The Surprising Value of Wind Farms as Generating Capacity

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Abstract:

Wind power is intermittent and has low predictability. Consequently it would seem to be of little use for helping system operators with reliability. However reliability is a statistical property of the system, so the contribution of wind to reliability must be based on its affect on the probability that net load will exceed available capacity. To the extent wind is uncorrelated with load and a very small part of total generating capacity, this paper demonstrates that a wind farm with X megawatts of average output provides X megawatts of capacity value. As the fraction of power provided by wind increases, its capacity value decreases, but it remains significant up to surprisingly high levels of wind penetration.

Introduction

Current power systems have been largely designed to deal with traditional dispatchable fossil fuel plants [3]. Wind generators differ fundamentally from those, posing additional challenges not only on the technical side, but also in the economic and policy side. Uncertainty, forecasting limitations and the non-dispatchability of wind plants are the key differences between wind turbines and dispatchable generation. However, these are all properties of load, so none of the issues are new to engineers. In fact for this reason, wind power is more usefully thought of as negative load, than as generation. When viewed this way, the addition of wind reduces average load and consequently the need for dispatcable generation. However, while reducing average load it increases the unpredictability and variability of load relative to its average value.

Some will continue to be confused by the fact that the profile of a wind farm or wind turbine does not correlate perfectly with system load, and has a similar but distinctive probability distribution [5]. Other's will argue that wind is not negative load because its probability distribution has certain peculiar and problematic characteristics. However this is true for many types of loads that no one would every think of suggesting were not loads.

Two classic examples of peculiar loads are hair dryers and tea kettles. Both have low correlation with system load and both can be quite costly in terms of their need for load-following capacity—hair dryers in the United States, and tea kettles in England. Of course an endless list of commercial and industrial examples could also be given, not to mention air conditioning. The point is simply that most types of physical devices that constitute load are peculiar. The fact the wind generation is also peculiar, in no way indicates it is not one more load. For loads, being peculiar is normal. The only property of wind turbines that is genuinely different form the properties of devices we classify as loads is the they use a negative amount of power. So wind is negative load. Since

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subtraction is in no way problematic for numerical calculations, wind can be analyzed with all of the normal numerical techniques applied to load.

For low levels of wind penetration the dominate factor is the reduction in average load, however for high levels of wind penetration the degradation in the quality of net load—true load minus wind generation—becomes dominant. The basic affect behind this result is the sub-additivity of the standard deviations of uncorrelated random variables. Over short time periods, wind and load are almost entirely uncorrelated. Consequently, over such time scales, if load has a standard deviation of 10 and wind of 1, the standard deviation of net load is only 10.05 (variances are additive).

Treating wind as negative load is not simply a conceptual matter, but has practical consequences for calculating the impact of wind on power systems. Generally, engineers have methods of calculating the system needs for various load profiles. Because wind is simply negative load these techniques can be applied without modification to wind. The general procedure operates as follows.

Suppose $C(L)$ is the system cost or some physical system requirement that results from a particular load profile L. This could be an hourly or an annual load profile. If the output profile of a wind generator, wind farm or collection of wind farms over the same period is W, then the net load profile is $L - W$, and the cost of serving this net load is $C(L - W)$. The cost, or benefit (negative cost), of the wind generation alone is then simply

$$\text{System Cost of Wind Generation} = C(L - W) - C(L)$$

This simple formula is applied in this paper to the calculation of the capacity value of wind generation. In the case $C(L)$ is the method of determining the amount of dispatchable generation needed to hold involuntary load shedding of load profile L to a level of one event in ten years.

Wind's Capacity Value

Capacity requirements are set to handle peak loads, but when such a peak occurs, there is a fair chance the wind won't be blowing at all. With only a single wind farm this probability may well be in the 10 to 20 percent region. Since reliability requirements typically require the chance of involuntary load shedding to be closer to 1 in 10,000, some conclude that wind capacity has no "capacity value."

No capacity value means that the same amount of displaceable generation must be built regardless of the amount of installed wind capacity. In fact wind capacity does have capacity value. As the following discussion will show, for small amounts of wind capacity that capacity value is exactly equal to the average power that the wind generation will produce on peak. For example if a 100 MW wind farm produces 30 MW on average, and its output is uncorrelated with load, then it will have a capacity value of 30 MW—assuming that 100 MW is very small relative to peak-load.

As wind capacity increases, If the output of the turbines stays highly correlated, wind capacity value declines relative to the average delivered wind power. These results suggest several conclusions. There is considerable benefit to keeping wind generation widely separated to minimize correlation of power production. Reducing transmission congestion to integrate more wind-producing regions will increase the capacity value of wind. Market rules that allow wind to be treated as a regional resource rather than a local resource will also increase its capacity value, provided the necessary transmission is available.

Analysis

The capacity value of generation always depends on the statistical properties of the generators being valued, because all generation is subject to forced outages. Wind can be viewed as generation that experiences almost constant partial forced outages and not-infrequent complete forced outages. This property earns wind the title of an "intermittent" resource and dictates that extra attention be paid to the statistical properties of its outages.

But the real complexity of wind arises not only from it's own outage distribution but from the interaction of this distribution with the distribution of load and other system resources. Without wind, the system can be described simple by two power flows: load, L, and imports, M, plus total non-wind generating capacity, C. Capacity can be classified as available capacity, G, and generation forced out of service, F, with C = G + F. Involuntary load shedding occurs when:

$$L + F - M > C$$

Conceptually, forced outages play a role very similar to load, and imports play a role similar to negative load, so we will call $L + F - M$ augmented load. Since augmented load is always what matters for these capacity calculations, and since we have no separate data on L, F and M, from here on we will simply refer to load, L, although we will always mean augmented load.

Reliability and the Reliable Capacity Level, *C**

The capacity adequacy problem asks how much capacity is needed to prevent an unwanted amount of involuntary load-shedding due to a lack of total generation capacity. A difficult part of this problem is to define "unwanted." However, in the United States, it is customary to use a standard suggested some years ago by two engineers working for General Electric, a supplier of generation capacity. They decided that more than one load-shedding event in ten years would be unwanted.

