. But how significant are these costs in practice?

Most utilities have found that intermittent generation has little impact on regulatory requirements. There are likely several reasons for this. First, with the exception of storms, intermittent output tends to shift gradually as discussed earlier. Second, fluctuation of intermittent power generation within the seconds time frame is within the same range of load fluctuations. As wind penetration increases, however, additional regulation capacity is likely to be required, albeit at a low cost (<$1/MWh).[24] The impact on load-following resources is based on the combined increase in variability from intermittent output *and* load. That is, what matters is the system variability rather than an independent generator's variability.

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[24] Adapted from J.C. Smith, et al., "Wind Power Impacts on Electric Power System Operating Costs: Summary and Perspective on Work to Date," (National Renewable Energy Laboratory, March 2004), NREL/CP-500-35946.

Forecast error can increase the demand for load-following reserves by requiring increased ramping capability. On the other hand, geographical distribution of intermittent generators can decrease the demand for load-following reserves by capturing any negative resource covariance between geographical locations as described above.

Once the additional system variability due to wind, this should be compared against the ramping capability (up and down) of the system during each hour of the year. If the additional ramping requirement is within the system ramping capability, no new generation is required (though there are still operational costs imposed on system). If the ramping requirement exceeds the ramping capability, then additional assets will be needed in order to integrate the wind resources.

Even if no new generation is needed, European studies have found intermittent generators can significantly impact the operation of resources that provide load-following reserves by increasing the number of start-ups for mid-merit plants.[25] Because start-ups have higher equivalent operating hours than steady-state generators, as well as higher initial fuel costs, this increases the operations and maintenance costs. Interestingly, the ramping duty of baseload plants increases as intermittent renewable penetration increases because these plants are called on for ramping when the mid-merit plants have been backed down. Again, the fuel and operating costs of this duty cycle are higher than during normal operations.

The extra system variability due to wind means that load-following resources have higher startup and lower operating efficiencies, particularly when penetration rates exceed 10%.[26] However, is the cost of these operating impacts significant enough to dissuade higher penetrations of wind?

In studies around the country, interconnected utilities have found that the cost of these reserves due to the addition of intermittent resources has been relatively low—between $2 and $6 per megawatt-hour (see Table 6).[27] While measurable, this cost is equivalent to the cost of including carbon dioxide emissions credits at $8/ton for gas-fired power plants, and far less than the cost of hedging gas volatility.[28]

It is important to understand the key drivers of operational costs so that one can see how these costs change from region to region and utility to utility. Four primary drivers of operational cost are:

- ***Geographical dispersion of wind power*:** As the geographic spread of wind farms increases, the wind speeds become less positively correlated or negatively correlated, smoothing output fluctuations, and lowering forecast errors by 30–50%;

[25] ESB National Grid, 2004. Impact of Wind Power Generation In Ireland On Operation of Conventional Plant
[26] Source: ESB National Grid, 2004. Impact of Wind Power Generation In Ireland On Operation of Conventional Plant
[27] Adapted from J.C. Smith, et al., "Wind Power Impacts on Electric Power System Operating Costs: Summary and Perspective on Work to Date," (National Renewable Energy Laboratory, March 2004), NREL/CP-500-35946.
[28] Internal RMI analysis.

- ***Forecasting accuracy of wind power output*:** Unit commitment is typically a day ahead. Hours ahead forecast errors are now very low (<5–7%). Forecast error for next day ahead averages 10–14%; advanced algorithms can reduce this to 6–8%.[29]
- ***Load following capability of generation mix*:** Increasing the mix of load-following units (gas turbines, hydro, storage, etc.) improves the ability of the system to respond to variation in output because these units can compensate better than baseload steam units; and
- ***Interconnection with other grids*:** Interconnection increases the ability to match supply and demand effectively.

Potential strategies to mitigate both variability and unpredictability have been developed. Unpredictability can be best addressed through improvements in persistence, meteorological, and climate-based forecasting models. Solar and tidal power are fairly straightforward to predict because both the sun and the tides have extremely regular cycles. Solar power output is changed by weather patterns that can be predicted reasonably well. Wind power, however, is much more complex to predict, since winds are driven by many factors. Therefore, this section will focus primarily on forecasting wind power output. There are three types of wind forecasting models:

- Persistence models: Persistence models set future prediction at the most recent current level; they are typically used for short time-frames (on the order of 15–60 minutes);
- Meteorological models: Meteorological models are physical or statistical models predicting wind based on atmospheric data, from one day to a week ahead; and
- Climate-based models: Climate-based models are statistically-based models predicting wind through the use of climate data, from a week to a year ahead.

These three types of models are based on two techniques:

- Physical models, which use physical considerations to estimate local wind speeds before using model output statistics; and
- Statistical models, which combine all explanatory variables to calculate wind power directly.

The current most accurate models include both physical and statistical techniques. Meteorological models currently in use around the world include eWind (U.S.), WindLogics (U.S.), Zephyr/WPPT (Denmark), Wind Power Management System (Germany), and Sipreolico (Spain).