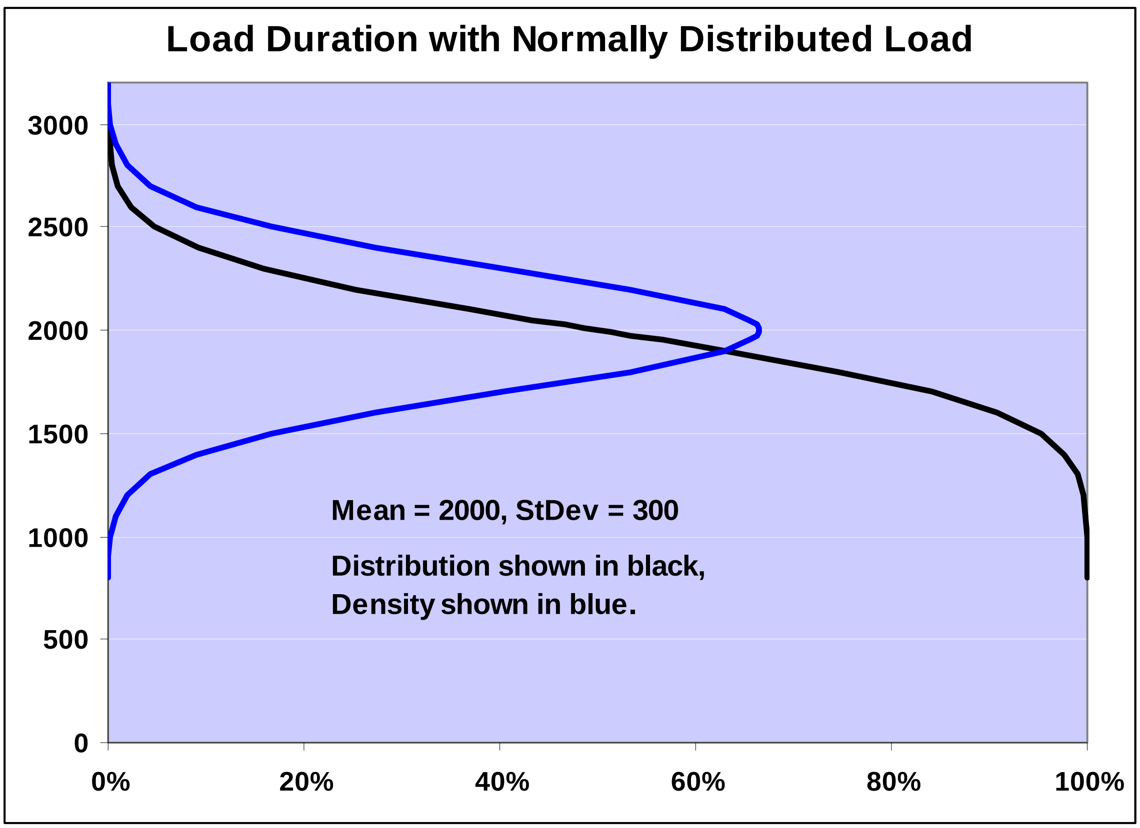
For our purposes the exact criterion is not important. A less stringent requirement might reduce total required capacity by a few percent, but this would make littler difference to the role of wind in providing the required capacity. Consequently we will use the traditional U.S. formulation. When interpreting the one-in-ten-year rule, the meaning of "one event" has caused confusion. Discussions with engineers at ISO New England reveal that a load-shedding event in that system would on average last three hours, and that they interpret the standard to mean one event in ten years, and not one full day in ten years. This allows a slightly different formulation of the fundamental reliability criterion:

$$\text{Prob}\,(L > C^*) = 3 / (10 \times 365 \times 24) = 1 / 29{,}200$$

This criterion defines the reliable capacity level, *C**, to be on which makes the probability that load is greater *C**, at a randomly chosen instant in time, less than 1 in 29,200. While it is possible that the presence of wind would alter the length of load-shedding events, it can easily be argued that Prob($L > C^*$) is a more fundamental approach to reliability than the frequency of events. After all, the length of the event should matter to consumers and using Prob($L > C^*$) captures this in a meaningful way. Hence, this criterion agrees with the standard 1-in-10 rule in ISO New England, and is a more sensible rule in general. It is also computationally more convenient for the following analysis.

A Simple Example without Wind

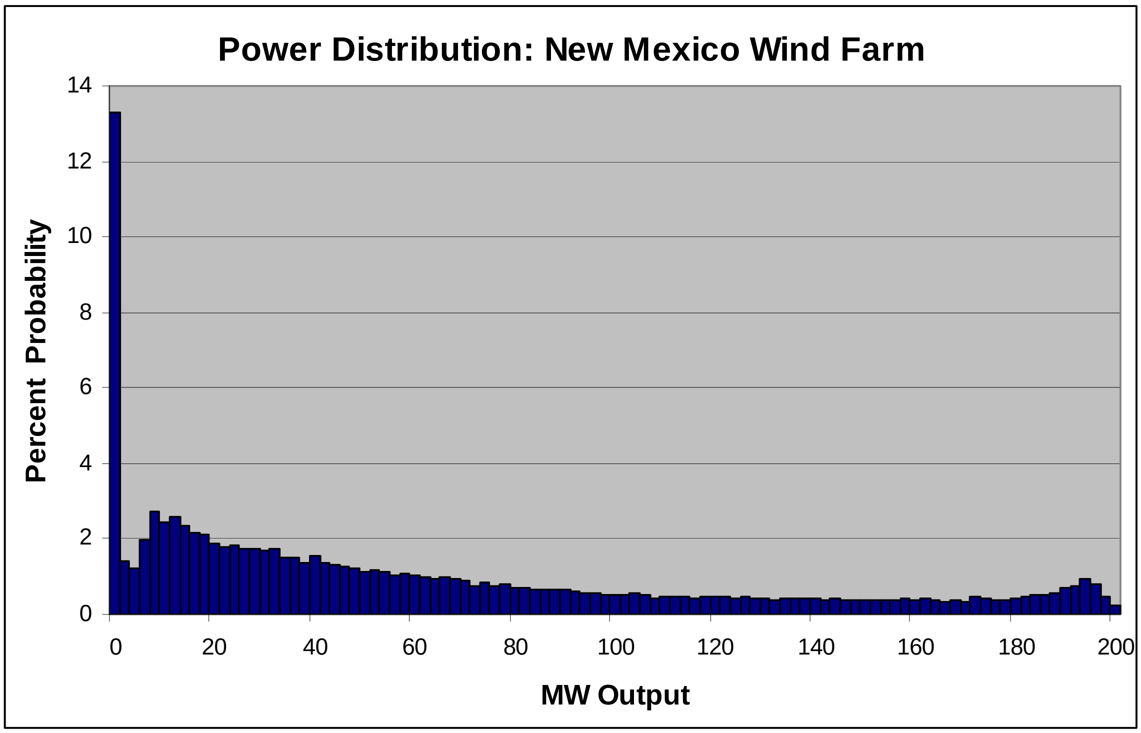
For this study, I have obtained concurrent load and wind data from a Balancing Authority in New Mexico. But to begin simply, suppose load is normally distributed with a mean of 2000 MW, and a standard deviation of 300 MW. This average is about 30% greater than the New Mexico load we have data on, but the shape is similar to their load-duration curve.



For normally distributed load, a probability of forced outage equal to 1 / 29,200 determines that the reliable level of capacity is 3.9815 standard deviations above the mean. For load with a mean of 2000 MW, and a standard deviation of 300, the reliable capacity level is 3194 MW. This will result in 3 hours of load shedding every 10 years on average.

The Capacity Value of Wind

The distribution of wind power from a wind farm is not at all normal, but the central limit theorem assures us that power drawn from a large number of statistically independent wind farms will be normally distributed. Unfortunately wind at two locations 100 km apart is still quite correlated. In fact, a separation of 1000 km may be needed to achieve near independence. For this reason, the largest relevant number of statistically independent wind farms may be somewhere around four. Which raises the question: Is four a large enough number to make total wind power from four independent farms nearly normal? To answer this, we will construct probability density functions for 1, 2, 3, 4 and 8 wind farms of the New-Mexican variety.



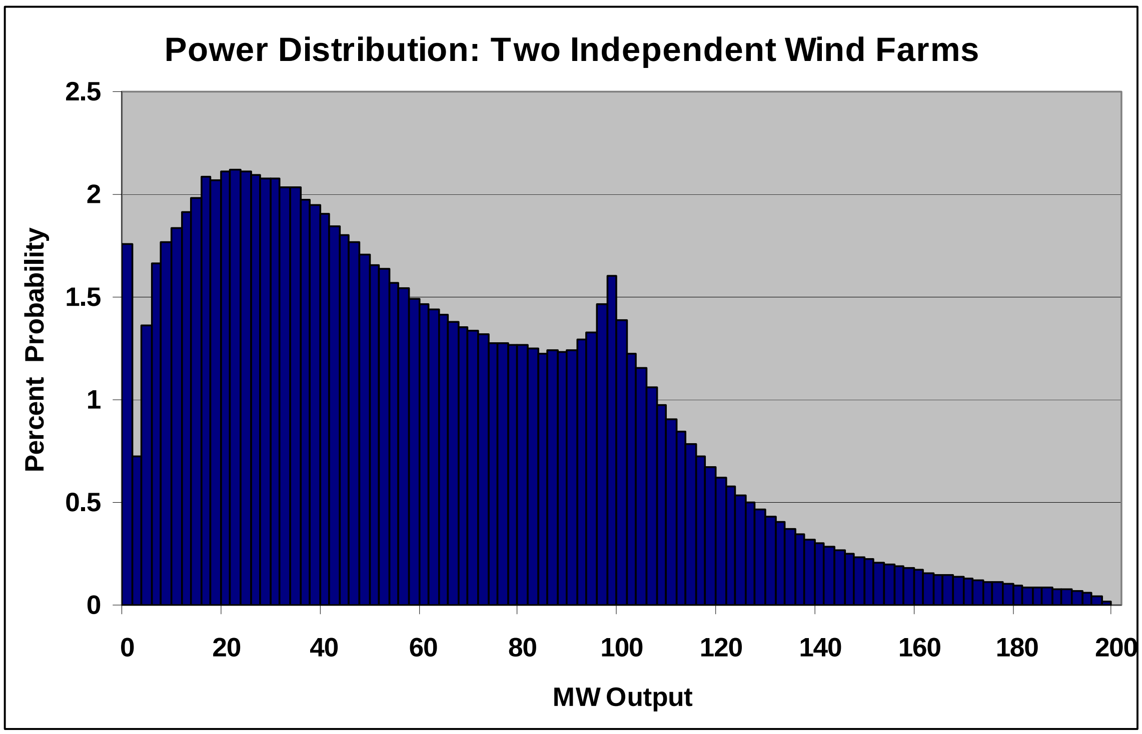
Note in the graph above that the wind farm has a probability of 13% of having zero output. In fact, over 12% of the time it has negative output. At these times, the wind-farms equipment is using more power than the farm is producing. The maximum output of this farm is 200 MW. The small peak just short of 200 MW is likely a combination of specific controls to limit output just below the maximum level for high wind levels, and the effect of individual units shutting down under high wind conditions. For example, as the wind speed passes this cut-off level, output will peak and then decline for the farm as a whole, as turbines are shut down. Hence output just short of maximum can be achieved at wind speeds just below and just above the maximum.

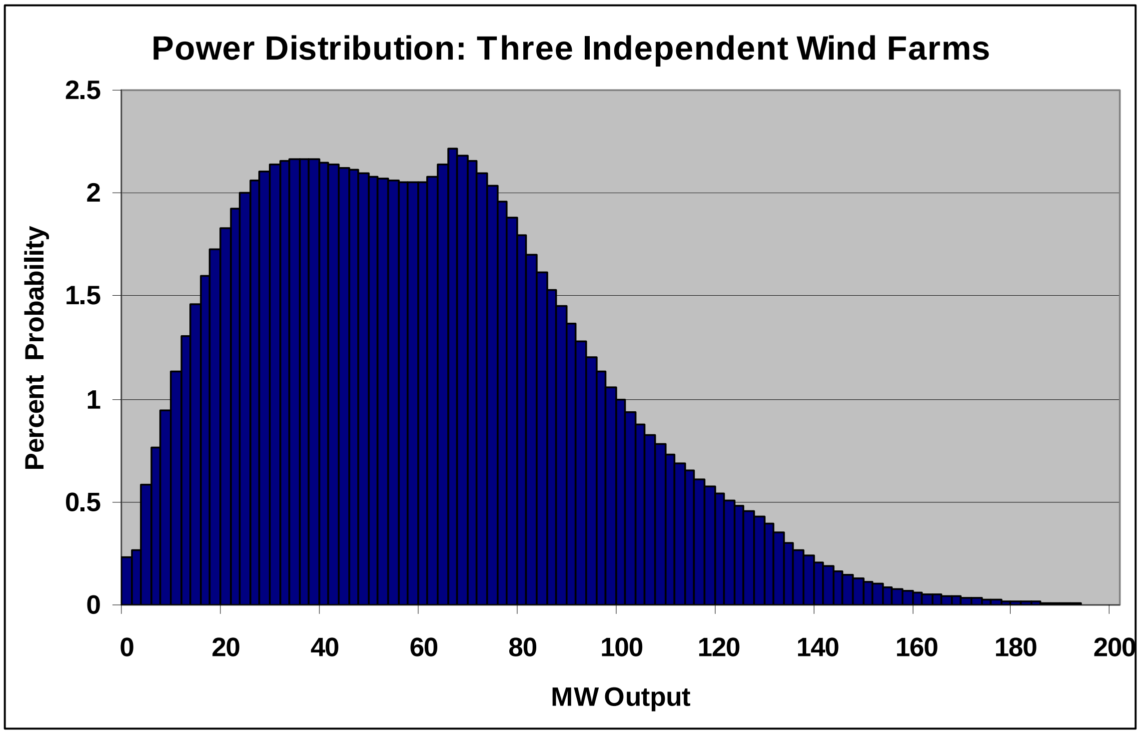
From a reliability perspective, having zero output—a full forced outage—13% of the time appears to be the most problematic aspect of this power distribution. It might even seem that this would dictate a zero capacity value for wind, since reliability requires such a small chance of a capacity shortage. Fortunately, as will be shown, statistics do not confirm this view.