Through continued improvement, these models are now reasonably accurate. Persistence modeling is generally accurate for one to three hours ahead, after which more sophisticated techniques, such as meteorological models, are needed. A study from EoN shows that the magnitude of error increases over time. However the error within the entire EoN control zone is smaller than the errors of either the coast or inland zones, highlighting the value of geographical

[29] K. Rohrig, "Online Monitoring and Prediction of Wind Power in German Transmission System Operation Centres." (Institut fur Solare Energieversorgungstechnik e. V.).

dispersion across different wind regimes.[30] Meteorological models, typically used for day-ahead forecasting typically have errors of +/- 10% for 85% of forecasts.[31]

Variability can be addressed by increasing the mix of quick-start/fast-ramp units in the utility's generation mix, adding electricity storage, or utilizing demand response to compensate for intermittent generation variability. Bulk energy storage technologies represent a range of physical assets that can provide a variety of different storage and output capabilities. These technologies can take several forms. The storage services and related storage requirements that can address the problems created by intermittent renewable power include:

- Regulating reserves: seconds or less;
- Frequency regulation: seconds to minutes;
- Voltage regulation: seconds or less;
- Increase minimum load: minutes and hours;
- Energy shifting: hours; and
- Peak-clipping: minutes and hours.

Different storage technologies are appropriate for different types of storage needs.[32] A combination of storage technologies will often be needed. For example, batteries can provide a full range of storage services, but are especially appropriate for regulating reserves and frequency regulation. However, batteries are quite expensive, often several thousand dollars per kW. Pump storage is far less expensive and is an ideal technology for energy shifting, peak clipping, and absorbing excess capacity during times of minimum load. However, pump storage is unable to provide the rapid response needed for regulating reserves and may not always be suitable for frequency regulation. As a distributed resource, the location of energy storage technology on the grid is particularly important for maximizing its overall value.

The potential value of energy storage at the utility scale can be seen in the Bonneville Power Administration's (BPA) hydropower firming service. BPA is using its large hydro resource to absorb the variance of wind power. BPA is offering two distinct services: a Network Wind Integration Service, and a Storage and Shaping Service. Through its Network Wind Integration Service, BPA effectively promises to fully utilize available wind power output and thereby offset output that it otherwise would have been required to provide. BPA recognizes that the reliability of wind generation can be tenuous and therefore holds enough generation capacity to fully back up the wind resources. In this way, BPA ensures that it will always be able to make up any difference between the customer's load and available wind output. BPA charges a $4.50 per MWh fee for all scheduled energy that it integrates into the system.

For customers interested in purchasing the power generated by wind resources but unwilling or unable to manage its hour-to-hour variability, BPA also provides storage and shaping services. Using the federal hydro system as a storage unit, BPA accepts the hourly output of wind projects and stores this energy over the period of a week. The following week the energy is redistributed

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[30] K. Rohrig, "Online Monitoring and Prediction of Wind Power in German Transmission System Operation Centres." (Institut fur Solare Energieversorgungstechnik e. V.).
[31] *Id.*
[32] Adapted from: J. Mariyappan, et al., GreenNet Interim Meeting presentation, (Brussels, 15 January 2004).

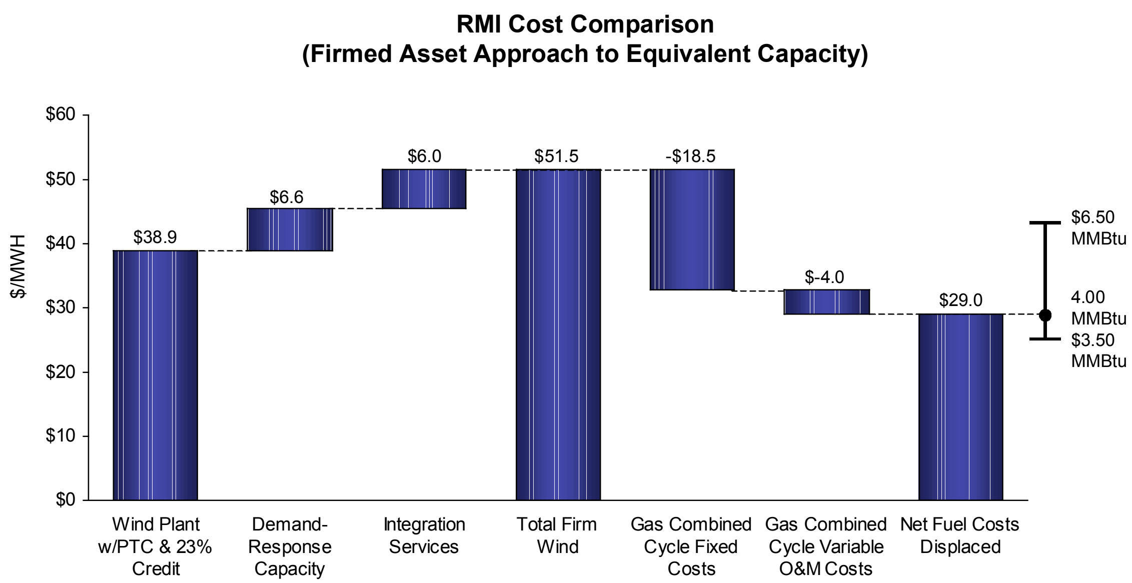
to BPA's customers in flat peak and off-peak blocks. These storage and shaping services are being sold for $6 per MWh. In essence, this is what it costs to eliminate the predictability error.