The next graph shows the total output of two wind farms with power distributions identical to the New Mexican wind farm. These farms are assumed to be located far enough apart that their outputs are statistically independent—uncorrelated. The density function of the sum of two independent random variable is given by the convolution of their two densities. The convolution of densities f(x) and g(y) is given by:

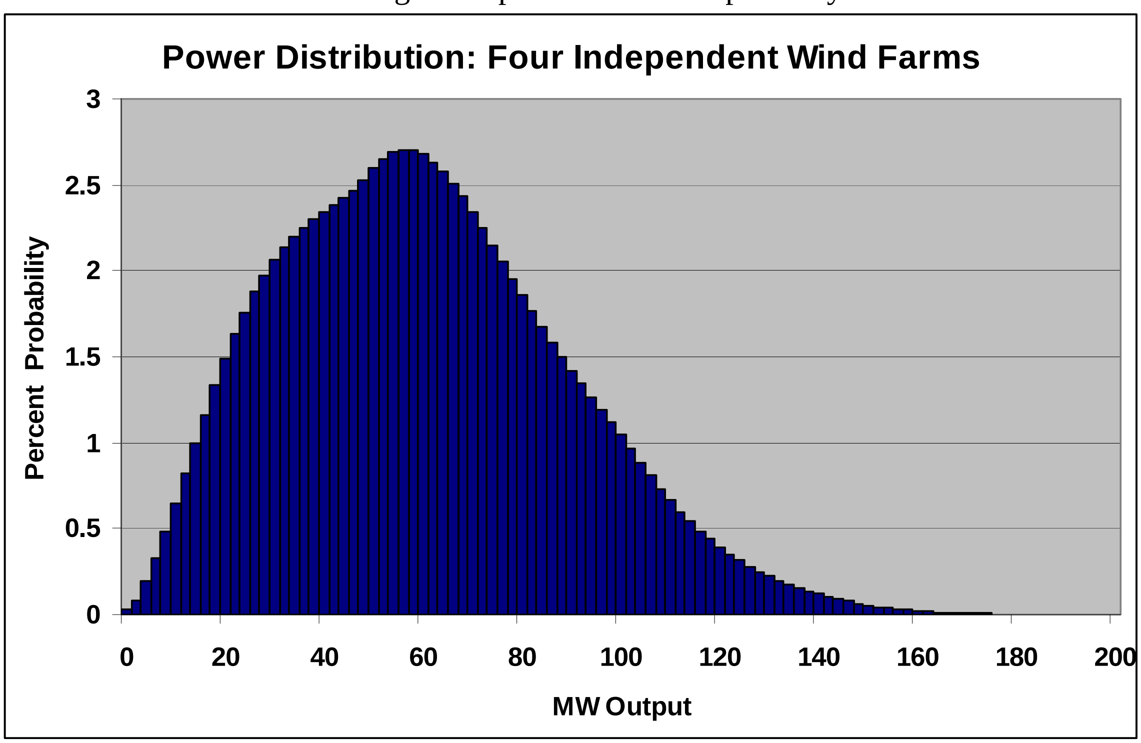
$$h(z) = \int f(x) \cdot g(z - x) dx$$

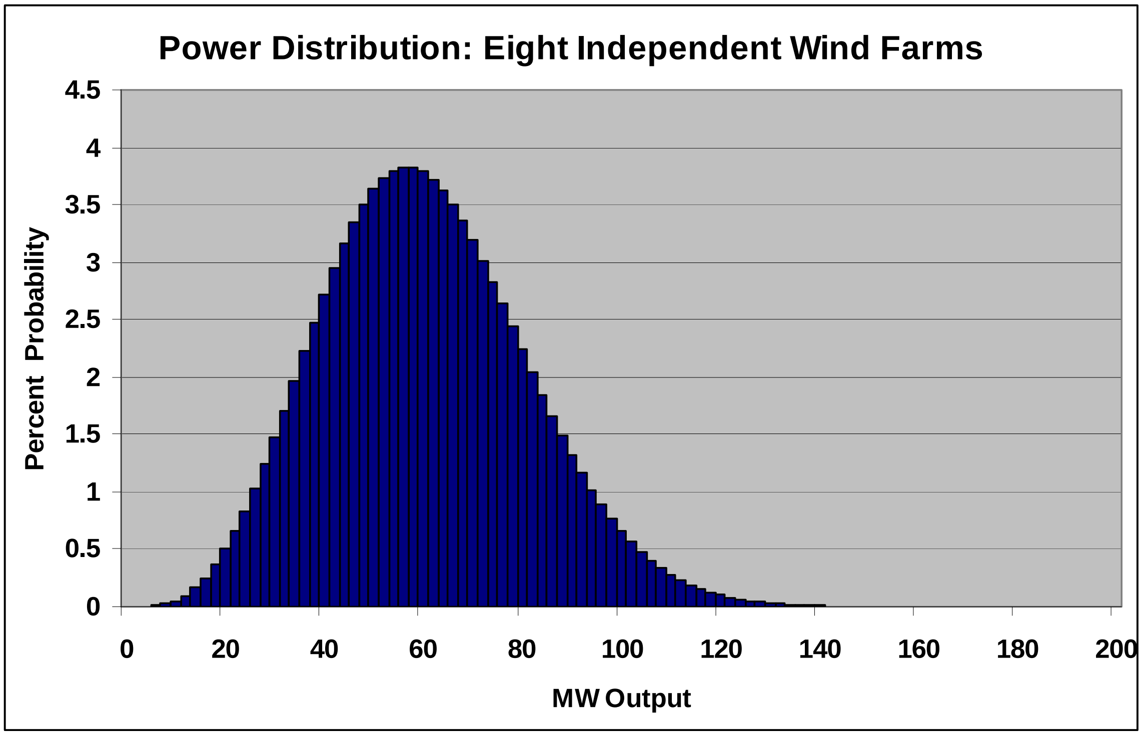
where z is the sum of the two independent variables. The figure below was calculated by convolving the New-Mexican wind-farm power density with itself.





The third graph in the power density sequence represents the sum of the power outputs from three independent wind farms identical to the original, and the two graphs below show the results for four and eight independent farms respectively.





From these graphs we conclude the four independent farms gives a roughly normal power distribution and the output of eight independent farms is very nearly normal.

Note that as more independent power outputs are added, the ratio of the standard deviation to the mean output declines. With four farms it is exactly half as large as with only one. Unfortunately, the actual wind farm has a Std Dev / mean ration of 97.6%, its standard deviation being 58 MW and its mean output 59.5 MW.

Because of the large relative variance of wind, even if eight independent farms were possible, wind is far from an ideal form of capacity. To take the next step in assessing the capacity value of wind, we model it as normally distributed but having the same variance-to-mean ratio as four independent wind farms. This step is taken because it provides a transparent approach to the problem while retaining some realism. Subsequent calculations will introduce increasing levels of realism.

Table 1. Wind Capacity Values for Normally Distributed Wind and Load
Load = 2000 +/– 300 MW. Wind has Std. Dev. / Mean = 0.5

Wind as % of Load	Average Wind Power	Average (Load – Wind)	Std Dev(.) (Wind) || (Net Load)	Wind's Capacity Value	Cap. Value as % of Total Cap.	Incremental Cap. Value % of Power
0%	0	2000	0 || 300	0	- -	- -
0.6%	12.5	1988	6 || 300	12	0.4%	98%
1.3%	25	1975	12.5 || 300	24	0.8%	94%
2.5%	50	1950	25 || 301	46	1.4%	88%
5%	100	1900	50 || 304	84	2.6%	75%
10%	200	1800	100 || 316	135	4.2%	52%
20%*	400	1600	200 || 361	159	5.0%	12%

All values, other than percentages, are in MW. Required non-wind capacity = 3194 MW.
Wind's capacity value is given a percent of 3194 MW.
* Suspect values due to negative wind output from normally distributed wind power.

Table 1 shows the capacity values for wind power that is normally distributed much like the output of four independent wind farms. The ratio of standard deviation to mean is assumed to be 50% instead of 49% as it is with the four independent farms. The assumption of normality mainly causes problems when wind output is very large. In this case the normal distribution implies significant, but impossible, negative wind-power values. For this reason the example stops at 20% wind penetration.

Capacity value is best understood relative to the mean value of wind power. If wind turbines were 100% reliable (constant power) then their capacity value would exactly equal their mean power output. Because they are intermittent, their capacity value is less. But notice that for a small wind farm of 12.5 MW, or 0.6% of load, the capacity value of intermittent wind from four uncorrelated wind farms appears to be about 98% as great as from generators that are 100% reliable and supply the same power. This is true in spite of the output, as shown above, being highly unpredictable. This is worth understanding, as the principle involved underlies all of the capacity-value results presented here.

The calculation of wind capacity values, with the technique used here, assumes that wind power is uncorrelated with load. This is not true because of diurnal and seasonal variations in load and wind. For example, wind power is often greater at night load is low. Wind power may also be less in the summer when load is greater. At the end of this section we will return to this problem and show how to take account of it. Until that point, we will assume wind and load are uncorrelated.

Wind power can be treated as negative load for the purpose of reliability calculations. Net load is simply load minus wind power, or load plus the negative of wind power. Viewing it this way makes it obvious that net load is the sum of two independent normal random variables. In the present example load has mean 2000 and the low-wind-power case, shown in the first line of the table, has mean 12.5 MW. That brings the mean of net load to 1988.5 MW. For independent variables, variances are additive, so net load has a variance of $300^2 + (12.5/2)^2$, because wind has a standard deviation that is half its mean. The standard deviation of net load is just the square root of its variance or 300.07 MW.

As can be seen the variability of wind contributes almost nothing to the variability of net load. Since adding wind shifts the load duration curve down by the average wind power output, and steepens it only by the increase in standard deviation which is negligible, peak load is reduced essentially by the full average wind power. So for small amounts of when, which increase the standard deviation of net load negligibly, average wind power has full capacity value.

As shown in Table 1, even wind farms that supply 20% of the power needs of load make a substantial contribution to capacity, although the present estimate indicates they make only 40% (159 MW / 400 MW) as much contribution as a perfectly constant source of power.

Capacity Value with Normal Load and Real Wind Power

The key problem with the first example is the assumption that wind power is normally distributed. This seriously distorts the analysis for large wind farms, and it assumes a more diverse wind-power distribution that is often the case. The next step is to replace the assumption of normally distributed wind with the actually wind-distribution from the New-Mexico wind farm. The data used for the histograms presented above is 10-minute interval data for the year 2005 from the Taiban Mesa wind power plant in New Mexico. While 2005 may not have been an entirely representative year, we are not concerned with this particular wind farm but with wind farms in general. Consequently there is no reason to think more data on this particular wind farm would be helpful. As we proceed it will appear that our results are quite robust to changes in the distribution, so the data set is probably completely adequate for the present exercise.

The first question that comes to mind is how much capacity value does the New Mexico wind farm have. This question can be varied in two ways. First what if the wind farm were scaled up or down by adding or subtracting turbines in the same area? This would increase or decrease average output and its standard deviation proportionally. In fact the shape of the wind-power density function would not change. Alternatively we could ask about a set of several independent wind farms. In this dimension we will choose only one alternative, which is four uncorrelated farms. The results are summarized in the table below.

Table 2. Wind Capacity Values for Normally Distributed Load
Load = 2000 +/– 300 MW.

Wind as % of Load	Average Wind Power	Average (Load – Wind)	Std Dev(.) (Wind) || (Net Load)	Wind's Capacity Value	Cap. Value as % of Total Cap.	Incremental Cap. Value % of Power
Wind Power from a Single Wind Farm						
0.6%	12.5	1988	12 || 300	11.6	0.4%	93%
1.3%	25	1975	24 || 301	21.4	0.7%	75%
2.5%	50	1950	49 || 304	37.2	1.2%	63%
5%	100	1900	98 || 315	58.6	1.8%	43%
10%	200	1800	195 || 358	83.4	2.6%	25%
20%	400	1600	391 || 493	108.5	3.4%	13%
40%	800	1200	781 || 837	129.4	4.1%	5%
80%	1600	400	1562 || 1591	142.6	4.5%	2%
Wind Power from 4 uncorrelated Wind Farms						
0.6%	12.5	1988	6 || 300	12.2	0.4%	98%
1.3%	25	1975	12 || 300	24	0.8%	94%
2.5%	50	1950	24 || 301	46.2	1.4%	89%
5%	100	1900	49 || 304	85.8	2.7%	79%
10%	200	1800	98 || 315	149.3	4.7%	64%
20%	400	1600	195 || 358	237.4	7.4%	44%
40%	800	1200	391 || 493	344.8	10.8%	27%
80%	1600	400	781 || 837	464.1	14.5%	15%
All values, other than percentages, are in MW. Required non-wind capacity = 3194 MW. Wind's capacity value is given a percent of 3194 MW.						