Renewables as a hedge against fossil fuels

"Firming" wind power (or other intermittent resources) with storage or demand response can provide a means to address risk preferences regarding fossil fuels. Consider the following example of what it would take to displace 21 MW of conventional fossil-fuel capacity. Let's assume the correlation between the 21-MW wind farm and the utility's peak load would result in a capacity credit of 20% using the ELCC method discussed earlier. Combining this wind with regulating energy purchased from the market and using demand response as virtual storage, a "firm" package is created that can first displace fixed and variable operating and maintenance, leaving predominantly fuel costs. Thise wind-demand response hybrid can be equivalent to a 15-year contract for natural gas at a cost of $4/MMBtu**.**

This is illustrated in Figure 9, where we progress from left to right, starting with the cost of the wind power itself, adding in the cost of DR capacity and integration services to reach a firm wind cost of $51.50/MWh. Continuing to the right, we now deduct from that total cost the fixed and variable cost of power from a CCGT, to reach a net cost of $29.00/MWh. Then using a typical combined cycle heat rate, we calculate an equivalent cost of natural gas of $4.00/MMBtu.

Figure 9. Calculating the Equivalent Fuel Price for Firmed Wind Power



Demand response (DR) programs have the potential to serve as "virtual" energy storage.[33] DR programs have typically been used for interrupting loads during system emergencies. However, DR can also be used more frequently to manage intermittent variability without completely interrupting the service that power provides. These load-flexing programs adapt to HVAC and lighting schedules in buildings without causing building temperatures to rise beyond a certain set

[33] B. Kirby, "Spinning Reserve From Responsive Loads," (Oak Ridge National Laboratory, March 2003), ORNL/TM-2003/19.

point. This type of program produces immediate, measurable reductions in load, and they can be designed as open-ended programs with customers.

The cost of demand response varies considerably with the type of load, the existing equipment, and the required incentives. In general, the cost of demand response varies from roughly $30 per kW-yr for commercial buildings with energy management systems to about $50 per kW-yr for residential air conditioning control. In either case, demand response is cheaper than development of a peaking combustion turbine. The implication is that load management should be designed to be a more active part of the approach for total system management.

Conclusions

It is clear that the incremental cost of ancillary services attributable to intermittent resources increases with penetration levels, while reliability value (capacity credit) decreases. This is due to the uncertainty and variability in the wind plant output, with the greatest uncertainty in the unit-commitment time frame. Though additional reserve generation may be needed to compensate for wind variation, the amount is far less than an equal amount of dispatchable fossil-fuel generation and modest relative to the size of the wind plant. The cost of required reserves is significantly lower when the combined variations in load and geographically-dispersed wind plant outputs are considered, as opposed to considering the variations in a single wind farm alone. Improving the accuracy of wind forecasts will result in lower cost of load-following ramping reserves and unnecessary unit commitment. Finally, physical and virtual storage can provide technical solutions to these problems, at a cost that may well be justified on many utility systems, particularly if off-peak renewable generation would otherwise be curtailed.

Only a few U.S. utilities, most notably PacifiCorp, apply the full range of valuation techniques described here to renewables. As a result, most of the integrated resource plans and resulting utility supply portfolios in the U.S. are underweighted with renewable power. As fossil fuel prices continue to rise, the cost of this failure to correctly value renewable power will become staggering.

From the outset, by undervaluing renewable resources, the U.S. is building more backup capacity than is necessary to operate the system. There were 6,740 MW of installed wind and solar capacity in the U.S. at the end of 2004.[34] If we take the most conservative estimate of ELCC (10%), then ~670 MW of generation capacity could be displaced. Assuming the cost of a CT to be $475/kW, U.S. utilities have overspent on generation capacity by $320 *million* dollars.

Lost fuel savings are likely even more substantial. Currently, renewable power (excluding hydroelectric) accounts for a mere 2.3% of the U.S. power generation mix.[35] Given the current and future prices of gas, each MW of additional wind capacity added to the U.S. is likely worth billions in reduced gas prices.[36] This level of savings dwarfs the integration costs that are so

[34] American Wind Energy Association, Wind Fact Sheets: Statistics. Accessible at www.awea.org/faq/tutorial/wwt_statistics.html.
[35] Energy Information Administration: Electricity Sector, Electric Power Generation by Fuel Type 2004. Accessible at www.eia.doe.gov/fuelelectric.html.
[36] Using 2006 NYMEX forward prices for gas until 2012, followed by conservative estimate of $4/MMbtu thereafter. Assumes that firmed wind would be is the costs the equivalent of $4/MMbtu. Based on capital cost of $847/kW, and inclusive of EPACT 2005 PTC.

often raised as a barrier to higher levels of wind penetration. Given Awerbuch's observation that a 20% Renewable Portfolio Standard would optimize the generation mix with respect to fossil fuel, we are leaving an extraordinary amount of money on the table.