First notice that the results for four uncorrelated wind farms are more favorable to wind than the results in Table 1. The difference is primarily due to actual wind farms never having large negative outputs—which would reduce reliability. Table 1 assumed normally distributed wind power, and consequently some negative power outputs. The improvement can be seen for wind producing 20% of required power. In this case the incremental capacity value of wind is 44% of average output instead of 12%. Incremental capacity value means the increase in capacity value from the row to row in the table, divided by the increases in average wind power from row to row.

Next compare the results for a single wind farm with Table 1. For 10% output, a single farm would get only 25% incremental capacity credit, instead of 52% in Table 1. This demonstrates the importance of having a transmission grid that is strong enough to integrate uncorrelated wind areas in order to capture the significant capacity value of wind.

Capacity Value with Real Load and Real Wind Power

So far we have assumed that load is normally distributed. This assumption seems generally plausible since load, or as noted above, augmented load, is composed of may small loads, and losses of generation, and many of these are uncorrelated. Again the central limit theorem gives us reason to hope the sum of these is normally distributed.

Unfortunately, although we have two years of load data at ten-minute intervals, this provides little ability to estimate the relevant part of the load distribution. Not only are we lacking data on generation outages and imports, but two years of data is simply far too little. The events of interest occur on average once every ten years, so two years of data provides us with approximately one-fifth of a data point—too small a data set for robust statistics. What can be done?

Fortunately this problem is faced annually by most control areas. To procure a reliable level of capacity they must estimate what level will reduce forced outages to roughly one in every ten years. To do this, they execute massive calculations involving outage probabilities for all of their generators as will as for importing transmission lines. They also make use of years of load data. While working on the design of ISO New England's capacity market, one of the authors acquired the Loss of Load Expectation (LOLE) function used by ISO-NE for its reliability calculations.

This function gives LOLE as a function of capacity, C, and the capacity level, C^* that provides one-event-in-ten-year reliability. The expectation is defined in events per decade, so that LOLE = 1, means one event in 10 years. The equation contains one crucial coefficient, which was 32.23161, however it had been slightly less than 32 the prior year, so some of the digits would seem to be unnecessary. We will simply use 32. We have tested, and found that using 31 or 33 makes very little difference, though higher values are unfavorable to load. The formula for LOLE is the following.

$$\text{LOLE} = \exp(\, 32(\, 1 - C/C^* \,)\,)$$

When $C = C^*$, LOLE is one as promised. When there is 5% to little capacity, LOLE = 5.0 events per decade—five times the target value. When $C/C^* = 105\%$, then of course, LOLE is one fifth the target value.

If LOLE equals one, and the expected length of an event is three hours, as discussed above, then the probability of finding $L > C$ is 1/29,200. If LOLE increases by, say, 5 times, then so does the probability of $L > C$, hence the above formula can be converted to the probability that $L > C$, and the result is as follows:

$$\text{Prob}(\, L > C \,) \;=\; (1 \,/\, 29{,}200) \times \exp(\, 32(\, 1 - C/C^* \,)\,)$$

This formula defines the tail of the distribution function for load, or equivalently the peak of the load-distribution curve. To convert it to a probability distribution function, $F(x)$, for random variable L, define:

$$F(x) = P(L < x) = 1 - (1/29{,}200) \times \exp(32(1 - x / C^*))$$

The density function for load is then f(x) given by:

$$f(x) = dF(x)/dx = (32/C^*)(1/29{,}200) \times \exp(32(1 - x / C^*))$$

The probability density for load is only good for the high load levels, the peak of the load distribution curve, but that is sufficient. Reliability involves only that peak. From the New Mexico data, we have already constructed the density for wind power, so let g(w) be the density of negative wind power, w, since we interpret wind as negative load. Net load, z, is then:

$$z = x + w,$$

and the density of net load, z , is the convolution of f(.) and g(.):

$$h(z) = \int_{-\infty}^{+\infty} f(x) g(z - x) dx$$

When this is carried out, the high values of net load, those of interest, have their probability density defined by the interaction of the reversed density of negative wind, and the density of load. The reversal is from the minus sign in the convolution integral. Reversing the negative wind density gives again the positive wind power density which goes only slightly below zero. As the convolute proceeds to lower z values, the left end of the reversed negative wind density (the zero-power end) slides left but does not run into the undefined region of the load density until well after h(z) exceeds 1/29,200, which is the point that gives the reliable level of capacity. Hence the lack of load data for low values of load causes no difficulty.

Using the LOLE function from ISO-NE, scaled down to a system with 2000 MW average load, along with the wind farm data produces Table 3.

Table 3. Wind Capacity Values for ISO-NE's Loss-of-Load Expectation Function
Load = 2000 +/– 300 MW.

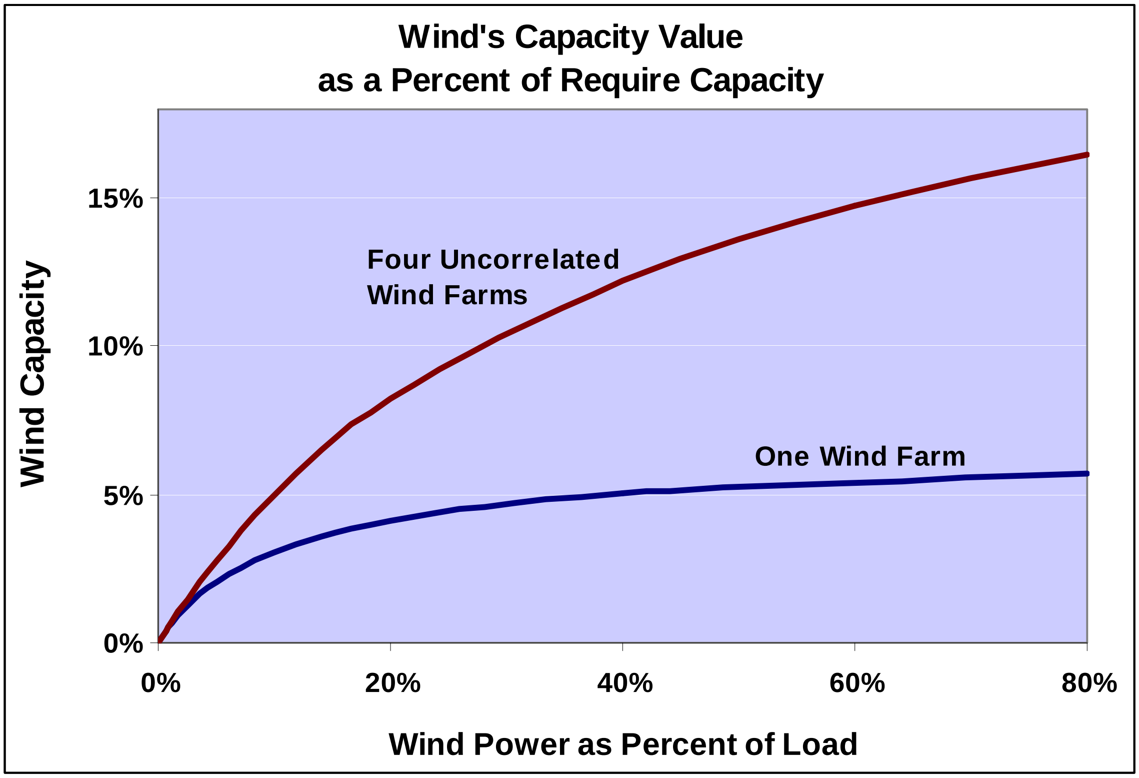
Wind as % of Load	Average Wind Power	Average (Load – Wind)	Std Dev(.) (Wind) || (Net Load)	Wind's Capacity Value	Cap. Value as % of Total Cap.	Incremental Cap. Value % of Power
Wind Power from a Single Wind Farm						
0.6%	12.5	1988	12 || 300	11.8	0.4%	94.4%
1.3%	25	1975	24 || 301	22.2	0.7%	83.2%
2.5%	50	1950	49 || 304	39.9	1.2%	70.8%
5%	100	1900	98 || 316	65.7	2.1%	51.6%
10%	200	1800	195 || 358	97.7	3.1%	32.0%
20%	400	1600	391 || 493	131.7	4.1%	17.0%
40%	800	1200	781 || 837	162	5.1%	7.6%
80%	1600	400	1562 || 1591	183.2	5.7%	2.7%
Wind Power from 4 uncorrelated Wind Farms						
0.6%	12.5	1988	6 || 300	12.3	0.4%	98.4%
1.3%	25	1975	12 || 300	24.3	0.8%	96.0%
2.5%	50	1950	24 || 301	47.1	1.5%	91.2%
5%	100	1900	49 || 304	89	2.8%	83.8%
10%	200	1800	98 || 316	159.5	5.0%	70.5%
20%	400	1600	195 || 358	263	8.2%	51.8%
40%	800	1200	391 || 493	390.9	12.2%	32.0%
80%	1600	400	781 || 837	526.9	16.5%	17.0%
All values, other than percentages, are in MW. Required non-wind capacity = 3194 MW. Wind's capacity value is given a percent of 3194 MW.						

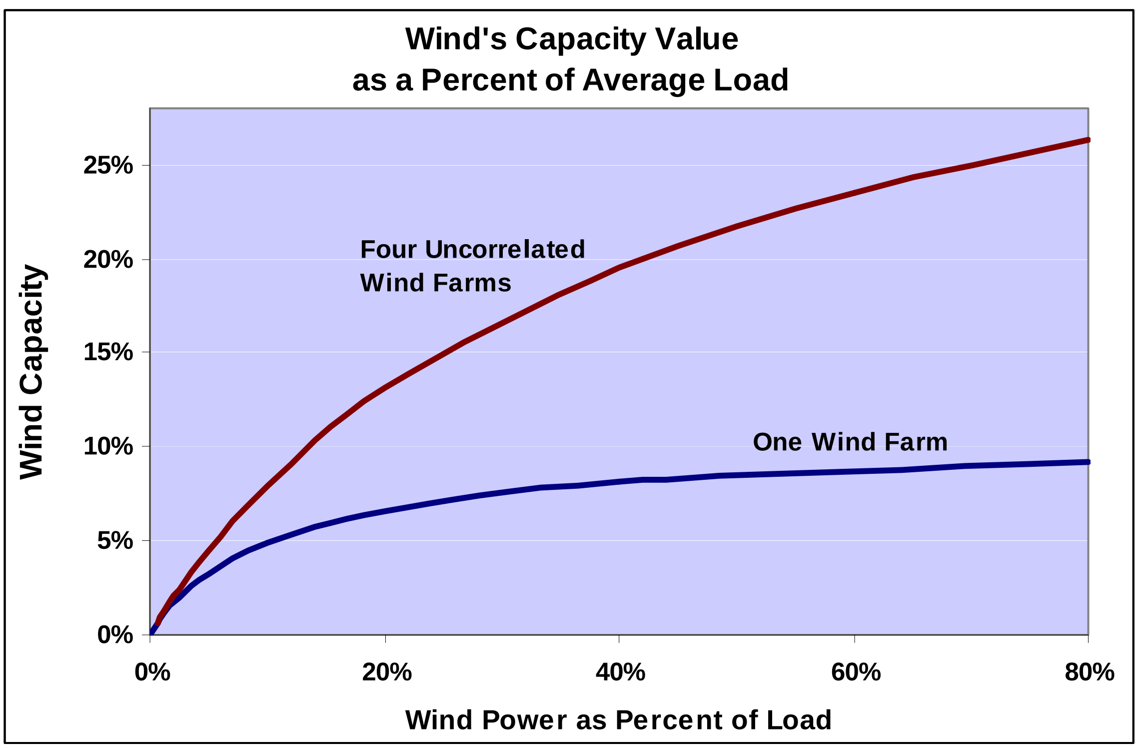
Only the last three columns in Table 3 should differ from Table 2. And they do, but only slightly. For example if wind supplies 80% as much power as required by load, it's capacity value would be 4.5% or 14.5% depending on the diversity of supply, according to Table 2. According to Table 3, it would be 5.7% or 16.5%. The difference is small and it occurs for a value of wind that is too extreme to be of much interest.

The point is that the normal-load assumption and the ISO-NE engineering calculations agree more closely than the likely accuracy of either calculation. This gives us confidence that the general story told by these calculations in qualitatively correct, and quantitatively reasonable.

Summary of Capacity Results for Wind that Is Independent of Load

The main results of these calculations are summarized in the following two figures. One shows wind capacity as a percentage of total required capacity, and in the other as a percentage of average load.





Gas turbines typically provide much greater capacity than their average power output. In fact their capacity value has nothing to do with their average power. If wind capacity is thought of in this framework, then its capacity value is quite disappointing. But an uncontrollable resource, in other words an intermittent resource, is limited to providing as much capacity as its average power output, unless by sheer chance its output correlates with peak load.

The average power output of wind is therefore a more useful benchmark for discussing its capacity value. The results of this investigation indicate that wind that is uncorrelated with load will achieve nearly benchmark capacity levels for small output levels. In fact if the wind power is from four uncorrelated locations, wind power will provide over half the benchmark capacity value up to a wind penetration level of 30%.

Marginal wind-capacity value. Unfortunately, to send the proper investment signal, resources should be paid their marginal value and that can be considerably less than their average value. The right-most column in the tables above shows incremental value which is close to marginal value. For example, from Table 3, for four wind farms, the incremental value from 10% to 20% wind penetration is 51.8%, while from 20% to 40% it is 32%. The marginal value at 20% penetration would then be about 40%. This means that ever 10 MW of average wind power, should be credited with 4 MW of capacity.

This holds not just for the “marginal” wind turbine, which some might think is the last wind turbine to be built, but for every wind turbine. Once wind capacity reaches 20% every wind turbine gets credit for only 40% of benchmark capacity. And that is with a mix of wind farms equivalent to four uncorrelated wind farms providing power.

Correlation of Wind and Load

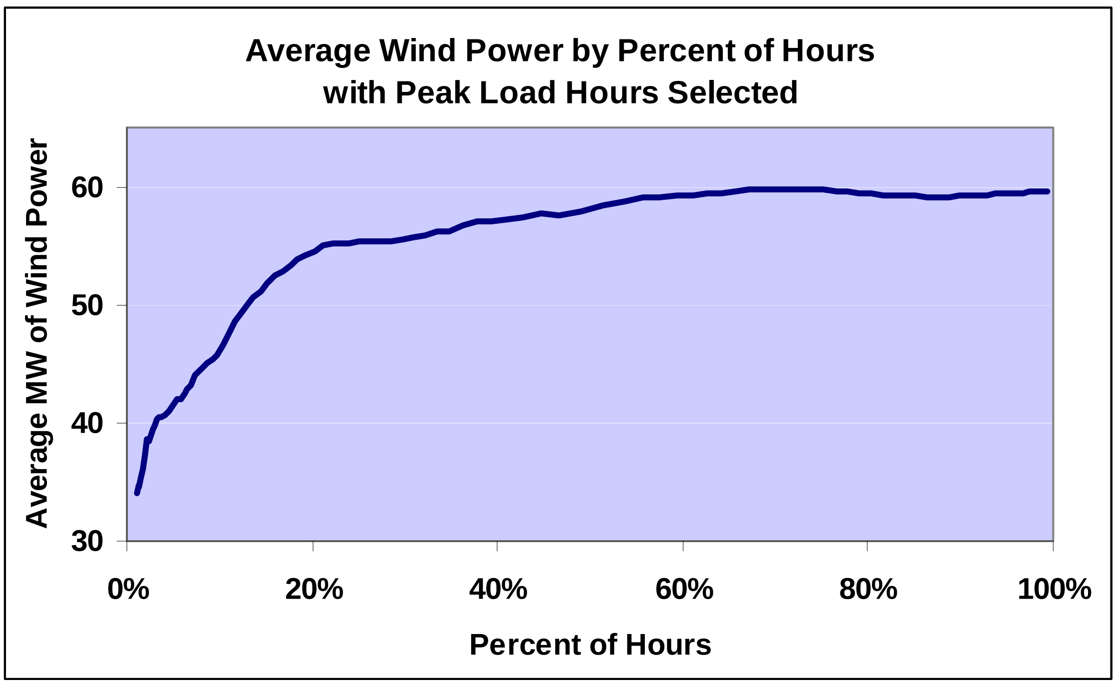
At least in New Mexico, when load peaks, the wind tends not to blow. This is likely due to both diurnal and seasonal effects. For the 1% of hours that cover the highest load levels, average wind-power is 34 MW compared with 59.5 MW for all hours (out of a wind capacity of 200 MW). The ratio of mean to standard deviation is still about 1-to-1, but the percent of time at zero load increases slightly from about 13% to about 17%. The story is not much different for the top 2% of hours.

Notice, that for this purpose we do not use the correlation of wind with load. That statistic can be dominated by what happens during the 80% of annual hours during which there is almost no chance of a peak load event. For example suppose, contrary to the case in New Mexico, that the wind was always strong in the late afternoon, and week at night, except for a very few, very hot days. On these days, the wind stopped and the temperature, and consequently load, soared in afternoon. The correlation of wind and load would be highly positive, yet wind’s value during peak load conditions would be low. This demonstrates calculating a correlation over all times, is not a useful approach.

The correct approach is to calculate a weighted-average wind-power output, where the weights are the probability of a peak-load event. We have approximated this by simply averaging wind power over the highest-load hours.

We are not sure how well the peak load hours in one year represent the likely times during which find load-shedding events would occur. For example, occasionally a summer peaking system will have a capacity shortage during spring maintenance and a surprising spring heat wave. In another case, the ISO-NE experienced a capacity shortage during the coldest day of the winter because of natural gas shortages and equipment outages. Both examples have to do with augmented load, and lie outside the reach of our conventional load data.

In spite of these questions it seems likely that the capacity value of the particular wind farm studied here, would be reduced 30 to 50% because the wind tends not to be strong during peak-load conditions. We believe this problem is to some extent generic, but have not looked into that question. In the graph below, average wind capacity fall from about 60 MW when all hours are considered, to about 34 MW during the peak 1% or 2% of hours.



Conclusions

Wind power has capacity value. A single wind plant in isolation will not produce power all the time, and its capacity value, in isolation, depends on its correlation to load. Often it is believed to have little value for capacity. However, because it is very small compared with load, if it is uncorrelated with load, it will have a capacity value equal to its average power output. Our analysis concretely demonstrates that the combined generation from multiple independent plants can offer significant capacity value, even though characteristics of the individual plants include times of zero output. Furthermore this analysis strongly suggests that the unit's capacity value should be defined in terms of the average output, and not the nameplate rating.

As total wind-power output increases relative to system load, the marginal contribution of wind power to system capacity decreases. But as the outputs from the mix of wind turbines becomes less correlated, their contribution to system capacity increases.

These results suggest several conclusions. There is considerable benefit to keeping wind generation widely separated to minimize correlations of power production between wind farms. Reducing transmission congestion to integrate more wind-producing regions will reduce correlation and increase the capacity value of wind. Market rules that allow wind to be treated as a regional resource rather than a local resource will also increase its capacity value provided the necessary transmission is available.

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